FARMIND
Farm Interaction and Decision Model

Model

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FARMIND: Sensitivity Analysis

Introduction

The purpose of a sensitivity analysis is to provide information on the relative importance of input parameters as well as assumptions underlying the model structure (Saltelli, Aleksankina et al., 2019). It addresses the question of what a model does when input assumptions and parameters vary over a specific range (Saltelli, 2019; Saltelli, Aleksankina et al., 2019). This helps to identify those parameter and assumptions that are of high importance for the model and its uncertain outcomes. In addition, it helps to identify those parameters for which more information should be collected to reduce model uncertainty (Saltelli, Aleksankina et al., 2019). Thus, the here presented sensitivity analysis identifies the most important parameters that should be tested extensively in real world applications of FARMIND and it helps to prioritize the search for data when applying FARMIND.

We applied three consecutive analyses: Morris screening, standardized regression coefficients and Sobol’ method (Saltelli, Tarantola et al., 2004; Saltelli, Ratto et al., 2008). The Morris's elementary effects screening allows to identify the relative importance of the assessed input parameters (Campolongo, Cariboni et al., 2007). Screening provides a relative measure of the different input parameter but not a straightforward quantification of the effect strength. In contrast, the absolute value of a standardized regression coefficient analysis gives a measure of the effect strength and the sign defines the direction of the effect (Lee, Filatova et al., 2015). Finally, to investigate non-linear relationships between the input parameters and outputs, we apply Sobol’ method, a variance decomposition approach (Saltelli and Annoni, 2010). The underlying idea is to vary the input parameters and then to identify the effect of the individual parameter on output variance.

Parameter range and assumptions

The model output variable in our sensitivity is the share of agents choosing a specific strategy. These shares always sum up to one i.e., to the total number of agents. The sensitivity focuses on the eight most important parameters in FARMIND i.e., parameters with respect to cumulative prospect theory and the CONSUMAT strategies i.e., reference income and tolerance values for activity dissimilarity and income growth differences. This provides a reasonable set of parameters also for global sensitivity analysis with high computational costs.

For the other parameters i.e., preferences and social networks, we use different input settings to test their influence on the model outcome. With respect to social networks we compare a random with a small world network. For the preference settings, we compare simulations in which agents have a preference for their initial activity with a setting in which agents have random preferences. We do not provide a specific analysis with respect to cognitive characteristics (memory length and learning rate) nor parameters determining the fuzzy choice set. These parameters affect the ranking of the different activities within a given choice set and thus are meaningful in calibrating the model to a specific research question. They are less important, however, to understand and assess model mechanisms.

In the implementation of the sensitivity analysis, we followed the instructions by Thiele, Kurth and Grimm (2014) and adapted the provided R code for the Morris screening method as well as for the standardized regression coefficients test and the Sobol' method. To test the impact of the different parameters on model outcomes, we use a random generation from a truncated normal distribution to determine individual values in each model run. Thus each agent gets a different parameter value drawn from a normal distribution with minimal and maximum (Table 1). The idea of global sensitivity analysis is to test parameters over a wide range of values. At the same time, values should be well-founded on empirical values. The values used for the sensitivity analysis of FARMIND are either derived from underlying bio-economic model (reference income and tolerance parameters) or based on empirical studies for the parameters derived from cumulative prospect theory. With respect to the reference income, we assume that the value does not exceed the minimal and mean gross margin under the condition that all agents optimize within the price range used in the applications of the bio-economic model (Böcker, Britz et al., 2018; Böcker, Britz et al., 2020). In our application, values above the mean gross margin would drive all the agents into optimization or opt-out behavior. The tolerance levels are also set with respect to the underlying bio-economic model. For the income tolerance parameter, we set the lower bound to 1% and the upper bound to 30%. The corresponding values for activity tolerance are set to 10% and 75%. Below and above these levels, agents will always be forced to information seeking or individual behavior, respectively. With respect to the cumulative prospect theory, we set the lower level parameters for the curvature of the value and weighting function as well as loss aversion according to the levels documented in Bougherara et al. (2017). It has to be noted, however, that empirical studies usually provide mean effects. Thus, we here increased the parameter range to capture the full range of possible parameter values.

Table 1: Parameter range for sensitivity analysis

Parameters	Values for truncated normal distribution				Description	References for sensitivity range
	Min. mean	Max. mean	Min.	Max		
α^+ α^- φ^- φ^+	0.5	1	0.5	1	Range of cumulative prospect parameters in the value and weighting function. All values being 1 represent an expected utility maximization.	Bougherara et al. (2017): reported ranges between 0.6 and 0.9
λ	1.5	4	1	3	Range of loss aversion coefficient in cumulative prospect theory.	Reported ranges between 1 – 2.6 (Bougherara et al. 2017; Tonsor 2018)
V_i^{ref}	100	400	1	400	Reference income in Euro that determines gains and losses in the value function.	Derived from Böcker et al. (2018): Range of average gross margin in simulated price range (see also Tonsor 2018).
g_i^{tol}	0.01	0.3	0.01	1	Tolerance level for % difference between agents' income growth and those of all agents.	Derived from Böcker et al. (2018): Mean income variation between agents
d_i^{tol}	0.1	0.75	0.01	1	Tolerance level for how many agents in my network perform the same activity (in %) without affecting strategic choice	Derived from available weed control activities in Böcker et al. (2018): Values above 0.75 are only possible if all agents use the same weed control option

The theoretical underpinning of our ABM allows to derive specific hypothesis for the input parameters in FARMIND (Table 2). The parameters can be grouped into four classes.

1. An increase in the reference income (V_i^{ref}) as well as in α- and loss aversion λ increase the probability of the strategies optimization and opt-out.

2. An increase of α+ increase the probabilities of repetition and imitation.

3. An increase in the two parameters that determine the threshold level for whether an agent chooses an individual or a social information seeking behavior i.e., d_i^{tol} and g_i^{tol}, increases the probabilities in seeking repetition and imitation strategies.

4. The signs of the parameters affecting the decision weights in the gain and loss domain φ+ and φ- respectively are ambiguous. They depend on the income distribution and the realized maize prices in each simulation run.

Table B2: Hypothesis of how input parameters affect the strategic choice in FARMIND

Parameter	Effect of parameter increase	Repetition (satisfied, individual oriented)	Optimization (unsatisfied, individual oriented)	Imitation (satisfied, peer oriented)	Opt-out (unsatisfied, social oriented)
ref_income V_i^{ref}	Increase in reference income implies a decreasing probability of being satisfied.	(-)	(+)	(-)	(+)
alpha_minus α^-	Increasing α^- reduces the distortion of the realized incomes below the reference income in the value function. This decreases the probability of being satisfied.	(-)	(+)	(-)	(+)
Lambda λ	Increasing λ increases the weight of low incomes in the calculation of satisfaction	(-)	(+)	(-)	(+)
tol_income g_i^{tol}	Increase the tolerance with respect to changes in income growth decreases the probability of choosing a social oriented decision strategy.	(+)	(+)	(-)	(-)
tol_act d_i^{tol}	Increase the tolerance of activity dissimilarity decreases the probability of choosing a social oriented decision strategy.	(+)	(+)	(-)	(-)
alpha_plus α^+	Increasing α^+ reduces the distortion of the realized incomes above the reference income in the value function. This increases the probability of being satisfied.	(+)	(-)	(+)	(-)
phi_plus φ^+	Increasing φ^+ reduces the subjective probability distortion of incomes above the reference income. The sign of this parameter can be positive or negative depending on the underlying (initial) income distribution.	(+)/(-)	(+)/(-)	(+)/(-)	(+)/(-)
phi_minus φ^-	Increasing φ^- reduces the subjective probability distortion of incomes below the reference income The sign of this parameter can be positive or negative depending on the underlying (initial) income distribution.	(+)/(-)	(+)/(-)	(+)/(-)	(+)/(-)

Results

Morris's elementary effects screening

The Morris's elementary effects screening allows to identify the relative importance of the assessed input parameters (Campolongo, Cariboni et al., 2007). Morris screening is based on a one-factor-at-a-time design and estimates the effects of changes in input factor levels, which are called elementary effects (Thiele et al. 2014). The results show two measures for every input parameter: μ (mu) represents the mean of the elementary effects and gives an estimate of the overall influence of the corresponding input. In addition, σ (sigma), the standard deviation of the elementary effects, represents an estimate of non-linear and/or interaction effects of the corresponding parameter compared to all the other parameters in the model (Morris, 1991).

The Results from the Morris elementary screening shows that the impact of the different parameters on the probability of choosing one of the four strategies in FARMIND (Figure 1). High mean values of the elementary effect indicate that a parameter has an important overall influence on the choice of the corresponding strategy. High values of the standard deviation of the elementary effects imply that the strategic choice depends on the choice of the other input factors. The signs of the threshold parameters are as expected: The higher the reference income the higher the probability that optimization and the opt-out strategies are selected. In contrast, increasing the reference income reduces the probability that the repetition or the imitation strategy is chosen. Vice versa, higher tolerance levels for income or activity tolerance increase the probability for repetition and optimization. The probability of choosing an imitation or opt-out strategies decreases with higher tolerance levels. The cumulative prospect theory parameters affect the prospect value calculated in FARMIND and thus influence the strategic choice only indirectly. Accordingly, threshold values have a higher direct impact on the choice of strategy compared to the cumulative prospect parameters and their impact strongly depends on the levels of the other input parameters. The signs of $\alpha+$ and $\alpha-$ i.e., the curvature of the value function, have the expected sign and have a higher impact compared to $\varphi+$ and $\varphi-$ i.e., the parameters defining the weighting function.

The effect of these weighting parameters is that higher values of $\varphi+$ increase the prospect value and thus the probability of choosing repetition or imitation. This means that on average, the underestimation of more probable events exceeds the potential gains from extremely high incomes with low probabilities in our simulation setting. The opposite holds for $\varphi-$, which reduces prospect value and thus increases the probability of optimization or opt-out in our simulation.

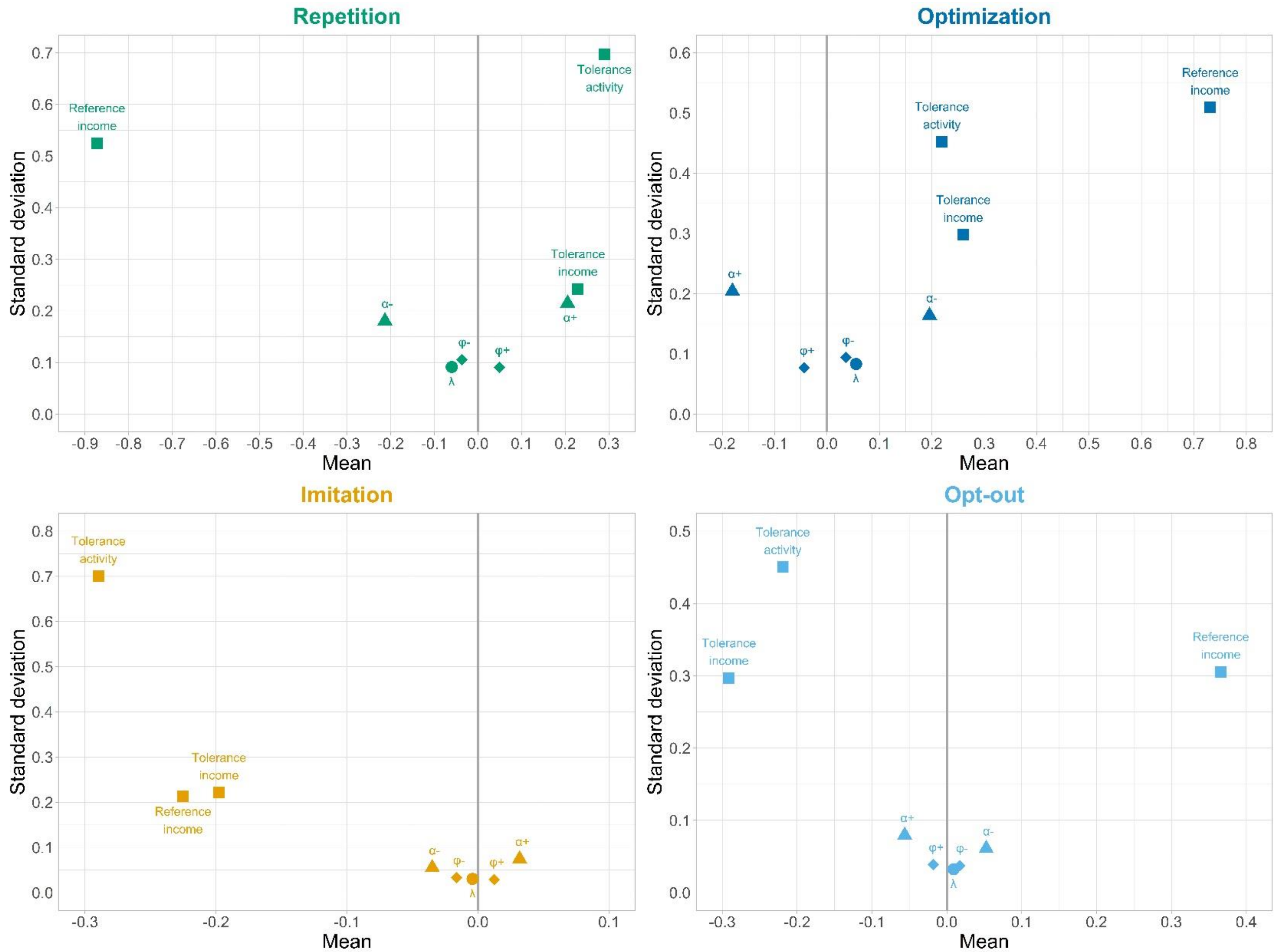

Figure 1. Results from Morris-Sensitivity analysis for the four strategies. The x-axis represents the mean elementary effects and describes the impact of increasing the parameter on the probability of the strategy choice. Positive (negative) values imply that the probability increases (decreases). The y-axis shows the indirect effect of the parameter change i.e., the standard deviation of the elementary effects for the corresponding strategy. Threshold values are depicted in squares; cumulative prospect theory parameters in triangles.

Standardized regression coefficient analysis

The Morris screening provides a relative measure of the different input parameter but not a straightforward quantification of the effect strength. In contrast, the absolute value of a standardized regression coefficient analysis gives a measure of the effect strength and the sign defines the direction of the effect (Lee, Filatova et al., 2015). The standardized regression coefficient analysis includes two steps. Firstly, a linear regression model fitted to the simulation data generated from a Latin Hypercube Sample of the eight different parameters. Secondly, the regression coefficients are standardized. Thereby, the coefficients are multiplied with the ratio between standard deviations of the input parameter and the output value (Saltelli, Tarantola et al., 2004). Thus, the regression analysis shows the effect of an input on the output variables both normalized with a mean of zero and standard deviation of one. This allows to interpret and communicate better the absolute relationship between the inputs and output of FARMIND.

The results from the standardized regression coefficient approach based on Latin hypercube sampling with 1000 samples shows the absolute effect of the single parameters and allows to rank the different parameters for different initializations of the model. The model coefficient of determination for these models lies between 70 and 90%. This implies that the impact of the different parameters on the choice of strategies i.e., the model output, is generally additive and that the standard regression coefficient analysis is an appropriate sensitivity test.

The regression results confirm the findings from the Morris screening with respect to the sign of each parameter on the different strategies (Figure 2). In addition, the results imply that, on average, reference income is the most important parameter for the choice of repetition, optimization and opt-out. For imitation behavior, activity and income tolerance are more important.

These parameters are also more important in the opt-out strategy compared to repetition and optimization. Income and activity tolerance have the smallest impact on optimizing behavior. Cumulative prospect parameters are less important compared to the threshold values i.e., reference income, income and activity tolerance. Nevertheless, an increase by one standard unit of $\alpha+$ and $\alpha-$ increases the standard deviation of the frequency of strategic choice between one and 15%. The impact of $\varphi+$ and $\varphi-$ as well as λ is lower and accounts for an impact of between one and 7%.

The minimal and maximal influence of the tolerance thresholds highly depend on the underlying social network and the preference settings in FARMIND. This is exemplified by disentangling the standard regression coefficients for the four initialization scenarios (Figure 3). The results reveal three mechanisms. Firstly, smaller networks increase the importance of activity tolerance since, all else equal, the probability to be dissimilar to other agents increases with fewer peers.

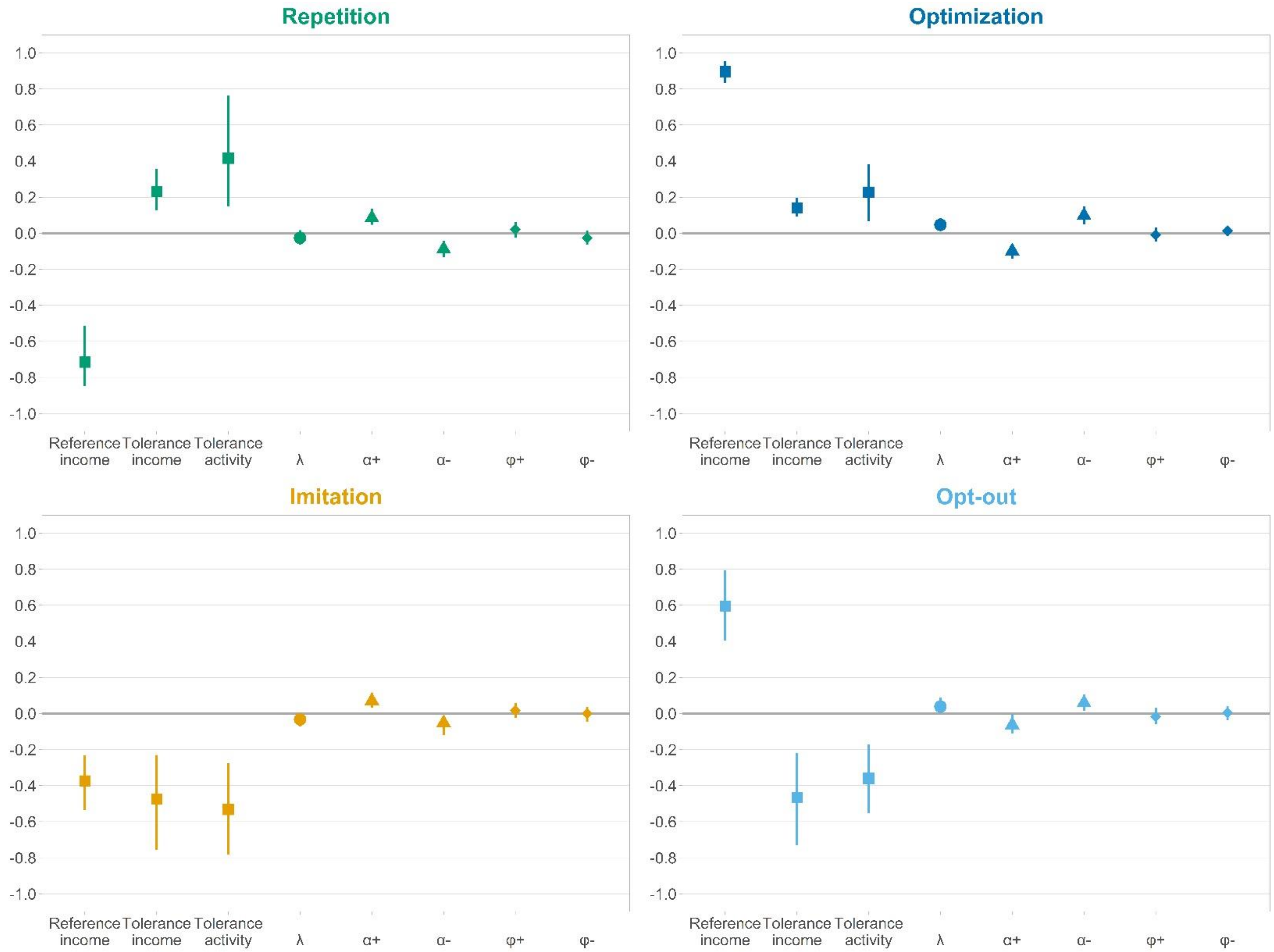

Figure 2. Standardized regression coefficients of FARMIND parameter on choice of the four strategies. Scenario 1: random network and preference for initial strategy. Scenario 2: random network and random preferences. Scenario 3: Small world network and preference for initial strategy. Scenario 4: Small world network and homogenous preferences. Mark show mean SRC value. Sticks show maximum and minimal values of bootstrapped 95% confidence intervals of corresponding sensitivity indices in four scenarios. R^2 *for all estimated models are above 0.7.*

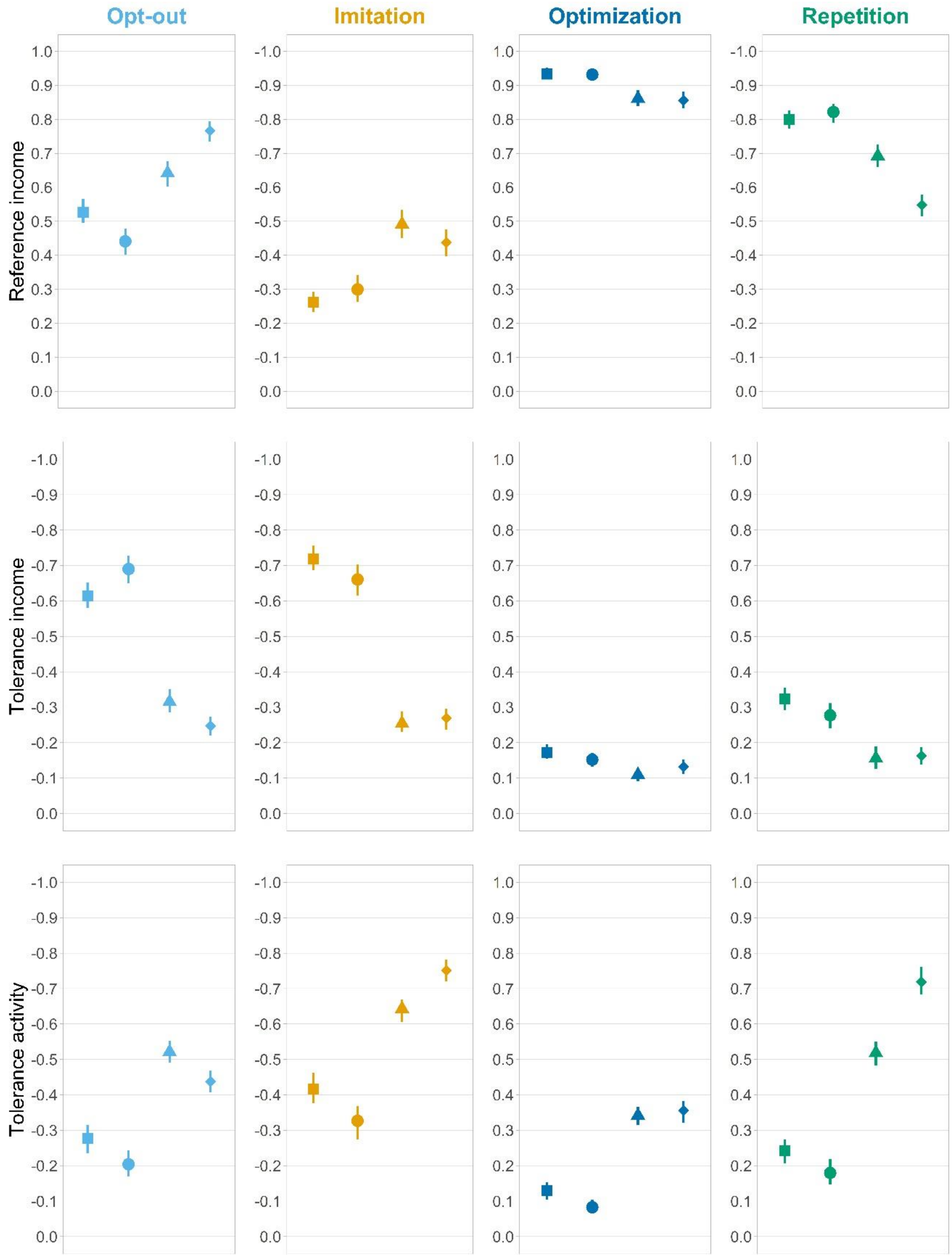

Figure 3. Impact of threshold parameters on choice of the four strategies in four different initializations of networks and preferences. Scenario 1: random network and preference for initial strategy (squares). Scenario 2: random network and random preferences (triangle). Scenario 3: Small world network and preference for initial strategy (rhomb). Scenario 4: Small world network and random preferences (circle). Mark show mean SRC value. Sticks show bootstrapped 95% confidence intervals of corresponding sensitivity indices.

This means that imitation becomes more frequent and the impact of the corresponding parameter that differentiates individual from social behavior also increases. For individual strategies, the effect is that a higher tolerance levels also increases their probability while a higher tolerance level decreases the probability of social oriented information seeking strategies. In contrast, the importance of income tolerance decreases. This reflects that the income dissimilarity originates from income independently from peers and activities and thus becomes less important if activity dissimilarity increases.

Secondly, if the probability that agents engage in information seeking behavior increases, reference income, i.e., the threshold parameter determining the choice between imitation vs. opt-out becomes also more important in the corresponding strategies. In contrast, reference income becomes less important in explaining the choice for repetition and optimization. This reflects the complementarity between the four strategies: if one strategy becomes more likely, this must come at the expense of another strategy since the share of all strategies sums up to the number of agents in our model output. Consequently, a mechanism that increases the importance of one input parameter in a positive way, the same input parameter must have a negative impact in one of the other strategies.

Thirdly, the effect of preference settings on the importance of the different input parameters is generally smaller than the impact of the underlying social network. Preference settings, however, still have an important impact on imitation and repetition. With random preferences, the initialized activity and the preferences might not be aligned anymore i.e., the agent is assumed to have performed a weed control activity that actually does not comply with his preferences. This reduces the number of activities in the choice set of imitating farmers since preferences, past experience and observed behavior of peers are equally weighted in our simulations. Less activities in the choice sets, in turn, increases the probability of being dissimilar. In other words, more peers or more activities increase the importance of activity tolerance.

As in the case of fewer agents in a smaller network, this effect increases the share of imitating behavior and thus the importance of activity tolerance. A higher share of imitation has to come at the expense of the repetition strategy. Again, the direction of change in these two strategies mirrors the complementarity of strategies resulting from an increase in activity tolerance. In contrast to the case of fewer agents, however, the increase in importance of the tolerance level through different preference settings does not reduce the importance of the tolerance income but affects the influence of the reference income. Thus, the underlying settings of the social network and the agents' preferences for weed control activities do not only affect the importance of the different input parameters but also their interaction.

Sobol'method

To investigate non-linear relationships between the input parameters and outputs, we apply Sobol' method, a variance decomposition approach (Saltelli and Annoni, 2010). The underlying idea is to vary the input parameters and then to identify the effect of the individual parameter on output variance. In Sobol'method, the total variance is composed of the so called main and interaction effect, which is determined by evaluating the partial effects using Monte-Carlo methods (Thiele, Kurth et al., 2014). As in the case of the regression analysis, we use a Latin Hypercube Sampling to generate the range of input parameters in the sensitivity analysis. We applied the sobol2007 function to identify the expected non-linear effect of the CONSUMAT parameters.

The elementary effects as well as the standard coefficient regression showed that the threshold levels are the most important model parameters. We applied Sobol' method to analyze the interactions between reference income and activity tolerance. The results show how much the different parameters can explain the model output variation. Thereby, we compared effect under a random and a small world network (Figure 4).

In a random network, the main effect of the reference income is higher for repetition and optimization strategies. In contrast, the effect of the activity tolerance on the output variance is higher in the imitation and opt-out strategy. Thus more of the variation in the individual and social oriented strategies is explained by the reference income and the activity tolerance respectively. In addition, the interaction effect between reference income and activity tolerance, i.e., the gap between the main and the total effect in Figure 4, is also higher in the imitation and opt-out strategy. As a consequence, the reference income is important for all the strategies while the tolerance levels are more important for the choice of the imitation and opt-out strategy.

In a small world network in which more information seeking behavior occurs, the interaction between the two parameters change. The importance of the reference income for opt-out and imitation increases since the variability of the model outcome is relatively more affected by the reference income if dissimilarity is more likely. For the same reason, the activity tolerance becomes less important in these two strategies. The opposite effect can be observed for repetition and optimization i.e., reference income become less, activity tolerance more important respectively. At the same time, interactions get more important in these two strategies.

In summary, in a small world network, the main and the interaction effect of activity tolerance decreases in imitation and opt-out while both effects increase in repetition and optimization. In a random network, the main effect of reference income increases while the interaction effect decreases for the imitation and opt-out strategy.

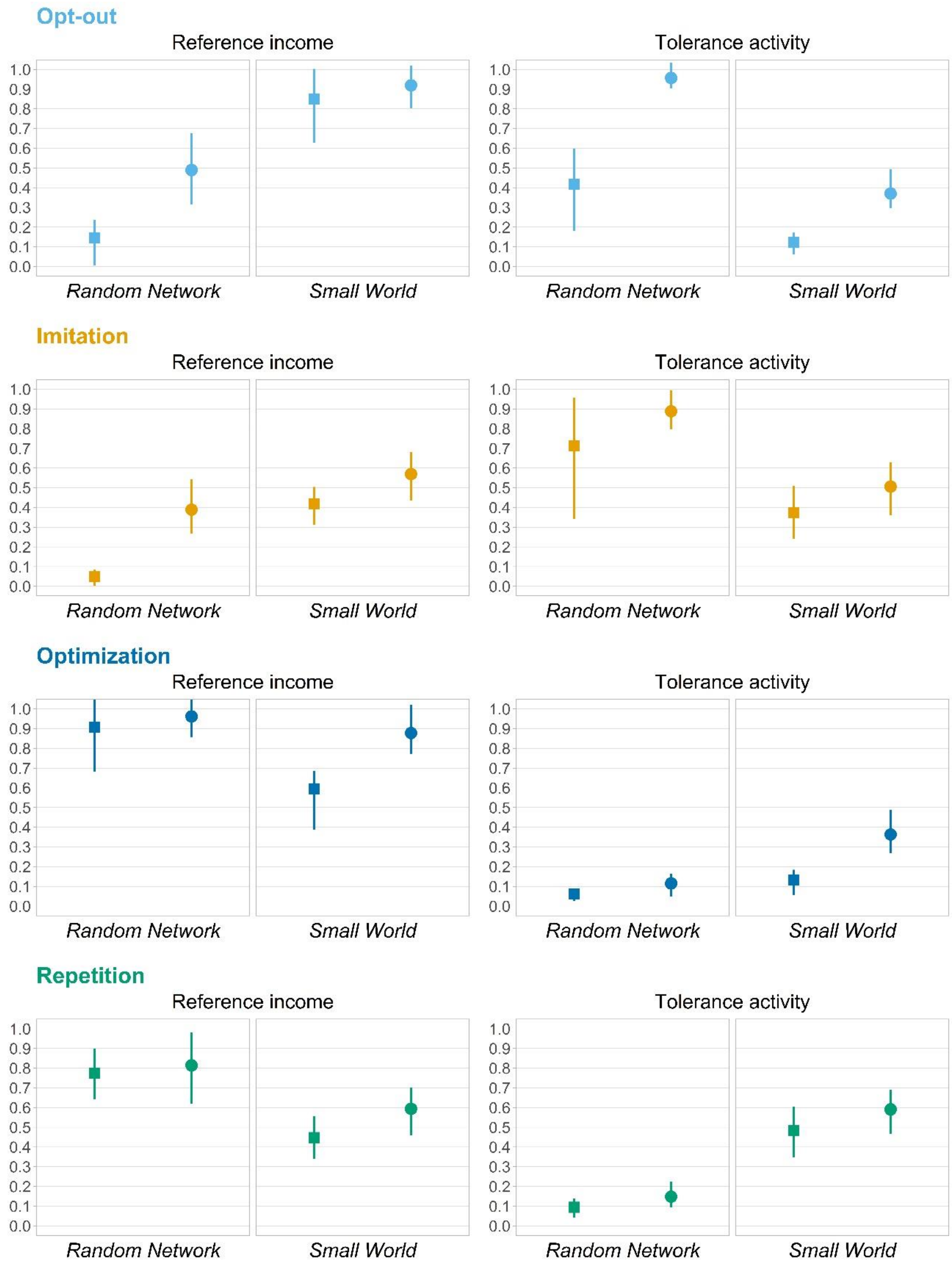

Figure 4. Results from Sobol-Sensitivity analysis for the four strategies. The x-axis shows the reference income and tolerance activity in a random and small world networks respectively. Dots represent the main effect of the parameter on the variability of the model outcome. Circles refer to the total effect, including interaction effects of the corresponding parameter on the strategy choice. Sticks show bootstrapped 95% confidence intervals of corresponding sensitivity indices.

Conclusion

We performed a comprehensive sensitivity analysis of FARMIND applying three consecutive analyses: Morris screening, standardized regression coefficients and Sobol’ method. The analysis shows that threshold values are key parameters in FARMIND. Thereby, the reference income is more important for individual focused behaviour, i.e., optimization and repetition. Tolerance levels for activity dissimilarity or income gap are more relevant in social oriented strategies, i.e., imitation and opt-out. The parameters derived from the cumulative prospect theory explain up to 20% of model uncertainty, depending on the underlying initialization of preferences and social networks. We conclude that satisfaction levels can have a relevant impact on the model results even though they are only indirectly affected by the parameters of the curvature of the value function and the subjective probability rating parameters.

The results of the sensitivity analysis are important for understanding FARMIND. However, future applications would need not only assess the structural and parameter uncertainty, but also the uncertainties arising from model calibration and future developments (e.g., Troost and Berger, 2015). Future analyses should also explore the sensitivity to different formulations of sub-models (Schulze, Müller et al., 2017).

The implications of the sensitivity analysis for an application of FARMIND to real behavioral data are twofold. First, the identification of threshold values in the specific decision context is of importance for any FARMIND application. This has to be done via surveys or experiments (e.g., Tonsor, 2018). If such data is not available, a careful uncertainty analysis must be run over these parameters. Secondly, assumptions concerning social networks, farming preferences, and income distributions should be carefully assessed in the application of FARMIND. The model fundamentally depends on linear and additive elements that are calculated based on normal distributions or average changes. If real world data and the specific decision-context would be influenced by an unequal distribution e.g., of agents’ income or social network, the uncertainty from these assumptions should also be carefully assessed.

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