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Peer Effects in Landowner Participation: Evidence from a Forest Incentive Program

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May 16, 2024

Abstract

Identifying landowners' social interactions helps garner a better understanding of the determinants of their participation decision in an incentive-based program for conserving private lands. However, little is known in the literature about such peer effects among neighboring landowners. This study uses contract data from a forest incentive program implemented in a Japanese mountainous area with more than 200 small local communities to estimate peer effects on individual participation. We identify peer effects using a binary choice model with social interactions, in which landowners are assumed to form heterogeneous expectations of community members' participation. The results reveal that their peers' participation significantly increases the likelihood of individual participation, suggesting that peer effects are relevant for conservation policy design. Using the results, we demonstrate how including peer effects in the analysis improves policy predictions in estimating the impact of interventions and understanding the spatial configuration of participating land.

Keywords: social interactions; rational expectation equilibrium; local communities; private land conservation

JEL Codes: D91; Q15; Q23; Q24

Editorial Summary: Peer effects among neighbors are a significant determinant of landowner participation in a forest incentive program, and incorporating social interactions in the analysis improves policy predictions.

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1 Introduction

Peer behavior shapes individual decision-making in a wide range of applications, including school performance (Sacerdote, 2011), juvenile bad behavior (Case and Katz, 1991; Gaviria and Raphael, 2001; Lundborg, 2006), group lending (Li et al., 2013), and working productivity (Herbst and Mas, 2015; Ashraf and Bandiera, 2018). Peer effects have also been found in individual participation in government social programs such as welfare programs (Bertrand et al., 2000), retirement plans (Duflo and Saez, 2002, 2003), disability pensions (Rege et al., 2012), and paternity leave (Dahl et al., 2014). Specifically, Dahl et al. (2014) found that participation is influenced by peer participation and that these effects spill over within peer groups. However, little attention has been paid to peer effects in landowner participation in agri-environment schemes, albeit identifying peer effects helps better understand non-pecuniary incentives in their participation decision.

Policymakers today widely use incentive-based schemes to facilitate the provision of environmental services by private landowners (Hanley et al., 2012). Participants receive financial compensation from the government for putting their land aside for reserves or adopting environment-friendly practices on their land. Policymakers are eager to improve overall participation under tight budget constraints. Despite many efforts that have been made to understand what drives participation in such schemes (see, e.g., Mitani and Lindhjem, 2022), little is known about non-pecuniary incentives in landowner participation decisions (Palm-Forster et al., 2019). Peer effects, if existing, work as non-pecuniary incentives since one's participation affects peers' participation through social interactions. If the effects spill over into a group of landowners, an intervention that influences a small portion of them will impact overall participation without relying on monetary incentives. However, the impact can go either way. That is, peer effects can discourage participation if one expects their peers to decline their participation. As a result, changes in participation costs induced by exogenous shocks, such as policy interventions, can lead to positive or negative impacts on participation, which then spill over into peer groups and influence overall participation (Moffitt, 2001; Dahl et al., 2014). Thus, it will be essential for efficient policy design to understand how peer effects influence the direction and magnitude of the impacts of such exogenous shocks on participation. To incorporate peer effects into policy designs, policymakers must (1) identify whether peer effects exist and (2) understand how peer effects influence policy predictions.

However, such evidence has never been presented in the literature on landowner participation in incentive-based schemes. This lack of empirical evidence is in part due to the difficulty in identifying peer effects. A major challenge is defining the appropriate reference groups within which landowners interact. Observational data rarely provide information that helps determine reference groups. Nonetheless, using a reference group that does not capture true interactions would lead to a biased estimate of peer effects. Even if the actual reference group is identified, the endogenous formation of groups (that is, the selection into groups) could introduce selection bias in the estimate of peer effects (Moffitt, 2001).[1] Individuals in an identical reference group could behave similarly because people with similar preferences tend to belong to the same group. Another well-known challenge is dealing with the simultaneity of behavior, which is also referred to as a reflection problem.[2] Simultaneity means that peer behavior affects individual behavior while their behavior simultaneously affects their peers' behavior, too (Manski, 1993, 2000). For binary choices such as participation, Manski's reflection problem is resolved by using a nonlinear specification (Brock and Durlauf, 2001). However, simultaneity creates a multiple equilibria problem in binary frameworks, which makes a model incoherent without dealing with multiplicity, resulting in an inconsistent estimator of peer effects (Tamer, 2003). The multiple equilibria problem makes it challenging to pin down a unique likelihood function (Krauth, 2006; Soetevent and Kooreman, 2007). Identification of peer effects in binary frameworks requires handling these two inherent problems: selection (i.e., endogenous group formation) and simultaneity (i.e., model incoherency).

In this study, we estimate peer effects on landowner participation in a forest incentive program operated in a rural Japanese area to promote forest conservation. We constructed a unique dataset consisting of contract information on non-industrial private forest (NIPF) owners obtained from census data provided by a local forest agency and their characteristics collected through a survey. Census data also inform us about the membership of local communities. In this study, we define these local communities as reference groups. The local community would be a valid reference group, considering that the landowners interact with each other daily within the community (Mitani, 2022). Such interactions have historically contributed to the successful management of commons (Ostrom, 1990; Rustagi et al., 2010; Kosfeld and Rustagi, 2015) and the adoption of new agricultural technology (Foster and Rosenzweig, 1995). The problem of endogenous group formation would be negligible in the current context because most landowners were born and grew up in their communities (Mitani, 2022). Thus, these landowners did not self-select into their community. We use

[1]Another type of selection issue discussed in the literature is self-selection into a payment for ecosystem service program in developing countries (Jack and Jayachandran, 2019). This type of self-selection is not a problem for the identification of peer effects in the present paper. Rather, we contribute to this literature by investigating the determinants of participation behaviors.

[2]The reflection problem is originally discussed as an identification problem that arises from the simultaneity in linear specifications (Manski, 1993). On the other hand, simultaneity is discussed as a cause of multiple equilibria in binary frameworks, in which Manski's reflection problem is mitigated by using a nonlinear specification (Brock and Durlauf, 2001).

this unique dataset to estimate a binary choice model with social interactions, in which landowners are assumed to form rational expectations about their peers' participation (Lee et al., 2014). This model enables us to resolve the simultaneity (reflection) problem by introducing nonlinearity between observable characteristics and expectations regarding peers' participation. A likelihood function is pinned down as long as social interaction effects are moderate. Therefore, together with the identification of a reference group, we obtain a consistent estimator of peer effects. We use the resulting estimates to demonstrate how peer effects influence the predicted probability of participation. We compare predictions based on our model that includes peer effects with those based on conventional analysis of landowner participation that ignores peer effects.

We find positive and significant peer effects on landowner participation that are robust to the model specifications. A naïve calculation of marginal effects, assuming that expectations are given exogenously, shows that a 10% increment in expected participation of community members increases the likelihood of participation by 3.6% on average. The existence of peer effects indicates that changes in one's likelihood of participation spill over within the community by changing community members' expectations. For example, a marginal reduction in a landowner's opportunity cost enhances their participation, subsequently increasing their peers' participation through social interactions. The net effect of this marginal reduction in the opportunity cost is 77.4% higher than the impact estimated by a conventional model that overlooks the peer effects.

Our results also suggest that excluding social interactions diminishes the precision of the predictions. Examining the consequences of overlooking the peer effects on the predictions reveals the following. First, the predicted rate of participation computed by varying opportunity or transaction costs becomes either overestimated or underestimated, depending on whether the simulated costs are above or below their observed mean. The deviation becomes substantial due to the feedback effects when an intervention significantly influences the landowner's cost characteristics. This will be especially relevant when policymakers want to know the impact of an intervention to enhance participation. Second, the predicted average participation at the community level is less varied when we overlook peer effects. The predicted average participation is underestimated in communities with a relatively high participation rate, whereas it is overestimated in communities with a relatively low participation rate. This implies that the spatial configuration of the participating land will be misunderstood because social interactions among neighboring landowners contribute to the polarization of community-level participation.[3] Thus, an important spatial heterogeneity

[3]Most landowners (81%) hold their forest land in the same area as their resident zip code in our study site.

amplified at the community level may be masked.

This study contributes to the large body of literature on landowner participation in incentive-based schemes (see, e.g., Bell et al., 1994; Nagubadi et al., 1996; Langpap, 2004, 2006; Mitani and Lindhjem, 2015; Nielsen et al., 2018). Despite these significant efforts to understand landowner behavior, only very few studies have investigated social interaction effects. Banerjee and Shogren (2012) theoretically explored the effects of social reputation on private land conservation. Early empirical studies investigating social interaction effects base their results on exogenously given peer behavior that is hypothetical (Chen et al., 2009; Matta et al., 2009; Rossi et al., 2011). However, such research designs could capture actual social interaction effects only if the exogenously given behavior reflects true expectations, which is usually not the case because true expectations are endogenously formed by landowners through real interactions among them. Moreover, hypothetical choice situations tend to overestimate participation rates (Mitani and Lindhjem, 2022). To the best of our knowledge, this is the first study to estimate peer effects on landowner participation using observational data. We demonstrate how conventional policy simulations of participation (e.g., Markowski-Lindsay et al., 2011) would deviate from actual participation due to the existence of peer effects.

We also contribute to the growing but still limited literature investigating the effects of social incentives on landowners' provision of ecosystem services. Researchers and policymakers have been paying increasing attention to the role of policy nudge interventions in designing incentive-based conservation schemes (Palm-Forster et al., 2019). Wallander et al. (2017) used a randomized control trial to investigate whether social comparisons encourage non-enrolled landowners to participate in the Conservation Reserve Program. Kuhfuss et al. (2016) surveyed participants in agri-environmental schemes to explore the effects of social comparisons on their intention to continue pro-environmental practices after the expiration of a contract. Banerjee (2018) used a laboratory experiment to examine whether spatial coordination is facilitated by providing players with information about the behavior and earnings of other players with whom they do not interact strategically. Our study differs from these studies in that we do not directly manipulate the interventions to estimate the causal effects of peers' participation.[4] At the expense of that, our results suggest that peer behavior shapes landowner participation decisions endogenously, even without these exogenous interventions. Therefore, policymakers need to consider the existence of peer effects when designing a policy. Otherwise, the effects of policy interventions, including those leveraging social comparisons, will be misunderstood.

Finally, and more broadly, we contribute to the vast literature on peer effects. Evidence

[4]See Sacerdote (2014) for how researchers have identified causal peer effects.

on peer effects comes primarily from the fields of labor and public economics (e.g., Duflo and Saez, 2002, 2003; Sacerdote, 2011; Dahl et al., 2014; Herbst and Mas, 2015). However, increasing attention has been paid to the identification of peer effects also in environmental and resource economics. The growing literature investigates the endogenous effects of social interactions at the individual level (Brekke et al., 2010; Garcia et al., 2014; Arimura et al., 2016; Lynham, 2017; Bollinger et al., 2020; Burkhardt et al., 2021) and resource parcel level (Van der Horst, 2011; Robalino and Pfaff, 2012). In the context of land conservation, Lawley and Yang (2015) explored the effects of spatial interaction between neighboring parcels on the continuity of reserves in a conservation easement. The difference in our study is that we focus on social interactions among landowners within local communities. Most previous studies on identifying peer effects in environmental and resource economics typically exploit survey responses (Arimura et al., 2016), exogenous shocks (Lynham, 2017), or time-series variations (Lawley and Yang, 2015). However, such natural experimental variations and survey responses are not available for most policy situations. Since peer effects depend on context, policymakers need to evaluate each policy scheme. We demonstrate an identification strategy, without relying on natural experimental variations and survey responses, that can be applied to any policy situations where peer groups are well defined and each player's decision is observable.

The remainder of this paper is organized as follows. In Section 2, we define a reference group and describe the forest incentive program we study. Section 3 presents the estimation method used to identify peer effects. In Section 4, we describe our data and its sources. Section 5 presents the estimation results of social interactions, and we discuss the results in Section 6. Section 7 concludes with policy recommendations.

2 Institutional Background

2.1 Local Community in the Study Site

In Japanese rural areas, neighboring households usually belong to a small and closed local community (Pekkanen et al., 2014). Villagers from the same community mutually interact through daily conversation, community meetings, and collective actions. The collective actions include maintaining common infrastructures, community farming, and working on traditional events such as seasonal and traditional festivals. Such interactions in local communities have contributed to the successful management of commons through self-governance, such as monitoring and sanctioning systems (Ostrom, 1990; Rustagi et al., 2010; Kosfeld and Rustagi, 2015). Thus, the community members have strong social cohesion, which can shape individual decision-making in various settings (Mitani, 2022).

The study site, Kuma-kogén town, is a mountainous area located in the center of Ehime prefecture, approximately 600 km southwest of Tokyo (Figure 1). The town has four districts: Omogo, Yanadani, Mikawa, and Kuma.[5] The total forest area of the town is 51,850 ha, which is approximately 90% of the town's total area. There are approximately 4,200 residential landowners who own forest lands in the town.[6] Almost all landowners belong to a local community, the minimum administrative unit. In total, there were 219 communities in 2014 (Mitani, 2022). Many communities are geographically remote and isolated. A mail survey was conducted in 2014 by reaching out to all community leaders, and 115 responses were collected with an overall response rate above 50% (Mitani et al., 2015; Mitani, 2022). The survey revealed the characteristics of the community. The average community size was 17.7 households, the average frequency of community meetings was 6.5 times per year, and 95% of these communities engaged in at least one collective action per year. In addition, 33% of them impose monetary penalties for the absence of these activities. These results indicate that social cohesion is vital in the community. Therefore, we expect that landowners share beliefs about neighbor behavior even in individual decision-making (Mitani, 2022).

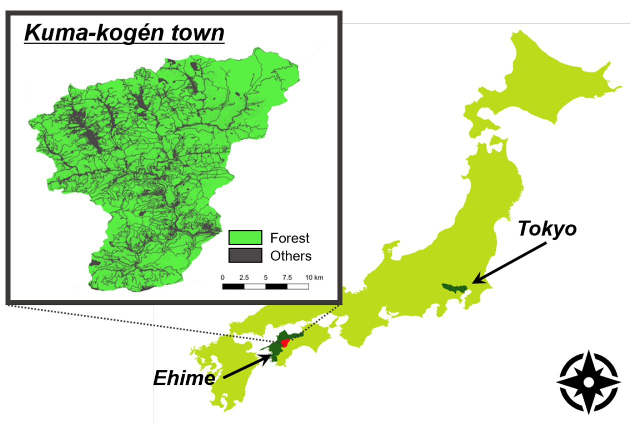


Figure 1: Location of the study site

We define the reference group as those landowners living in the same local community. A major concern in defining reference groups is the introduction of selection bias into estimators: those who are inherently inclined to participate in conservation programs might self-select into the same groups (Moffitt, 2001). However, this problem is negligible with our definition of a reference group. The local communities had been organized long before the forest incentive program was launched in the town, and most people were born and grew up

[5]These districts had been administrative villages before they were merged into Kuma-kogén town in 2006. The center of the town is in the Kuma district. We add district-level fixed effects in the estimation to control differences between districts.

[6]Forest owners in this study are referred to as landowners who own trees on their land.

in the town. Hence, residents rarely choose the community to which they belong. The survey of community leaders revealed that most communities do not have any single migrated household in their current generation and that only 7% of all households have migrated to the town in their generation (Mitani et al., 2015; Mitani, 2022). In addition, it is unlikely that migrants choose a community based on the characteristics of community members since these characteristics are usually unobservable for migrants. If any, such an influence would be negligible considering the small fraction of migrants.

2.2 Forest Incentive Program

Incentivizing private landowners to provide additional environmental services is becoming a major policy scheme to conserve private lands. Eligible landowners can choose whether or not to participate in such policies. Participants receive economic incentives, such as compensation and tax exemption, in exchange for changes in land-use practices or for land retirements that additionally provide environmental services. Examples of such policies include the Conservation Reserve Program (CRP) in the United States, agri-environmental schemes in the EU, and Pagos por Servicios Ambientales in Costa Rica (Schomers and Matzdorf, 2013). In this paper, we study a forest incentive program operated in Kumakogén town, which has the largest enrolled land area and the second-longest history of implementing forest incentive-based schemes in Japan, and it aims at assisting sustainable forest management and conservation on private land (Shimada, 2020; Mitani and Shimada, 2021).

Forests provide various environmental services in Japan, such as biodiversity, carbon sequestration, and the prevention of floods and landslides in mountainous areas. However, there has been public concern about the deterioration of these services for decades. The primary cause of the deterioration is the abandonment of forest management after extensive afforestation. Extensive afforestation occurred from the 1950s to the 1970s. During this time, conifers were planted in large areas to meet the growing demand for timber created by rapid economic growth. The lack of regular and active forest management in recent decades has led to the deterioration and decline of these environmental services. However, the motivations of private forest owners to carry out forest management have decreased significantly with declining wood prices and the aging of forest owners (Forestry Agency of Japan, 2018).[7] Another problem in Japan is small-scale forestland ownership.[8] This small-scale ownership

[7]The stumpage price of the Japanese cedar (*Cryptomeria japonica*) drastically declined from 22,707 JPY/m^3 in 1980 to 2,995 JPY/m^3 in 2015. During this period, the number of people involved in forest management decreased from 146,321 to 45,440, and the percentage of elderly, that is, 65 years or older, increased from 8% to 25%.

[8]Among people who held at least one hectare, 74% owned less than 5 hectares in 2016 (Forestry Agency

incurs higher unit costs and, therefore, discourages forest management. To prevent further deterioration of environmental services, the Forestry Agency launched subsidy schemes with the annual goal of managing 520,000 ha of forestland, which is equivalent to 2.1% of the total forestland in Japan (Forestry Agency of Japan, 2018).

Under the above-mentioned national subsidy scheme, the Kuma Joint Management Program (hereafter referred to as "KJM program") was introduced in 2006 by the Kuma Forest Association (KFA), the local forest agency in Kuma-kogén town. The KJM program seeks to implement joint forest management of continuous land with several owners so that environmental services and cost-effectiveness would be improved in larger areas than single-ownership parcels. It is an incentive-based conservation program in which participants can receive lump-sum payments if the KFA manages the participant's forestland jointly with adjacent enrolled plots within five years. The KFA determines the amount of payment based on the income from thinning, management costs, and government subsidies for joint forest management.[9] Therefore, payment is conditional on joint-management implementation. Forest owners are presented with an estimated payment by the KFA during a negotiation process.[10] If joint management is not implemented over a five-year period, the participants will not receive any payment. Participants will receive a conditional payment in exchange for transferring all their rights, except ownership and access to the forest, to the KFA for a period of five years. Therefore, participants relinquish all rights to forestry activities during the contract period.[11] All this information is provided by the KFA to landowners during a negotiation process. To proceed to the management step, the KFA needs to decide on an area to be managed based on the spatial configuration of the enrolled forest. Once the target area is established, the KFA develops a management plan, obtains forest owners' approval, implements joint forest management, and makes a payment to forest owners.

of Japan, 2018). Even industrial private forest owners whose forest is larger than 20 hectares earned an average of only 110,000 JPY per year from forestry activities in 2013 (Ministry of Agriculture Forestry and Fisheries, 2019), indicating how costly it is for small-scale NIPF owners to manage the forest. Since the income from forestry is very limited, most industrial forest owners have other income sources. https://www.maff.go.jp/e/data/stat/nenji_index.htm (accessed July 20, 2020).

[9]The amount of subsidy is determined by the total area under management, the type of management practices (e.g., planting and thinning), and whether a management plan has been developed.

[10]The KJM program is thus different from other incentive-based schemes such as the CRP, in which a payment is made for participation per se and unit price is determined in advance (USDA Farm Service Agency, 2019). Instead, this program is similar to collective payment for ecosystem services (PES) schemes (Kerr et al., 2014; Kaczan et al., 2017) in that the payment is conditional on the enrollment of the aggregated areas. The difference is that participation is ascribed solely to individual choice in the former, whereas it is determined through collective decision-making in the latter since land is communally titled, and the monetary rewards are calculated based on landowners' own forest conditions. The average estimated payment is 29,040 JPY/ha or 267 USD/ha (as of November 2019).

[11]Although participants are supposed to enroll for the contract period, they could request early termination of their contracts.

In summary, the compensation payment is conditional and indeterminate at the time of the contract agreement. While the ownership of the enrolled forests remains with the participants, all rights to forestry activities are transferred to the KFA during the contract period. Thus, the opportunity cost to enroll in the KJM program is expected to be higher for owners who engage in forestry activities, such as timber production and silvicultural activities. The expected gain from participation for this type of active owners would be pretty low or even negative because they can manage their land better on their own. On the other hand, the opportunity cost would be pretty low for owners who do not engage in forestry activities, and their expected gain would be higher. The KJM program has an incentive structure similar to forest conservation easement programs (Markowski-Lindsay et al., 2011; Mitani and Lindhjem, 2015), in which all rights to forestry activities are usually transferred, thus it is different from forest management or sustainable forestry programs (Kilgore et al., 2008), which usually support participants' forestry activities.

Figure 2 presents the spatial configuration of the enrolled forestlands in 2011, indicating that the enrolled forestlands are spatially disconnected in many areas.

Spatial connectivity will increase if peer effects exist at the local community level and landowners in the same community have neighboring forestlands. Hence, identifying peer effects is also of interest to policymakers who want to improve the spatial coordination of enrolled areas. Note that the KJM program does not refuse participation because the enrollment parcels are not spatially connected with the enrolled parcels. In other words, there is no requirement that the enrollment parcels be spatially connected with the enrolled parcels. As explained above, participation is voluntary, and the KFA does not actively persuade landowners to participate in the KJM program. In addition, target areas for forest management are determined based on spatial connectivity of the enrolled parcels. Therefore, peer effects, if any, are not driven by the design of the KJM program.

3 Estimation

3.1 Estimation Strategy

The main objective of this study is to estimate the endogenous effect of community members' participation on a landowner's binary decision. It is widely recognized that identifying endogenous effects is a challenging task (Manski, 1993, 2000). A simultaneous equation problem introduces difficulty in separately identifying endogenous effects from exogenous effects (i.e., effects of peers' characteristics) and correlated effects (i.e., effects of group-specific unobservables) (Manski, 1993). Brock and Durlauf (2001) established an incomplete infor-

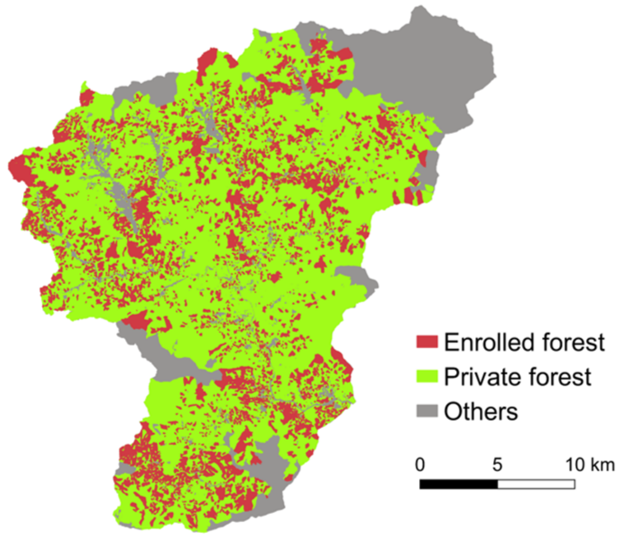


Figure 2: State of the Kuma Joint Management Program

mation model for a binary choice in which individuals cannot observe peers' unobservables and form expectations about their behavior based on observable group characteristics. The nonlinearity between observable characteristics and expectations regarding peers' participation allows identification. The expectation is assumed to be rational in the sense that it is model-consistent and can be obtained as a rational expectations equilibrium. Lee et al. (2014) extend Brock and Durlauf's model to allow each individual to form heterogeneous expectations regarding each peer's behavior based on peers' observable characteristics. In incomplete information models, endogenous effects can be identified if the rational expectation equilibrium is unique. A sufficient condition for the equilibrium to be unique is that the social interaction effect is not too strong, which is plausible empirically (Lee et al., 2014).[12]

In this paper, we apply the binary choice model with incomplete information to identify endogenous effects.[13] The following assumptions need to be satisfied. First, a key assumption of incomplete information models is that landowners do not observe peers' idiosyncratic shocks. It is reasonable to assume that landowners do not observe other members' every single decision because the community size is not that small.[14] Also, only 5% of the respon-

[12]More precisely, under the model of Lee et al. (2014), a sufficient condition for an equilibrium to be unique is that the coefficient of endogenous effects, γ in Equation (3) below, satisfies $|\gamma| < 1$.

[13]Many empirical studies exploit exogenous variations of peer behavior using experimental or quasi-experimental data to identify and estimate the endogenous effects (e.g., Sacerdote, 2014). In the context of a binary choice, these studies apply the linear probability model and use a quasi-experimental variation of peer behavior (Dahl et al., 2014; Lynham, 2017) or an instrument for peer behavior with peers' average characteristics (Duflo and Saez, 2002; Gaviria and Raphael, 2001). Although these exogenous shocks enhance the validity of identification, this approach is not feasible in other settings, including ours, where exogenous shocks are not available.

[14]The number of households in a community is 17.7 on average (Mitani et al., 2015).

dents answered forestry as their main occupation and fewer landowners are involved in forest management these days, suggesting that forest-related topics rarely attract the attention of community members. Second, for these reasons, the social interaction effect should not be too strong in our context so that the equilibrium is likely to be unique.

To account for the heterogeneity in expectations, we apply the model of Lee et al. (2014) rather than Brock and Durlauf (2001). Heterogeneous expectations are likely when the group size is small enough that peers' individual characteristics are observable to decision-makers. In our application, it is reasonable to assume that landowners can observe the characteristics of other members. That is, landowners should know their neighbors' occupation, educational background, forest ownership, the possession of forestry-related equipment such as a truck and chainsaw, and the approximate frequency of visits to their forest. Through this observable information, landowners are aware of how active their neighbors are or are not in forest management, even though they cannot observe every decision of their peers, including participation in the KJM program. Landowners may have low expectations of participation in the KJM program for their peers who are actively involved in forest management. In contrast, they may have high expectations for their peers who are not. These assumptions will be investigated in Section 6.

3.2 Estimation Method

Suppose that there are n landowners. Each landowner $i \in \{1, \dots, n\}$ faces a binary choice of whether or not to participate in the KJM program. Let y_i denote the participation status. y_i becomes 1 if the landowner i participates in the program and -1 otherwise.[15] The utility is given by $u_{1i} = U_1\left(R_i + B_i - C_i, m_i, \varepsilon_{i(1)}\right)$ if participation is chosen and $u_{-1i} = U_{-1}\left(0, m_i, \varepsilon_{i(-1)}\right)$ otherwise, where R_i, B_i, C_i, and ε_i, respectively, denote the expected lump-sum payment from the KJM program, non-monetary benefits of participation, costs incurred by participation, and unobservables of landowner i, while m_i captures social interactions. We assume that landowners cannot observe peers' idiosyncratic shocks. Therefore, they form expectations regarding peers' participation based on peer characteristics observable within the same peer group. The social interaction term $m_i \in [-1, 1]$ can be specified as

$$m_i = E\left[\mathbf{w}_i \mathbf{y} \mid \mathbf{X}\right] = \mathbf{w}_i \mathbf{m}, \tag{1}$$

where $\mathbf{w}_i = (w_{i1}, \dots, w_{in})$ is an n-dimensional row vector that specifies the landowner i's community members: $w_{ij} = 1$ if the landowner j belongs to the landowner i's community

[15]We follow the previous studies of the incomplete information model (e.g., Brock and Durlauf, 2001; Lee et al., 2014) for this coding strategy, which simplifies our analysis, as we will see below.

and $w_{ij} = 0$ otherwise.We rule out self-influence: $w_{ii} = 0$. The vector $\mathbf{w}_i$, which is then normalized in the row direction, constitutes the ith row of a $n \times n$ weighting matrix W. $\mathbf{y}$ is an n-dimensional column vector, whose ith element represents the participation status $y_i \in \{1, -1\}$. The matrix $\mathbf{X} = (\mathbf{x}_1', ..., \mathbf{x}_n')'$ represents the exogenous characteristics. The n-dimensional column vector $\mathbf{m}$ represents expectations about peer participation. The choice rule is as follows:

$$y_i = \begin{cases} 1 & \text{if } U_1\left(R_i + B_i - C_i, m_i, \varepsilon_{i(1)}\right) \geq U_{-1}\left(0, m_i, \varepsilon_{i(-1)}\right), \\ -1 & \text{otherwise.} \end{cases} \tag{2}$$

We specify the landowner i's utility as follows:

$$\begin{aligned} u_{1i} &= 2\mathbf{x}_i\boldsymbol{\beta} \quad + \gamma\mathbf{w}_i\mathbf{m} + \varepsilon_{i(1)}, \\ u_{-1i} &= \qquad\quad\; - \gamma\mathbf{w}_i\mathbf{m} + \varepsilon_{i(-1)}, \end{aligned} \tag{3}$$

where $\varepsilon_{i(\cdot)}$ measures the idiosyncratic shock that is observable for landowner i but is unobservable for peers and researchers. The second term measures the impact of peer participation on the landowner i's expected utility. In this specification, the parameters to be estimated are $(\boldsymbol{\beta}', \gamma)$. The parameter γ that measures peer effects is of interest. If $\gamma > 0$, landowners are positively influenced by peers' participation.

By the choice rule (2), and assuming that the difference between the two idiosyncratic shocks is logistically distributed, the participation probability can be computed as

$$P(y_i = 1) = \frac{1}{1 + \exp\left[-2(\mathbf{x}_i\boldsymbol{\beta} + \gamma\mathbf{w}_i\mathbf{m})\right]}. \tag{4}$$

The participation probability in Equation (4) is the same as the standard logit model except for the term of social interactions, $\gamma\mathbf{w}_i\mathbf{m}$, being added. The expectation $\mathbf{m}$ can be obtained as a rational expectation equilibrium, which can be calculated as a solution of the following nonlinear equation:[16]

$$\mathbf{m} = \tanh(\mathbf{X}\boldsymbol{\beta} + \gamma\mathbf{W}\mathbf{m}). \tag{5}$$

When maximizing the log-likelihood function, we must solve Equation (5) for each iteration

[16] The derivation of Equation (5) immediately follows from the definition of hyperbolic tangent and coding of participants as $+1$ and non-participants as -1:

$$(+1) \times \frac{1}{1 + \exp(-2z)} + (-1) \times \frac{\exp(-2z)}{1 + \exp(-2z)} = \frac{\exp(z) - \exp(-z)}{\exp(z) + \exp(-z)} = \tanh(z).$$

because $\mathbf{m}$ depends on the parameters to be estimated. Hence, we estimate the parameters using the nested fixed-point algorithm, where the MLE nests algorithms to solve Equation (5) (Rust, 1987, 2000). If $|\gamma| < 1$, Equation (5) has a unique equilibrium and, therefore, we can obtain a unique likelihood function using Equation (4).

There are two options for estimating marginal effects: a naïve calculation, where the expectations are regarded as exogenous, and a sophisticated calculation, where they are treated as endogenous. The former can be obtained in a conventional manner. Namely, we can calculate the naïve effects induced by a change in the variable s as follows:

$$\frac{\partial P(y_i = 1)}{\partial x_i^s} = 2P(y_i = 1)(1 - P(y_i = 1))\beta^s, \tag{6}$$

where β^s is the coefficient of x_i^s. The naïve calculation allows us to compute the marginal effects of expectation, $\mathbf{w}_i\mathbf{m}$, because it is considered exogenous.

On the other hand, the sophisticated effects involve further calculation. We must consider changes in the rational expectation equilibrium caused by a change in the landowner i's characteristics. The changes in the rational expectation affect the participation of the *changer* itself. The effects on the changer are given as

$$\frac{\partial P(y_i = 1)}{\partial x_i^s} = 2P(y_i = 1)(1 - P(y_i = 1))\left(\beta^s + \gamma\mathbf{w}_i\frac{\partial \mathbf{m}}{\partial x_i^s}\right). \tag{7}$$

This term expresses the impact of changes in expectations about peers' participation induced by the marginal change in their own (i.e., the landowner i's) characteristics. This means that the change in the landowner i's variable affects the participation of the other community members (*affected neighbors*) through changes in rational expectations. The effects on affected neighbors are given as follows:

$$\frac{\partial P(y_j = 1)}{\partial x_i^s} = 2P(y_j = 1)(1 - P(y_j = 1))\gamma\mathbf{w}_j\frac{\partial \mathbf{m}}{\partial x_i^s}. \tag{8}$$

That is, affected neighbors are influenced by the change in their peers' expectations induced by the change in the landowner i's variable.

3.3 Threats to Identifying Peer Effects

In the presence of omitted variables, the calculated expectations would deviate from true expectations, resulting in inconsistent estimators. Therefore, we collected as many variables that would affect landowners' participation as possible through a survey (see Section 4 and Appendix A.5). In addition to these variables, contextual effects (influences from exogenous characteristics of other landowners) and correlated effects (group-specific factors) could cause omitted variable bias if we ignore them since these effects can cause group members to behave similarly (Manski, 1993, 2000). In this study, we assume no contextual effects and exclude them from the estimation, which is a conventional assumption in the literature (e.g., Gaviria and Raphael, 2001; Krauth, 2006; Arimura et al., 2016). To deal with correlated effects, we include district-level fixed effects in our model instead of community-level fixed effects, since there are too many local communities to be controlled as fixed effects. Mitani et al. (2015) confirm that various attributes differ at the district level.

Variation in weighted expectations, $\mathbf{w}_i\mathbf{m}$, is critical for the identification of peer effects in a binary decision. In Appendix A.2, we investigate the variation utilizing our expectations estimates. We find substantial variation at the individual and local community levels. In particular, we argue that expectations vary significantly between local communities with different participation rates. This large variation comes from the large variation in observable characteristics. For example, one of our main variables of interest is the forest size, as we see in Section 4. This variable varies substantially within and between local communities. Thus, such a variation in observable characteristics generates a large variation of expectations, allowing for our identification.

Our incomplete information model assumes that landowners cannot observe their peers' idiosyncratic shocks. If the landowners can observe them, a complete information model should be applied. The primary concern in a complete information model is the existence of multiple equilibria that arise due to the simultaneity of equations. A model with multiple equilibria results in inconsistent estimates without dealing with the multiplicity (Maddala, 1986; Tamer, 2003). Krauth (2006) develops a complete information model that imposes equilibrium selection rules that lead to a unique likelihood, and Arimura et al. (2016) apply this model to identify peer effects in energy-saving behavior. Another complete information model proposed by Soetevent and Kooreman (2007) assumes that a unique outcome appears with a probability equal to one over the number of equilibria to deal with the multiplicity. Despite these efforts to overcome the multiplicity problem, it is difficult to validate these assumptions empirically. Bajari et al. (2010) propose simulation-based estimators, where an equilibrium selection mechanism is modeled by calculating all pure-strategy and mixed-strategy equilibria. However, as the number of equilibria grows rapidly with the number of players, the computation is almost infeasible in settings where the number of players is large, as in our study. In Appendix A.1, we apply the model with complete information developed by Soetevent and Kooreman (2007) to investigate the robustness of the assumptions on peers' idiosyncratic shocks.

Another potential problem is the validity of the assumption on how landowners interact with their peers. We construct the weighting matrix by assuming that landowner decisions in a community influence each other in the same way. To relax this restriction, we also consider a weighting matrix in the way that each landowner receives a different weight depending on their characteristics (see Section 6.4 and Appendix A.1). We also assume that landowners can observe peers' characteristics. To relax this assumption, we consider the model developed by Yang and Lee (2017) to allow for further heterogeneity in expectations. In their model, each individual forms heterogeneous expectations based on both public and private information about peers' characteristics. In Appendix A.1, we apply their model to show that our results are robust to the possibility that some of the variables might be private information (see Section 6.4 and Appendix A.1).

4 Data

4.1 Dataset

This study uses two datasets to analyze participation in the KJM program. The first is the census data of the NIPF owners as provided by the KFA. Census data record the actual contract status of all listed landowners of the KJM program, the total size of the forest owned, the total size of forest under contract, their address, and the local community to which they belong. The second is a mail survey conducted by the KFA to gather information from NIPF owners about their forestry practices, perception and evaluation of existing programs, and intention and preference for future land use. The questionnaire consists of five main sections, and we used four of them to collect information about individual characteristics of landowners.[17]

The first section contains questions about forest property, the frequency of forest management activities, and their motivation to own forest land. In addition, landowners were asked if they had experience with joint forest management with neighboring owners before the KJM program was launched. The second section contains questions related to the KJM program and the KFA. These questions include asking landowners about their degree of knowledge about the program. This section also asks landowners how often they used the services provided by the KFA in the past five years. In the third section, landowners are asked about their relationship with their neighbors, such as the frequency of their attendance at community meetings. The final section includes questions asking landowners about their demographic information such as gender, age, family size, job, postal code, education, and membership in various organizations.

[17] The English translated version is available upon request from the authors.

A list of names and addresses of landowners who owned forests in the municipality was taken from the census data. The census data, which cover KFA members and non-members who own forest land in the municipality and are eligible for the KJM program, were the most comprehensive list of NIPF owners available at the time of the survey. From the registry of 3,535 landowners, we excluded those who were not NIPF owners, did not have forests in the municipality, refused to receive any questionnaire, or whose addresses were unknown from the sample. A total of 2,286 landowners remained after this process. In December 2011, the KFA sent the survey to eligible owners, followed by a reminder letter sent ten days after the initial letter. The number of respondents was 1,160, and the overall response rate was 50.74%.[18] Among them, we use those who live in the municipality, resulting in a sample of 733 respondents. After excluding those with incomplete responses and those who do not belong to any community in the municipality, we obtained the final sample size of 602, which is merged with the census data.[19]

4.2 Data Description

Table 1 summarizes the variables used in our main estimation. The two variables reported in Panel A are taken from census data. The first is landowners' participation in the KJM program. Since we assign $+1$ to participants and -1 to non-participants, the mean value of -0.505 is equivalent to the participation rate of 24.8%. The second variable is the forest size registered in the census data. Forest size is expected to capture the variation in lump-sum payments and therefore be positively associated with participation. This is because a larger forest is associated with more wood, which means a larger total payment.

Panel B of Table 1 reports on the independent variables collected from the survey data. We choose these variables based on the literature on NIPF owners' participation in forest incentive programs (Mitani and Lindhjem, 2022). To control the opportunity cost of participation, we include two variables: "Recognition of forest borders," the extent to which a landowner recognizes the forest borders, and "Active forestry management," whether a landowner has been involved in forest management every year. Landowners who recognize the border well would be more attached to forests and tend to avoid loss of autonomy (Sorice

[18]See Appendix A.4 for a possible concern about biases in peer effects introduced by the survey response.

[19]The final response rate, which is calculated as the sample size divided by the eligible landowners who live in the municipality (i.e., the target population), is 42.10% (602/1430). To understand a possible non-response bias, we examine the differences in forest size and contract status between respondents (i.e., our sample) and non-respondents in the target population. The Mann–Whitney U and Pearson's Chi-squared tests detect statistically significant differences in the forest size ($z = -4.313$, $p < 0.001$) and participation status ($\chi^2 = 23.32$, $p < 0.001$), respectively. This suggests that the landowners in our sample tend to own larger forests and are more likely to participate in the program than all landowners in the census. Therefore, the results in the following sections require caution to be generalized.

Table 1: Summary statistics ($N = 602$)

Variables	Mean	Std. Dev.
(A) *Census data*		
Participation (= 1 if yes, else −1)	−0.505	0.864
Participation (= 1 if yes, else 0)	0.248	0.432
ln(forest size (ha))	1.444	1.330
(B) *Survey data*		
Recognition of forest borders (the degree of recognition : 1 = not at all,..., 5 = perfectly)	4.249	1.052
Active forestry management (= 1 if manage every year, else 0)	0.233	0.423
Experience of joint management (= 1 if yes, else 0)	0.355	0.479
Well informed about the KJM (= 1 if yes, else 0)	0.623	0.485
High school graduate (= 1 if yes, else 0)	0.374	0.484
College degree (= 1 if yes, else 0)	0.153	0.360

et al., 2013).[20] Similarly, those conducting forestry activities every year would be more likely to have their own management plan regarding timber and non-timber and would be reluctant to participate in the KJM program.[21] The opportunity cost to participate in the KJM program would be high for active landowners who engage in forestry activities during the contract period. Therefore, the variables related to the opportunity cost are expected to have a negative impact on participation as high opportunity costs discourage participation (Engel et al., 2008; Hanley et al., 2012). The decline in forest owners' interest in forest management, which we discussed in Section 2.2, can be confirmed by the fact that the rate of active forestry management is low on average (0.23). On the contrary, the average recognition of forest borders is as high as 4.25, which suggests that most owners recognize forest borders well.

We include two variables to control for the transaction cost regarding the program for

[20] Many Japanese small-scale private forest owners do not recognize their property line. This variable reflects how connected landowners are to their forests. 53.2% of our sample answered that they recognized the border of their forest entirely, while 2.9% of them answered they did not recognize it at all.

[21] One may be concerned that this variable is endogenous: participants would quit forest management after participation. However, this is not the case in our context because landowners can enroll part of their forest and implement forest management in unenrolled areas. The ratio of enrolled areas to forest size is less than one for 48% of the participants, indicating that half of the participants do not register their entire forest. Furthermore, among participants who do not manage their forest every year, only 9.5% (9 out of 95) answered that the last year they managed their forest was the previous year of their participation. These results suggest that most participants do not quit forest management because of their participation.

landowners: “Experience of joint management” and “Well informed about the KJM.” The first is the experience of joint forest management with others. Experience would lower the transaction cost of participation because those who have experienced joint management before are thought to know more about joint management and would reduce resistance toward joint management. The second is whether the landowner is familiar with the KJM program. The literature shows that familiarity with a program plays an essential role in program participation (Bell et al., 1994; Dahl et al., 2014; Duflo and Saez, 2003; Kilgore et al., 2008). Higher knowledge about the program would be associated with lower transaction costs because it would be positively correlated with landowners' interest in the KJM program and reduce resistance to participation incurred by the uncertainty about the program. Thus, higher values of these two variables would increase participation (Hanley et al., 2012; Mettepenningen et al., 2011).

Finally, we control the education levels of the landowners. It is well documented in the literature that education level is a significant determinant of program participation (Beach et al., 2005; Langpap and Kim, 2010). In our setting, higher education would contribute to a better understanding of the economic and environmental benefits of the KJM program. Therefore, dummy variables that indicate higher education are expected to have positive coefficients. Furthermore, the level of education could be correlated with the level of income, which can significantly influence participation (Langpap and Kim, 2010).

5 Results

Table 2 presents the estimates of the utility parameters in Equation (4). Column 1 reports the results without social interactions, that is, the conventional analysis of program participation, while Column 2 reports the results incorporating social interactions. As seen in Column 2, the coefficient of peer effects is positive and statistically significant at the 1% level, suggesting the existence of social interaction effects.[22] That is, the more (less) peers participate in the program, the higher (lower) the individual probability of participation. Since the estimate of γ is 0.577 and smaller than 1, a rational expectation equilibrium is unique (Lee et al., 2014). Column 3 includes random effects specific to each local community instead of district-level fixed effects. We randomly generated 500 random numbers for each community and

[22] One may be concerned about the source of social interaction effects. Possible sources include conformity, social learning (Mobius and Rosenblat, 2014), and strategic complementarity (Shimada, 2020). Unfortunately, we cannot identify these sources in our setting. To examine the existence of social learning, we looked at a question asking landowners whether they talked with peer landowners about the KJM program, and the majority of respondents (65.6%) answered no. Hence, if any, we consider the effect of social learning limited.

maximized the simulated log-likelihood function. Note that these random effects are assumed to be independent of other explanatory variables. Column 4 presents the results where we add five variables to investigate the sensitivity of our results to variable selection: the gender of a landowner; whether they have used any services provided by the KFA; whether they are a member of the KFA; whether they attend every community meeting; and the size of the community to which they belong.[23] Our estimate of peer effecs remains similar; the sign and significance levels in Columns 3 and 4 are almost identical to those in Column 2, indicating the existence of social interaction effects. We base our following discussion on the estimates in Column 2.

Positive and significant peer effects on landowner participation in incentive-based schemes are inconsistent with the findings of Matta et al. (2009) and Rossi et al. (2011). They used choice experiments to measure the effects of the participation rate of neighboring landowners but did not find statistically significant effects. Two reasons can explain the difference between their results and ours. First, the participation rates are exogenously given by the researchers in their choice experiment. If these exogenously given participation rates do not reflect the landowners' true expectations, the estimated effects of neighbor participation fail to capture social interaction effects precisely. In contrast, our model allows landowners to form expectations endogenously. Second, the reference groups defined by Matta et al. (2009) and Rossi et al. (2011) may not reflect the true social groups. Group members are described by the terms "landowners in your county" in Matta et al. (2009) and "local owners" in Rossi et al. (2011). If reference groups do not reflect landowners' true social groups, social interaction effects are mismeasured. In this study, unlike their definition, landowners interact with others in the same local community, as discussed in Section 2.1. The difference in the definition of reference groups is highlighted by the fact that our results are consistent with those of Chen et al. (2009), in which a reference group is defined as "a well-defined administrative unit within a village," which is quite a similar definition as ours. In this group definition, landowners clearly recognize and interact with their group members frequently.[24] Thus, our results shed light on the importance of defining an appropriate reference group when measuring social interaction effects.

When comparing Columns 1 and 2, we see that incorporating social interactions in the analysis does not drastically change the estimates of explanatory variables. Both models provide the same sign and similar significance levels. The signs of the estimates are as expected in the previous section. Forest size is positively and significantly associated with participa-

[23]See Table A.3 in Appendix A.5 for the estimates of the added variables.

[24]However, the difference between our study and Chen et al. (2009) is that they exogenously provide landowners with peer participation rates to measure social interaction effects in their choice experiment.

Table 2: Estimation results

	(1)	(2)	(3)	(4)
Peer effect		0.577***	0.540***	0.593***
		(0.190)	(0.198)	(0.192)
ln(forest size)	0.099**	0.066*	0.089*	0.072*
	(0.041)	(0.039)	(0.051)	(0.037)
Recognition of forest borders	−0.182***	−0.147***	−0.178**	−0.175***
	(0.050)	(0.050)	(0.084)	(0.052)
Active forestry management	−0.343**	−0.376***	−0.412**	−0.401***
	(0.136)	(0.120)	(0.176)	(0.126)
Experience of joint management	0.465***	0.506***	0.583***	0.500***
	(0.108)	(0.099)	(0.206)	(0.102)
Well informed about the KJM	0.595***	0.496***	0.587**	0.486***
	(0.124)	(0.132)	(0.233)	(0.136)
High school graduate	0.224*	0.106	0.216	0.114
	(0.116)	(0.099)	(0.147)	(0.116)
College degree	0.351**	0.275**	0.330*	0.241*
	(0.149)	(0.135)	(0.194)	(0.143)
Constant	−0.610**	−0.340	−0.474	−0.285
	(0.282)	(0.222)	(0.292)	(0.269)
Fixed or random effects	Village fixed	Village fixed	LC random	Village fixed
Other controls	No	No	No	Yes
Observations	602	602	602	599
Pseudo R^2	0.118	0.126	0.124	0.135
Log likelihood	−297.112	−294.346	−295.199	−289.642

Notes: Column 1 reports the results without peer effects, whereas Column 2 presents the results with peer effects. We include village fixed effects in these models. Column 3 shows the results where we include random effects that are common to each local community (LC), rather than village fixed effects. In column 4, we add other control variables and the village fixed effects. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

tion, though more precisely estimated in the model without social interactions. This result is consistent with the earlier explanation that enrolling larger forests is expected to yield higher lump-sum payments. The negative and significant effects of border recognition and active forestry management indicate that landowners' opportunity costs of participation are negatively correlated with the likelihood of participation. The positive and significant effects of the experience of joint management and being well-informed about the program confirm that the lower the landowners' transaction costs, the higher the probability of participation. Finally, the landowner's educational background is positively associated with participation.

Although the coefficient of high school graduation is insignificant in Column 2, having a college degree positively and significantly correlates with participation in both models. This suggests that owners with higher education are more likely to participate in the program, which is consistent with the literature (see, e.g., Langpap and Kim, 2010).

Although signs and significance levels are similar between the two models, their impacts on participation can differ. To measure the impacts, we present the marginal effects of the explanatory variables in Table 3, using the estimates in Columns 1 and 2 of Table 2. Column 1 shows the marginal effects when excluding social interactions. In contrast, Columns 2–4 present those incorporating social interactions. As discussed in Section 3.2, we provide naïve and sophisticated calculations of marginal effects. Column 2 is based on the naïve calculation in Equation (6). This calculation assumes that a change in one's variable does not affect others' participation. Thus, the expectations are regarded as exogenous. Instead, this calculation computes the direct effects of change in one's explanatory variables and the expectation of others' participation on its participation. Columns 3 and 4 are based on the sophisticated calculation in Equations (7) and (8) and represent the marginal effects of a changer and an affected neighbor, respectively. When comparing Columns 1 and 2, the impacts are only slightly different, and there is no clear pattern in the direction of the differences. Comparing Columns 2 and 3, we see that the absolute values in Column 3 are slightly higher than those in Column 2. This divergence reflects the feedback effects of social interactions (see Equation (7)). In other words, in addition to direct effects, a marginal change in an explanatory variable indirectly affects participation through changes in a rational expectation equilibrium. However, the differences seem to be marginal. Column 4 presents the effects of marginal changes in a landowner's characteristics on their neighbor's participation (see Equation (8)). Their impacts are limited compared to Columns 1, 2, and 3, which aligns with the findings of Lee et al. (2014). There appears to be no apparent difference in signs and impacts of explanatory variables when we compare the estimation results with and without social interactions. However, as we discuss in the following section, we find that the estimated impacts of a change in an individual's explanatory variable on the participation rate at the community level that the individual belongs to would be much larger due to the aggregated impact on the *affected* neighbors when social interactions are incorporated.

Table 3: Marginal effects ($N = 602$)

		With Interactions		
	No	Naïve	Sophisticated Calculation	
	Interactions	Calculation	*Changer*	*Affected*
	(1)	(2)	(3)	(4)
Peer effect		0.180***		
		(0.055)		
ln(forest size)	0.032**	0.021*	0.023*	0.004
	(0.013)	(0.012)	(0.013)	(0.003)
Recognition of forest borders	−0.058***	−0.046***	−0.051***	−0.010*
	(0.015)	(0.016)	(0.015)	(0.005)
Active forestry management	−0.102***	−0.107***	−0.119***	−0.025
	(0.038)	(0.030)	(0.035)	(0.017)
Experience of joint management	0.158***	0.169***	0.190***	0.039
	(0.037)	(0.033)	(0.036)	(0.024)
Well informed about the KJM	0.180***	0.148***	0.163***	0.031**
	(0.031)	(0.036)	(0.035)	(0.016)
High school graduate	0.076*	0.052	0.056	0.011
	(0.039)	(0.034)	(0.037)	(0.009)
College degree	0.125**	0.091*	0.105**	0.020
	(0.055)	(0.046)	(0.051)	(0.014)

Notes: Standard errors are calculated based on Krinsky and Robb (1986) with 1,000 random draws and are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6 Discussion

6.1 Net Effects of Social Interactions

Although we find a positive and significant peer effect on landowners' participation, incorporating social interactions into the estimation model does not make much difference in the estimated coefficients of other explanatory variables. However, this result does not imply that the peer effects are insubstantial. In Table 4, we measure the net effects of social interactions by calculating how a change in a landowner's characteristics impacts the community-level average participation rate (Column 1). Using the notation in Equations (6)–(8), we consider the net effects of social interactions for the variable s as follows:

$$\Gamma_i^s = \frac{1}{|N_i|}\left(\underbrace{2P(y_i=1)(1-P(y_i=1))\left(\beta^s+\gamma\mathbf{w}_i\frac{\partial\mathbf{m}}{\partial x_i^s}\right)}_{\text{effect of the changer}}+\underbrace{\sum_{j\in N_i\setminus i}2P(y_j=1)(1-P(y_j=1))\gamma\mathbf{w}_j\frac{\partial\mathbf{m}}{\partial x_i^s}}_{\text{effects on affected neighbors}}\right),$$

where N_i is the set of landowners who belong to the landowner i's community. This means in words that we add a changer's marginal effects and the marginal effects of the affected neighbors and then take an average of them. We then compare it with the effect in benchmark models where no such spillover exists in Column 2. We consider two benchmark models: one without social interactions (Panel A) and one with social interactions where expectations are exogenous (Panel B). Let $\tilde{\boldsymbol{\beta}}$ and $\tilde{P}(y_i=1)$ denote the coefficients and participation probability in the model without social interactions, respectively. The benchmark effects in Panel A are $2\tilde{P}(y_i=1)(1-\tilde{P}(y_i=1))\tilde{\beta}^s/|N_i|$. Similarly, the benchmark effects in Panel B are $2P(y_i=1)(1-P(y_i=1))\beta^s/|N_i|$. Percentage changes are reported in Column 3 to measure how incorporating social interactions increases the impacts relative to the benchmarks at the community level.

Panel A shows that percent changes range from 10% to 83%. For example, by considering social interactions, a marginal change in a landowner's opportunity cost measured by the frequency of forestry management increases the community-level average participation rate by 77.37%. The same can be said for Panel B, where the percent change is as large as 64%.[25] Thus, although estimates and their marginal effects are similar with and without incorporating social interactions, we confirm the substantial effects of social interactions on program participation.[26]

6.2 Social Interactions and Predictions

To further investigate the effects of social interactions on program participation, we examine how incorporating social interactions influences predictions of participation rates. Conventional analysis of program participation often simulates participation rates by varying policy

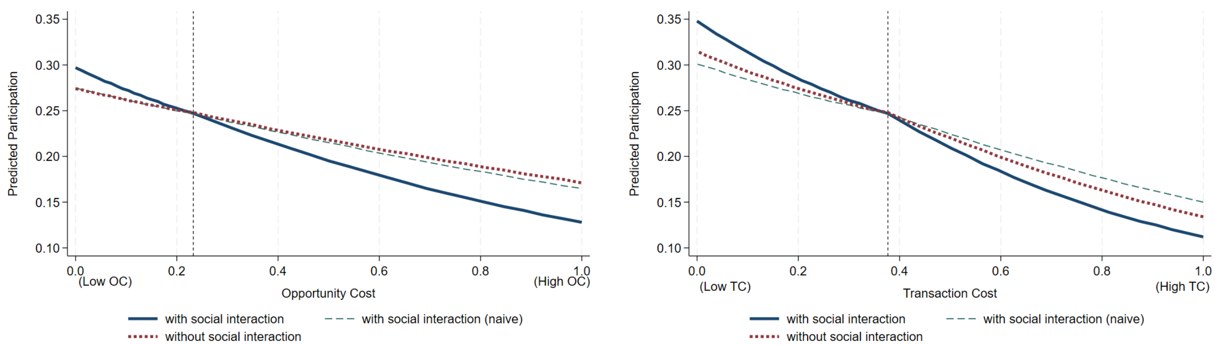
[25] All the percent changes in Panel B are around 60%. This is because the numerator and denominator of a ratio are proportional to β_s; hence, the ratios do not directly depend on β_s. This follows from the fact that a numerator in Panel B is $\sum_{j\in N_i} 2P\left(y_j=1\right)\left(1-P\left(y_j=1\right)\right)\mathbf{w}_j\left(\partial\mathbf{m}/\partial x_i^s\right)$, where the last term is proportional to β_s (Lee et al., 2014).

[26] The large differences in the net effects are not attributed to the small net effects in the benchmark model. For example, the experience of joint management shows the largest percent change of 83%. This variable's net effects in the benchmark are also the largest.

Table 4: Net effects of social interactions

	Net Effects (1)	Benchmark (2)	% Change (3)
(A) Benchmark: No Interactions			
ln(forest size)	0.014	0.012	10.34
Recognition of forest borders	−0.030	−0.022	33.25
Active forestry management	−0.070	−0.039	77.37
Experience of joint management	0.111	0.060	83.08
Well informed about the KJM	0.094	0.068	36.77
High school graduate	0.033	0.028	16.73
College degree	0.061	0.047	27.01
(B) Benchmark: Naïve Calculation			
ln(forest size)		0.079	62.59
Recognition of forest borders		−0.017	62.59
Active forestry management		−0.041	59.68
Experience of joint management		0.065	63.80
Well informed about the KJM		0.056	60.13
High school graduate		0.019	63.04
College degree		0.035	64.84

attributes or individual characteristics (e.g., Markowski-Lindsay et al., 2011). In Figure 3, we run a conventional simulation by ranging landowners' opportunity and transaction costs from low to high for three different models. We vary the values of cost-related variables for all landowners except those whose values go beyond or below its dimension (e.g., $[0, 1]$ for dummy variables). The solid lines are participation rates obtained from a sophisticated model with social interactions. The dotted lines plot the rates based on a model without social interactions, a conventional simulation result. The dashed lines show participation rates with social interactions where the calculation is naïve; we hold landowners' expectations constant in the simulation. The difference between the solid and dotted lines measures the net influence of excluding social interactions. The influences can be decomposed into those excluding the parameter of the endogenous effects obtained with the naïve estimation (difference between dotted and dashed lines) and excluding changes in a rational expectation equilibrium (difference between solid and dashed lines). The dashed vertical lines show the sample mean of opportunity and transaction costs. To demonstrate the impact of opportunity cost, we vary whether landowners conduct forestry management yearly. Tables 2 and 3 indicate that the frequency of forestry management (i.e., Active forestry management) has large marginal and net effects. This finding is important because this variable would fluctuate significantly depending on many factors, such as market conditions of timber and landowners' physical conditions. As transaction costs, we use the extent to which landowners are well informed about the program, which significantly affects participation. This variable is policy-relevant because knowledge can be enhanced by policy interventions such as information campaigns.



(a) Opportunity Cost (b) Transaction Cost

Figure 3: Simulated participation

Notes: The vertical lines indicate the sample mean.

Figure 3 indicates that peer effects would not enhance participation dramatically when the changes in opportunity and transaction costs are marginal. Around the dashed vertical lines in Figure 3, the difference between the solid and dotted lines is indistinguishable. However, a divergence emerges between these two lines when the cost deviates away from the sample mean. The difference is generated by the feedback effects of social interaction, as confirmed by the difference in solid and dashed lines. Namely, landowners are not only affected by changes in their own costs but also by changes in expectations induced by changes in their own costs as well as their neighbors' costs. In addition, the divergence increases as the simulated values move away from the mean. This is because the changes in rational expectations are larger in these areas. These results indicate that if a policymaker who wants to forecast participation rates excludes the social interaction effects, the participation rates will be underestimated or overestimated, thus leading to inaccurate predictions.

6.3 Local Community Level Predictions

In this subsection, we explore how incorporating social interactions influences predictions at the local community level. With peer effects, a landowner is more likely to participate if a large proportion of his or her community members expect that their peers tend to participate, resulting in a higher participation rate in their community when compared to one without peer effects. If we exclude social interaction effects, we will make biased predictions regarding the group-level outcome. To shed light on the impacts of excluding peer effects on the community-level outcome, we investigate how the endogenous effects influence the average predicted participation of each local community. The prediction is based on the estimates in Table 2. The result is shown in Figure 4, where we plot percentiles of predicted group-level participation based on the model incorporating social interactions against percentiles of it based on the model excluding social interactions.[27]

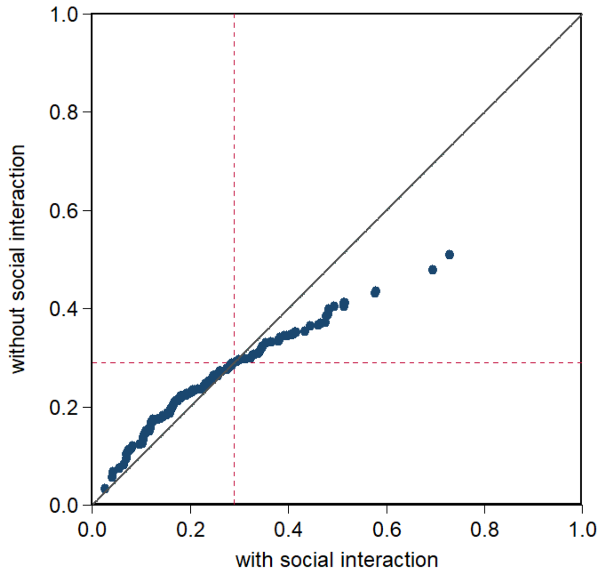


Figure 4: QQ-Plot of predicted participation aggregated at the local community level
Notes: The dashed lines indicate the values where the two quantiles match.

Figure 4 demonstrates that the community-level participation rate is distributed differently depending on whether or not social interactions are included. This finding has two implications. First, this result confirms the theoretical argument that the existence of social interactions contributes to the polarization of groups, characterized as multiple equilibria in theory. For groups where participation is expected to be likely (unlikely), aggregated participation will be high (low) due to the social interaction effects. An important policy implication is that social interaction effects do not always increase local-level participation rates. Peer effects can discourage landowners in communities whose members expect participation rates to be low, while the effects can enhance participation in other communities.

[27]Each community's participation rates are calculated based on the two models, i.e., incorporating and excluding social interactions. Then, we sort them respectively in ascending order and calculate percentiles of the rate of community-level participation. Figure 4 plots percentiles calculated from a model incorporating social interactions versus percentiles calculated from a model excluding social interactions.

Second, whether or not including peer effects in policy analysis influences the understanding of the spatial configuration of participation when peer effects exist among neighboring landowners. Figure 4 suggests that for communities whose participation rates are higher (lower) than the median, a conventional model excluding social interactions tends to underestimate (overestimate) their participation rates and overlook spatial variations across the communities. Since the spatial configuration of participation matters for policy outcomes in many Payment for Ecosystem Services (PES) schemes, the identification of a reference group and its peer effects will be key for successful program evaluation and predictions.

6.4 Robustness Tests

To examine the robustness of our estimation results, with a particular focus on the estimate of peer effects, we run supplemental analyses categorized into four classes. In this subsection, we only provide essential ideas behind the robustness tests, and detailed methods and results appear in Appendix A.

First, we examine how different assumptions on landowner behavior affect the estimates. Identification of peer effects in this study builds on the assumptions of (1) each landowner influencing others to the same degree, (2) idiosyncratic shocks of participation being unobservable by peers and the researcher, and (3) exogenous variables being observable by peers (i.e., community members). We relax each of these assumptions and confirm the existence of peer effects (see Table A.1).

The second is the test on the validity of our social group definition. One may be concerned that the incomplete information model of Lee et al. (2014) might detect social interaction effects even for other groups. In this test, we randomly form pseudo (i.e., placebo) groups where peer effects should not exist. This calculation can be interpreted as the power of the test where a null hypothesis is that γ is statistically significant at the conventional level. Table A.2 shows that the model correctly rejects the null hypothesis of the existence of peer effects in those pseudo groups.

Third, we explore whether our estimate of peer effects is contaminated by selection bias introduced by the survey respondents and non-respondents. Although we cannot directly test the existence of the selection, by resampling, we can indirectly examine whether our estimates are overestimated. The results presented in Figure A.4 provide a piece of counter-evidence of overestimation.

Nevertheless, there remain several limitations that this study cannot deal with and that provide us with directions for future research. Economists are keenly interested in identifying paths of peer effects (e.g., Bursztyn et al., 2014). Peer behavior can positively affect one's behavior if one has the predisposition to conform to peer behavior (i.e., conformity), cares about how they are evaluated by peers (i.e., social image), or learns from peer behavior and resulting outcomes (i.e., social learning). Our estimate of peer effects might capture some or all of these sources, and their identification is an interesting extension of this study. In addition, a feature of the KJM program is that management is conducted once enrolled forestlands are set as a target area. This causes strategic interactions among forest parcels (Shimada, 2020). If landowners in the same community own neighboring forests, our estimate of peer effects can capture the effect of strategic interactions. The strategic interactions provide different implications for policymakers since the welfare gain from an intervention can vary (Bhattacharya et al., 2019). Hence, identifying these paths can provide critical insights for policymakers but is beyond the scope of this study.

Another direction for future work is to exploit the complex structure of social networks. In this study, we consider a simple network where a landowner interacts to the same degree with all landowners in the same community. However, some landowners may be more influential than others. For example, the participation behavior of community leaders might be more influential than non-leaders because they might be believed to be trustworthy or know more about the program. Also, some specific landowners may play an essential role in spreading information about the program (Banerjee et al., 2019). In addition, landowners might interact with a subset of landowners in the same community or with landowners outside the community. Although we test this by approximating leaders' influences by forest size in Appendix A.1, more detailed information on the network structure enables researchers to analyze these cases more precisely. For example, the Add Health (the National Longitudinal Study of Adolescent Health) dataset contains information on self-reported friendship links of high school students, which specify heterogeneous social networks and enable researchers to identify peer effects (e.g., Bramoullé et al., 2009). Although such a complex weighting matrix of landowners is difficult to access, it might reflect true social interactions more than the current one.

Finally, investigating the relationship between peer effects and group characteristics would be interesting. If peer effects are heterogeneous over group characteristics, policymakers can exploit the information on sources of heterogeneity for policy designs. For example, Japan has been facing an era of aging and the elderly moving from rural to urban areas. The depopulation of rural areas might undermine peer effects. As a result, policymakers in such areas can no longer utilize peer effects for policy designs. Thus, a better understanding of the association between peer effects and group characteristics such as average age, average residence year, and group size would be helpful for policymakers.

7 Conclusion

This study investigates whether landowner participation in an incentive-based program is affected by landowners in the same local community. To identify the social interaction effects, we combine a unique data set, which records actual contract information, landowner attributes, and information of reference groups, with a binary choice model of social interactions. We find significant peer effects in landowner participation in an incentive-based program. We also provide evidence that conventional analyses of landowner participation, which ignore peer effects, deteriorate the precision of predictions at both the individual and group levels.

This study thus deepens understanding of landowner participation behavior by providing new behavioral evidence of peer effects. The results that landowners face social incentives shaped by social interactions are also policy-relevant in that they suggest to policymakers the necessity of designing a policy that accounts for the existence of peer effects. In local communities with a high participation rate, policymakers can enhance participation in a cost-effective manner by leveraging social incentives. A conventional policy intervention includes using nudges such as public announcements of peer landowners' participation. On the other hand, in communities where the participation rate is low, policymakers need to design a stronger intervention to enhance participation, as participation is discouraged in these communities by peer effects. Based on our results, lowering transaction costs by, for example, information outreach would be effective. Employing such policies should be based on their cost-effectiveness.

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Online Appendix

A Robustness Checks

A.1 Robustness of Assumptions

In Table A.1, we examine the robustness of the assumptions we have imposed. Column 1 shows the results obtained with a different weighting matrix. In the analyses of the main text and the other parts of this appendix, we construct a weighting matrix in a way that each landowner in the same community is weighted equally. In other words, it is assumed that each landowner homogeneously influences other community members. The weighting matrix in Column 1 is constructed in a way that landowners in the same community are weighted according to the size of the forest they own; landowners with larger forests receive larger weights. In some regions in Japan, landowners who own larger forests historically have a larger presence in meetings. Therefore, we expect that this definition of the weighting matrix captures the influence of leaders, who might be more influential than other members. Column 1 of Table A.1 shows that the results are consistent with Column 2 of Table 2 and support the existence of peer effects even when landowners' influence is heterogeneous.

Identification of peer effects in this study exploits the assumption of incomplete information. We cannot directly test the validity of this assumption. Therefore, as a robustness check, we estimate peer effects under the assumption of complete information. As discussed in Section 3, a main challenge of complete information is the existence of multiple equilibria. To overcome this problem, we apply a model of Soetevent and Kooreman (2007), which imposes an equilibrium selection rule that if multiple equilibria exist, each equilibrium is chosen with the same probability. The results reported in Column 2 of Table A.1 show that the sign and statistical significance of peer effects are consistent with Table 2, indicating the existence of peer effects.

The identification of peer effects also requires the assumption that landowners observe peers' characteristics listed as regressors in Table 1 (i.e., variables except for *Participation*). Again, this assumption cannot be directly verified. To relax this assumption, we apply the model developed by Yang and Lee (2017), where peers' characteristics are divided into those of public information (observable among peers) and those of private information (known only to a landowner itself). In their model, landowners expect peers' private information based on distribution or public information. We regard the familiarity with the program (i.e., Well informed about the KJM) as private information and assume that it follows the Bernoulli distribution with the mean of its sample average (i.e., 0.623). The estimation results are reported in Column 3. Although the statistical significance of some regressors differs from that in Column 2 of Table 2, the parameter of peer effects is positive and statistically significant. Thus, our estimation results are robust to the possibility that the familiarity with the program is private information.

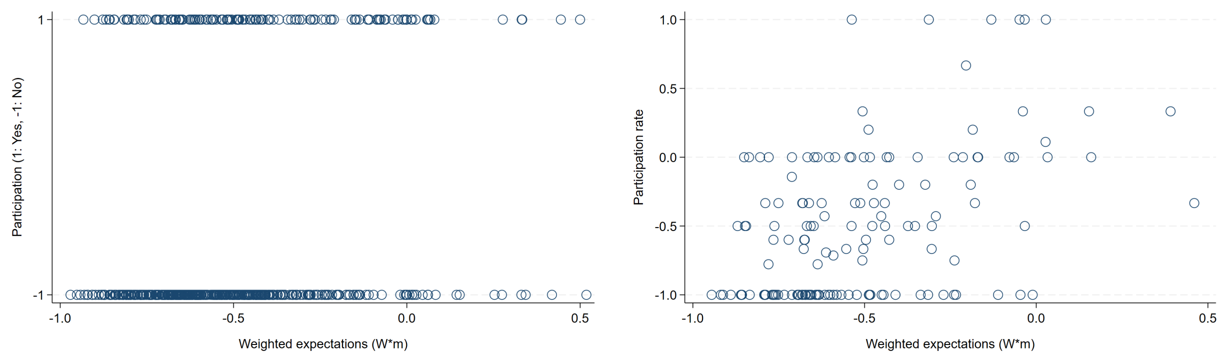
Table A.1: Robustness of Assumptions

	Leaders (1)	Complete Info. (2)	Private Info. (3)
Peer effect	0.423**	0.244***	0.600***
	(0.185)	(0.077)	(0.233)
ln(forest size)	0.075*	0.117***	0.073
	(0.041)	(0.044)	(0.044)
Recognition of forest borders	−0.151***	−0.224***	−0.151**
	(0.051)	(0.067)	(0.060)
Active forestry management	−0.370***	−0.355**	−0.399***
	(0.127)	(0.152)	(0.116)
Experience of joint management	0.505***	0.508***	0.536***
	(0.101)	(0.152)	(0.100)
Well informed about the KJM	0.537***	0.683***	0.486***
	(0.127)	(0.156)	(0.122)
High school graduate	0.190*	0.240	0.169
	(0.111)	(0.153)	(0.106)
College degree	0.294**	0.396**	0.259*
	(0.145)	(0.187)	(0.138)
Constant	−0.444*	−0.557	−0.344
	(0.249)	(0.399)	(0.218)
Observation	602	602	602
District fixed effects	Yes	Yes	Yes

Notes: Column 1 shows the results obtained with a matrix weighted according to the size of forest that landowners own, rather than weighted equally. Column 2 reports the results with the assumption of complete information. Column 3 presents the results of estimating the model with private information. *** p<0.01, ** p<0.05, * p<0.1.

A.2 Variation of expectations for identification

As discussed in Section 3.3, the identification of peer effects in our binary choice model relies on the variation of expectations. In this Appendix, we explore the variation utlizing expectations computed in our model (2) of Table 2. The left panel of Figure A.1 plots the weighted expectations, $\mathbf{w}_i\mathbf{m}$, by participation status. The right panel of Figure A.1 draws the correlation between participation rate at the local community level and the weighted expectations averaged at the same level.

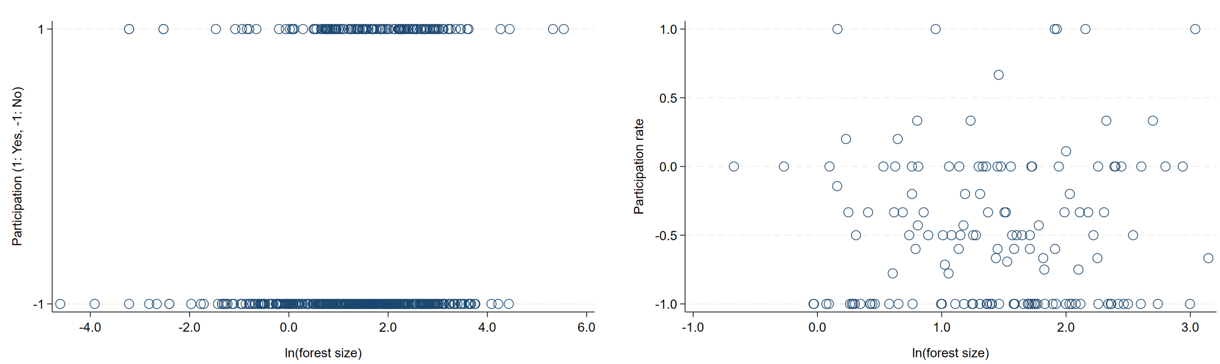


(a) Individual level (b) Local community level

Figure A.1: Variation of expectations

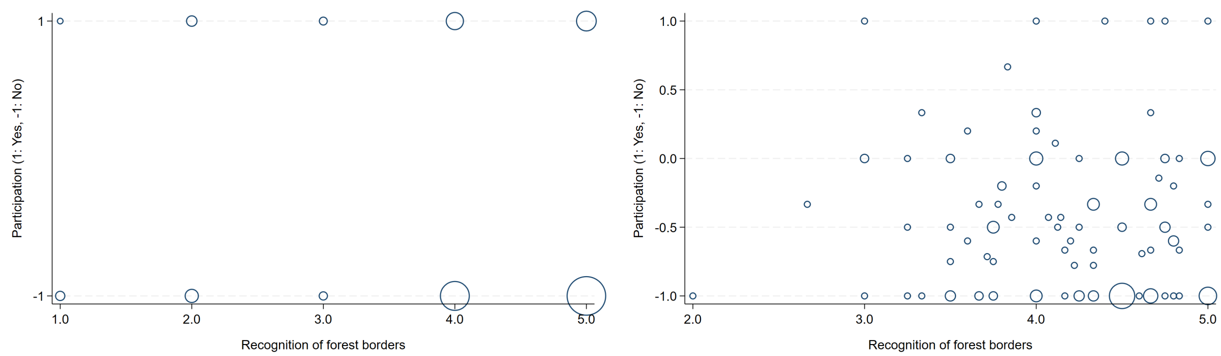
Figure A.1 shows the significant variation in expectations both at the individual and local community levels. At the individual level, the weighted expectations have large variation regardless of the participation status. At the local community level, expectations vary significantly between local communities with different participation rates.

This large variation comes from the large variation in observable characteristics. In Figures A.2 and A.3, we visualize the variations of forest size and recognition of forest borders. These variables differ substantially within and across local communities. Thus, such variation in observable characteristics brings large variation of expectations, allowing our identification.



(a) Individual level (b) Local community level

Figure A.2: Variation of forest size



(a) Individual level

(b) Local community level

Figure A.3: Variation of forest size

noindent *Notes*: The size of bubbles corresponds to the number of observations.

A.3 Robustness Check with Pseudo Groups

In Table A.2, we examine the robustness of our model. We estimate peer effects using pseudo-social groups, where peer groups are randomly formed. Since each landowner is randomly assigned to a pseudo group, peer effects should not exist. The number of groups (group size) was set at 50, 100, 149 (the group size of our data), and 150. For each group size, we match landowners 500 times and calculate the fraction of the trials where we find significant peer effects. This calculation can be interpreted as the power of the test where the null hypothesis is that γ is statistically significant at the conventional levels. As seen in Table A.2, we correctly reject the null hypothesis for more than 80% of the trials for each group size, suggesting the validity of our model.

Table A.2: The Frequency of Failures to Reject H_0

	$G = 50$	$G = 100$	$G = 149$	$G = 150$
$p < 0.01$	0.08	0.05	0.04	0.03
$0.01 \leq p < 0.05$	0.04	0.04	0.04	0.04
$0.05 \leq p < 0.1$	0.03	0.03	0.06	0.05
Sum	0.15	0.12	0.14	0.12

Notes: G represents the number of groups.

A.4 Selection Bias in Peer Effects

Our efforts to suppress omitted variable bias are built on the survey of landowners. Although the response rate of our survey is high (i.e., 50.74%), we can still miss some social interactions among landowners. For example, peer effects can be overestimated if influential landowners are more likely to respond to the survey than uninfluential landowners.

To examine whether our estimate of peer effects is robust to the selection, we randomly eliminate 25% of landowners from our sample and estimate peer effects with Equations (4) and (5). Note that we also eliminate landowners whose resulting community size is 1. We iterate this procedure 500 times. If our estimate suffers from overestimation (i.e., the sample includes influential landowners) and if peer effects increase nonlinearly with the number of influential landowners, resulting estimates will distribute leftward compared to the estimate in Table 5 as such landowners are removed from new samples for some iterations. In contrast, if our estimate is not overestimated, the new estimates will be distributed centrally around our estimate with less statistical power. Thus, this additional analysis enables us to test whether our peer effects estimate is overestimated indirectly.

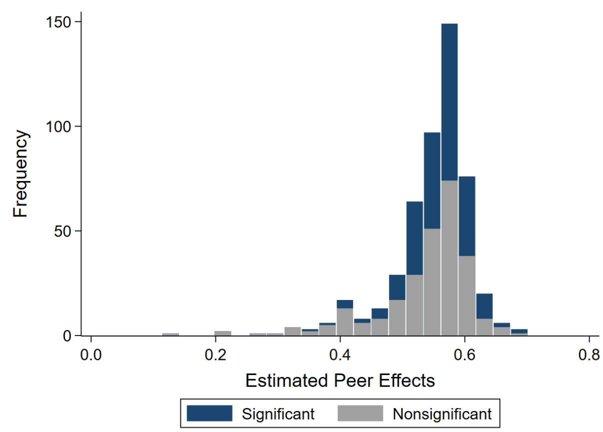


Figure A.4: Estimates of Peer Effects with Selection

Figure A.4 represents the distribution of the new estimates. The new estimates distribute centrally around 0.577, the estimate of peer effects in Table 5, while about half of the estimates are statistically insignificant partly due to the lack of statistical power. The results provide evidence that our estimate is unlikely to suffer from overestimation.

A.5 Sensitivity to Variable Selection

Table A.3 is the complete version of Table 2, showing the estimates of the added five variables: the gender of a landowner; whether they have used any services provided by the KFA; whether they are a member of the KFA; whether they attend every community meeting; and the size of the community to which they belong. The additional variables were not statistically significant.

Table A.3: Sensitivity Analysis

	(1)	(2)	(3)	(4)
Peer effect		0.577***	0.540***	0.593***
		(0.190)	(0.198)	(0.192)
ln(forest size)	0.099**	0.066*	0.089*	0.072*
	(0.041)	(0.039)	(0.051)	(0.037)
Recognition of forest borders	−0.182***	−0.147***	−0.178**	−0.175***
	(0.050)	(0.050)	(0.084)	(0.052)
Active forestry management	−0.343**	−0.376***	−0.412**	−0.401***
	(0.136)	(0.120)	(0.176)	(0.126)
Experience of joint management	0.465***	0.506***	0.583***	0.500***
	(0.108)	(0.099)	(0.206)	(0.102)
Well informed about the KJM	0.595***	0.496***	0.587**	0.486***
	(0.124)	(0.132)	(0.233)	(0.136)
High school graduate	0.224*	0.106	0.216	0.114
	(0.116)	(0.099)	(0.147)	(0.116)
College degree	0.351**	0.275**	0.330*	0.241*
	(0.149)	(0.135)	(0.194)	(0.143)
Male				−0.064
				(0.151)
KFA services in the past 5 years				0.123
				(0.103)
Membership of the KFA				0.124
				(0.159)
Community size				−0.010
				(0.010)
Attending every community meeting				−0.016
				(0.098)
Constant	−0.610**	−0.340	−0.474	−0.285
	(0.282)	(0.222)	(0.292)	(0.269)
Fixed or random effects	Village fixed	Village fixed	LC random	Village fixed
Other controls	No	No	No	Yes
Observations	602	602	602	599
Pseudo R^2	0.118	0.126	0.124	0.135
Log likelihood	−297.112	−294.346	−295.199	−289.642

Notes: Column 1 reports the results without peer effects, whereas Column 2 presents the results with peer effects. We include village fixed effects in these models. Column 3 shows the results where we include random effects that are common to each local community, rather than village fixed effects. In column 4, we add other control variables and the village fixed effects. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B Description of Nested Fixed-Point Algorithm

This appendix is devoted to describing the nested fixed-point (NFXP) algorithm (Rust, 1987, 2000). The algorithm consists of an inner algorithm to compute a fixed point given the current parameters and an outer algorithm to update the parameters with the resulting fixed point (Figure B.1). The inner algorithm applies two algorithms to calculate a fixed point: the contraction iteration and Newton–Kantorovich iteration. The contraction iteration is a simple recursive method, where we start with an arbitrary value $\mathbf{m}^0$ and obtain $\mathbf{m}^{k+1}$ with current parameters $(\boldsymbol{\beta}', \gamma)$ as follows:

$$\mathbf{m}^{k+1} = \tanh\left(\mathbf{X}\boldsymbol{\beta} + \gamma \mathbf{W}\mathbf{m}^k\right). \tag{B.1}$$

Although the contraction iteration is easy to program, it is known that convergence is slow within a sufficiently small neighborhood of an equilibrium (Rust, 2000). Therefore, we also use the Newton–Kantorovich iteration, which applies the first-order Taylor expansion of Equation (B.1) appropriately near an equilibrium:

$$\mathbf{m}^{k+1} = \mathbf{m}^k - \left(I - \frac{\partial \tanh(\mathbf{X}\boldsymbol{\beta} + \gamma \mathbf{W}\mathbf{m}^k)}{\partial \mathbf{m}^{k\prime}}\right)^{-1} \left(\mathbf{m}^k - \tanh(\mathbf{X}\boldsymbol{\beta} + \gamma \mathbf{W}\mathbf{m}^k)\right),$$

where I is an $n \times n$ identity matrix. Compared to the contraction iteration, the Newton–Kantorovich iteration is faster near an equilibrium but slower far away from it (Rust, 2000). Therefore, we use the contraction iteration until $\mathbf{m}^k$ is sufficiently close to equilibrium and then switch to the Newton–Kantorovich iteration to calculate a fixed point rapidly. When $\left\|\mathbf{m}^{k+1} - \mathbf{m}^k\right\|$ is sufficiently small (e.g., 1×10^{-6}), the NFXP algorithm moves to the outer algorithm. The outer algorithm applies the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm to calculate the approximate Hessian. To implement the NFXP algorithm, a statistical package GAUSS was used.

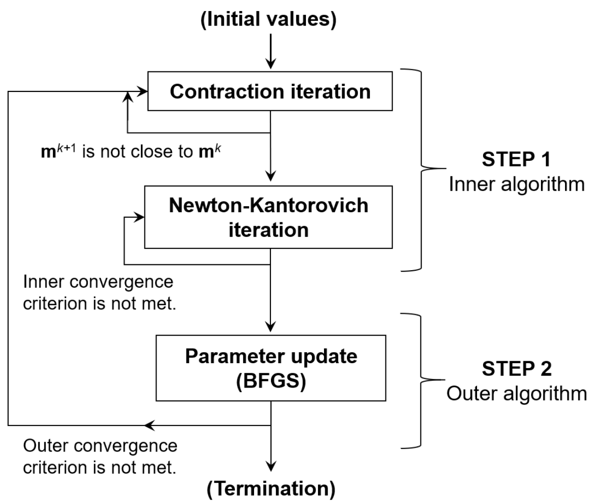


Figure B.1: Procedure of the NFXP Algorithm

Notes: The figure was made by the authors based on Rust (2000).

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