Exploring heterogeneity in farmers’ willingness to cooperate in four EU member states: Insights from public goods games

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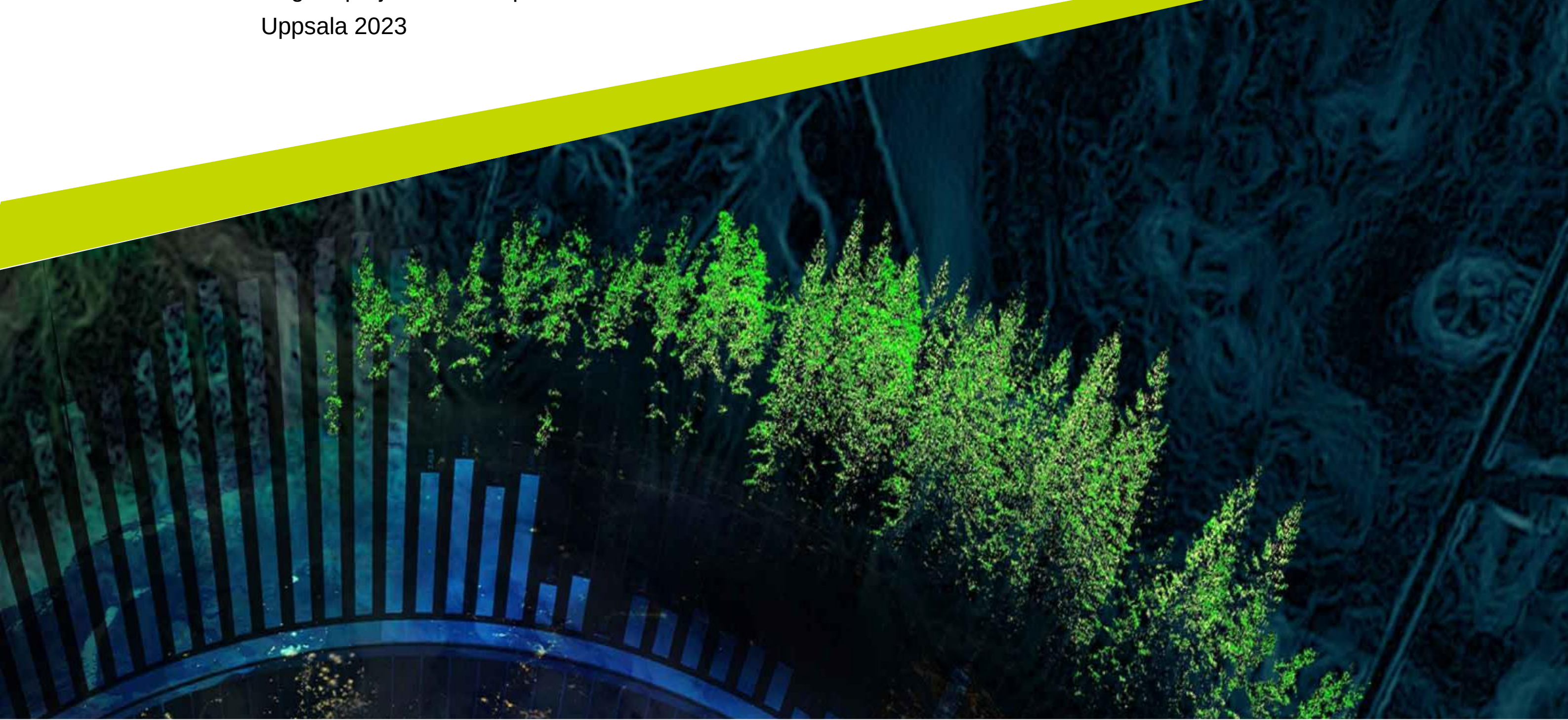

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Abstract

Agri-environment-climate measures (AECMs), as part of the European Union's Common Agricultural Policy, incentivize environmentally friendly farming practices for multiple ecosystem services provision. However, AECMs are criticised for their low cost-effectiveness. Moving towards the collective implementation of AECMs is discussed as a possibility to coordinate ecosystem services provision at larger scale and to economize on administrative costs. The thesis investigates European farmers' willingness to cooperate and the heterogeneity in cooperation by means of public goods game (PGG) experiments conducted with farmers in Germany, Hungary, Netherlands, and Poland. A finite mixture model estimates the probability of belonging to different latent classes of decision-makers. The results show that German and Dutch farmers are willing to contribute more on average (70% and 75% of the initial endowment respectively) than Polish and Hungarian farmers (57% and 50% of the initial endowment respectively). German and Dutch farmers can be categorised into two different classes, whereas in Hungary and Poland, three different classes of farmers are evident. The higher prevalence of freeriding observed in Hungary and Poland calls into question collective schemes that have to onboard everyone for example for rewetting a landscape. The overall heterogeneity in farmers' willingness to cooperate highlights that holistic approaches are necessary to promote collective AECMs among European farmers.

Keywords: Agri-environment-climate measures, Cooperation, Common Agricultural Policy, Finite mixture model

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Abbreviations

AECM	Agri-environment-climate measure
AES	Agri-environment scheme
AIC	Akaike's Information Criteria
BIC	Bayesian Information Criteria
CAP	Common Agricultural Policy
EAFRD	European agricultural fund for rural development
ECA	European Court of Auditors
EU	European Union
FMM	Finite mixture model
MPCR	Marginal per capita return
MS	Member state of the European Union
PGG	Public goods game
VCM	Voluntary contributions mechanism

1. Introduction

This thesis explores European farmers' willingness to cooperate for collective Agri-environment-climate measures, using data from experiments conducted with farmers from Germany, Hungary, Netherlands, and Poland. The thesis addresses the question, to what extent European farmers are willing to cooperate on AECMs. It investigates possible differences in farmers’ willingness to cooperate between the four European countries and compares the results of the farmers’ responses, both for each country individually and the data pooled together. It studies the observed and unobserved heterogeneity of the farmers in the respective countries to show whether there are characteristics of farmers that anticipate cooperativeness and whether there are differences in cooperative behaviour that cannot be explained by the observed variables. Moreover, this thesis contributes insights into the debate on the implementation of collective AECMs at the European level for policymakers.

Agri-environment-climate measures (AECMs) are important voluntary environmentally friendly practices providing multiple ecosystem services in agricultural landscapes in Europe. They are a crucial instrument for policymakers of the European Union (EU) to contribute to the EU’s ambitious environmental and climate objectives (European Commission, 2017). AECMs, with a budget share of EUR 4.5 billion in 2017, are an essential part of the second pillar of the Common Agricultural Policy (CAP) (Pe’er et al., 2019). The European agricultural fund for rural development (EAFRD) co-finances the AECMs together with the member states. Via the Rural Development Programmes of the respective member states or regions, the AECMs are implemented on farm level. Voluntary approaches like AECMs are providing an incentivized toolbox of various practical actions for European farmers, out of which farmers can choose freely which of the environmentally sustainable practices to implement (e.g. buffer strips, organic farming, or rewetting a landscape). The goal of AECMs is the provision of positive externalities on biodiversity, water, soil, landscapes, air quality and climate change (BMEL, 2019).

The current AECMs are criticised (Brown et al., 2019; Pe’er et al., 2014, 2017, 2019; ECA, 2021; Hardelin and Lankoski, 2018). One of the key criticisms is the AECM's poor cost-effectiveness. European citizens are demanding cost-effective policies supporting sustainable agriculture since it is taxpayers’ money that funds policies like AECMs (Pe’er et al., 2020). The European Court of Auditors (ECA) noted that funds allocated for AECMs, intended to meet environmental and climate goals under the CAP 2014-2020, were insufficiently cost-effective (ECA, 2021). Cost-effectiveness is *“a holistic concept that takes into account environmental effectiveness, different kinds of costs (e.g. compliance costs and policy-related* *transactions costs), and can incorporate dynamic considerations*“ (OECD, 2022, p. 17). This means an environmental goal should be achieved at the lowest cost. Another criticism is the lack of coherent AECM designs across the EU. Since AECMs focus on farm-level actions, potential benefits can be cancelled out, resulting in an inefficient distribution of spending across the EU (Pe’er et al., 2017). National ecosystem assessments are not fully integrated into the policy-making process, and comprehensive impact evaluations of existing AECM policies are often incomplete (Hardelin and Lankoski, 2018).

Collective AECMs can play a key role in achieving higher cost-effectiveness (Groeneveld et al., 2019; Merckx et al., 2009; Nguyen et al., 2022; OECD, 2013; Westerink et al., 2017). Collective AECMs offer several benefits, including an increase in cost-effectiveness, economies of scale, and environmental effectiveness (Hardelin and Lankoski, 2018). Certain public goods such as threshold public goods, for example preserving a critical habitat for an endangered farmland bird species, or the reduction of negative externalities require even the collective action of multiple farmers. Collective action can be defined as “*a set of actions taken by a group of farmers, often in conjunction with other people and organisations, acting together in order to tackle local agri-environmental issues*” (OECD, 2013, p. 11), for example maintaining the local landscape or protecting certain species. Collective AECMs can be implemented through collective agri-environmental contracts, where farmers collaborate or coordinate beyond the level of a single farm. The Netherlands is the only member state, that has implemented collective AECMs up to now (Ministry of Economic Affairs, 2016).

Research on European farmers' willingness to cooperate for collective AECMs is scarce and inconclusive. “*Most behavioural research focuses on farmers’ voluntary adoption of sustainable practices, but it is unclear how behavioural factors affect farmers’ decisions*” according to Dessart et al. (2019, p. 454). An overview of research on collective and agri-environmental contracts can be found in the paper of Kuhfuss et al. (2019). Researchers such as Colen et al. (2016), Lefebvre et al. (2021) and Pe’er et al. (2022) have emphasized the increased need for policy-oriented, experimental research that considers the complex drivers of farmers' decision-making. As AECMs are applicable to all EU farmers, more research is needed on the cross-national differences in farmers' behaviour (Dessart et al., 2019). Most of the available literature in this field of collective AECMs was conducted in specific regional contexts. Analysing the willingness to cooperate on AECMs across countries is needed because, despite the diverse AECM designs across member states, they share identical goals throughout the EU. There is one noteworthy exception in this scarcity of literature. Bouma et al. (2020) conducted a threshold public goods game with Dutch farm management students, but there is limited evidence on the behaviour of actual farmers.

As it is challenging to identify causal effects regarding farmers' willingness to cooperate on AECMs, conducting experiments is a suitable research method. To analyse the cooperative behaviour of individuals, thoroughly controlled experiments are necessary (Ledyard, 1994). “*Experiments are also the best option to assess the effectiveness of the policy options*” (Dessart et al., 2019, p. 454). The thesis uses data from public goods games experiments, conducted within the context of the European research project "Contracts2.0" in Germany, Hungary, Netherlands, and Poland. Farmers had to decide how much of an initial amount of money to allocate between a private and a group account with the total amount of the group account being multiplied by a factor and then – in most cases – split equally among all participants, regardless of individual contribution levels. Although the experimental design of the PGGs may differ across countries, there is a shared baseline version across all four countries. Note that for the context of the thesis "*cooperation*" shall be defined as making contributions to the group account of the public goods game.

European farmers are heterogenous in their willingness to cooperate (OECD, 2013), therefore applying finite mixture models to analyse the experimental data is a suitable method. People's willingness to cooperate is driven by different motivations, which applies also to European farmers. Each farmer operates based on a unique decision-making process, so there is no one-to-one correlation of farmers' willingness to cooperate (Dessart et al., 2019). Moreover, there are considerable differences in AECM implementation across member states, depending on the overall AECM design, different farm characteristics, and political and economic circumstances, among others (Vesterager et al., 2016). It would be inappropriate to estimate European farmers' behaviour in cooperation according to a single model. Applying a finite mixture model to the observed experimental data allows for estimating the farmers' probability of belonging to different latent classes. This approach can help to understand the factors that influence farmers' behaviour and conclusively identify possible political strategies for promoting cooperation among farmers for collective AECMs in the EU.

The following is the structure of this thesis. Chapter two outlines the theoretical framework. The experimental design, the data, and the applied empirical strategy are explained in chapter three. The fourth chapter presents the results of the thesis, while chapter five discusses the findings and policy conclusions. Finally, the main outcomes of the thesis are summarised in chapter six.

2. Empirical background

Cooperation among humans has been a main concern of the experimental economics literature. In the experimental economics literature, a commonly used tool to investigate cooperation among humans is the public goods game, which was developed by Isaac et al. (1984). In the standard public goods game, participants are put into groups consisting of n players. Each player receives an initial endowment e_i (typically money) that must be anonymously allocated between a private account and a public group account. Each individual contribution to the group account x_i is in the range from 0% to 100% of the initial endowment, with $0 \leq x_i \leq e_i$. The total sum of the contributions x_i of all n players is then multiplied by a factor a, with $1 < a < n$. The total multiplied sum is subsequently divided equally among all n players, which is always positive and can be called the marginal per capita return (MPCR). Each player will receive the same amount of the endowment, regardless of how much of the initial endowment they contributed. The PGG played once is called a one-shot game, and if played multiple rounds it is called a repeated game. The setup of a PGG is often based on the voluntary contributions mechanism (VCM) (Moffatt, 2016).
The following function summarizes the payoff for each subject i in a one-shot public goods game (Isaac et al., 1984):

$$\pi_i = \frac{a\left(\sum_{j\neq i}^{n-1} x_j + x_i\right)}{n} + e_i - x_i$$

x_j are the contributions of the other n-1 players.

The steps of a one-shot public goods game are illustrated in Figure 1.

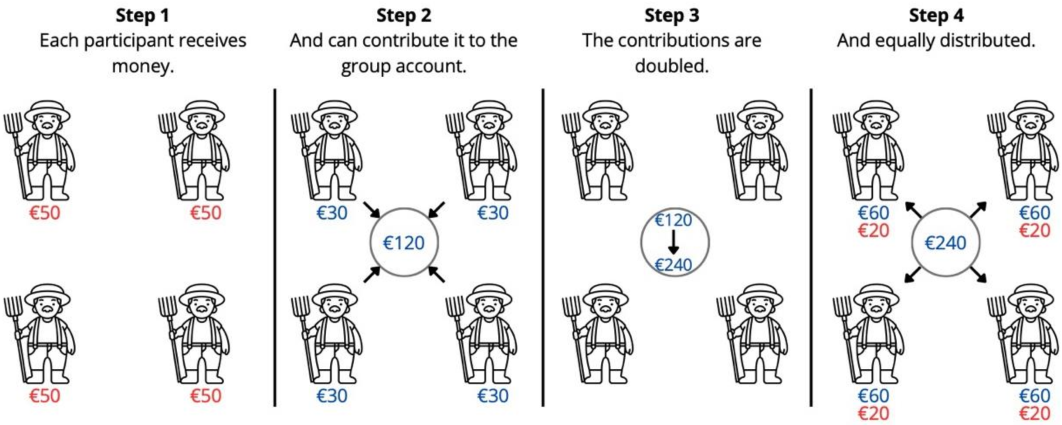

Figure 1. Representation of public goods game.

Source: Own design inspired by contracts2.0 material

The theoretical prediction under standard preferences (full information, no other-regarding preferences) is that all players should contribute zero to the group account (Bardsley and Moffatt, 2007; Fischbacher et al., 2001). Contributing zero to the group account is the unique Nash equilibrium of the game (Moffatt, 2016). A Nash equilibrium occurs when there is no incentive for any single player to deviate from their strategy given the strategies of the other players. The players face a dilemma because the social inefficiency of the Nash equilibrium is evident, generating the final outcome of endowment e_i for each player. If all players would contribute their full endowment e_i to the public group account, each player would receive $a_i * e_i$. Free-riders are players who have solved the PGG, because they are contributing 0% to the group account (Fischbacher et al., 2001). The free-rider problem is measured by the rate of zero contributions (Davis and Holt, 1993). The theoretical existence of this public goods dilemma wherein individuals act against the interest of the group has been recognized by economists for a long time (Ledyard, 1994).

In contrast to the theoretical predictions, the actual observed outcomes of PGGs in the empirical literature differ significantly. A considerable number of players make positive contributions and do not freeride (Fischbacher et al., 2001). "*The strong free-rider prediction is clearly wrong*" (Dawes and Thaler, 1988, p. 196). Ledyard (1994) highlighted that on average, subjects tend to contribute approximately 40% to 60% of their endowment to the group account, which means they do not play the unique Nash equilibrium. Assuming rational and selfish behaviour, the observed contributions are heterogenous and decline over time when the game is played repeatedly (Fischbacher et al., 2001).

In a public goods game, people can be classified based on their behaviour (Fehr and Gächter, 2000). Several authors including Fischbacher et al. (2001), Moffatt (2016) and Bardsley and Moffatt (2007) have categorised the various types of subjects in a population because each player's contribution is motivated by different factors.

Fischbacher et al. (2001) examined cooperation in a one-shot public goods game and categorised the participating people into three classes. The participants were required to indicate their level of contributions depending on the average contributions of the other group members. 50% of the participants can be classified as conditional co-operators, who are willing to contribute more, the more others are contributing. 33% of the participants are free-riders, who are contributing little or zero, regardless of the actions of the others. And 14% of people's contribution can be labelled as "hump-shaped". In a "hump-shaped" pattern, subjects' conditional cooperation is similar to others' contributions up to a certain amount but then steadily declines beyond that. Fischbacher et al. (2001) concluded that overall, it is highly unlikely for contributions to the public good to be positive and stable. Contrary to many other experiments in the literature, the game design was a one-shot game, to avoid repetitions and to analyse unambiguously the subject's willingness to be conditionally cooperative (Fischbacher et al., 2001).

Even though Moffatt (2016) used data from a repeated PGG to distinguish between different classes, we can still refer to this approach. Moffatt (2016) assumes the following three types of agents. Reciprocators are contributing only if others meet a sufficient level of contributions. Strategists are acting selfishly but they are willing to make positive contributions with the expectation of receiving reciprocity from others at a later stage in the game. The third class implies free-riders (Moffatt, 2016).

Bardsley and Moffatt (2007) classified participants in a repeated public goods game into four categories distinguishing between selfish and non-selfish agents. Under the category of selfish agents, there is the group of strategists and the group of free-riders. Non-selfish agents can be separated into reciprocators and altruists. Altruists are contributing out of genuine concern for others without any conditions. Bardsley and Moffatt (2007) concluded, that most subjects act selfishly. While altruism plays a minor role, a significant portion of the subjects acts reciprocally. Note that this classification can only be seen as a complement to the thesis since the analysed PGGs are one-shot games.

One crucial difference between repeated and one-shot public good games is the fact that this setting influences the players' strategies. In the research context of analysing farmers' willingness to cooperate for collective AECMs, collective action realistically would take place repeatedly (long-term, every five years), not knowing the number of "played rounds of the game". Knowing the number of played rounds would allow for using backward induction. However, playing an infinite repeated game in the long run, backward induction cannot be applied. In the long run, contributing can lead to higher returns than not contributing, even though people tend to think in the short run rather than in the long run (OECD, 2013). Further, repeated PGG are often used to reduce errors in decision-making, but they can worsen the problem, that the same action can be motivated by either selfish or non-selfish reasons. In the literature this problem is called the "elision problem" (Bardsley and Moffatt, 2007).

A one-shot public goods game requires careful consideration of the difference between heterogeneity and error terms. Heterogeneity reflects differences in contribution levels among subjects, whereas an error term is purely random. In the literature, there is a discussion known as "Mistakes versus motivations" controversy, in which some authors argue that contributions are predominantly random errors (Brandts and Schram, 2001; Ledyard, 1994; Palfrey and Prisbrey, 1997). The authors argue that the limited amount of contributions made in the final period of the PGG is due to motivational heterogeneity. However, some authors argue on the other hand, that due to the interior equilibrium design of the game, not all contributions are random errors (Isaac and Walker, 1988; Sefton and Steinberg, 1996; Willinger and Ziegelmeyer, 2001).

In conclusion, people's behaviour in a PGG can be classified, based on their contributions to the public group account. Some authors like Fischbacher et al. (2001) or Moffatt (2016) categorize participants into three classes. Whereas other authors like Bardsley and Moffatt (2007) classify participants into four classes. The experimental design of the PGG, specifically whether it is a one-shot or a repeated game, plays a crucial role in the different classifications of the participants.

3. Experimental design, data, and empirical strategy

3.1 Experiments

The public goods game experiments were conducted in Germany, Hungary, Netherlands, and Poland. To get a better understanding of the various perspectives on collective AECM contracts and to establish the treatments for the PGGs, workshops were organised in each of the four countries previously to the experiments. In each country, at least one farmer or farmer representative was among the workshop panels, ensuring a diverse range of perspectives. Across all four countries, the same baseline version of the PGG was conducted, which is the cornerstone of the thesis. However, the overall experimental design of the PGGs differs between the four countries. The treatments selected for this thesis vary between the countries, depending on the results of the workshops conducted in each country (Rommel et al., 2021).

3.1.1 Germany

The workshop took place in Berlin (Germany) in January 2020, during the "International Green Week" event. The workshop involved a diverse group of six participants with varied backgrounds and expertise, including two farmers, an agricultural administrator, a representative from the farmers' union, a representative from the Cultural Landscape Foundation, and a scientist who is specialized in incentive-based nature conservation. The participants were asked to vote on their preferred treatments anonymously. The results showed that understanding norms, highlighting the social optimum, heterogeneous endowments, and leading by example were the most favoured treatments among the participants (Rommel et al., 2021).

Due to the SARS-CoV-2 pandemic, an online survey was conducted to collect data on farmers' decision-making in Germany through a one-shot game with ex-post matching. The online survey was conducted from December 2020 to February 2021, with the collaboration of a German market research company (https://www.agri-experts.de/). The farmers were endowed with an initial amount of EUR 50, with randomly every tenth farmer receiving a payment based on the decisions in the public goods game. Participants were randomly assigned to one of five treatments of a one-shot linear voluntary contribution public goods game with four players: Baseline, heterogeneity, leading, norms, and optimum. Participants in the baseline treatment received an initial endowment of EUR 50 which they had to allocate between their private account or the group account. In the heterogeneity treatment, participants received either EUR 25 or EUR 75 as an initial endowment. Participants in the leading treatment were asked to indicate their contribution from an initial endowment of EUR 50 as a leader if they were the first to decide in a group of four players, as well as their contribution as a follower after one person had already decided. The norm treatment involved adding an explanation to the baseline treatment that informs participants about the significant contributions made by individuals in similar studies to the group account. In contrast, the optimum treatment included a statement that emphasized the importance of contributing everything to the group account, as it would align with the social optimum (Rommel et al., 2021).

3.1.2 Hungary

The treatments were developed based on a workshop conducted in October 2020 in Őrség National Park (Hungary). The workshop brought together eight participants with diverse backgrounds, including an agri-environmental policy expert, farmers, local food and beverage business owners, and a national park employee. During the workshop, the participants were introduced to the following nine different treatments: Larger group size, risky provision of the public good, rewards, sanctions, unequal endowments, leading by example, two thresholds, and social norms. The ultimate treatments used in the PGG were selected via a majority vote (Nassila, 2022).

The online survey was conducted with a market research institute (https://www.kynetec.com) in Hungary from June 2021 to December 2021. One out of every ten participants randomly received a payment based on treatment and the decisions made during the game. The study's experimental design involved the inclusion of the following four additional treatments to the baseline version. In the baseline scenario, four farmers were required to allocate HUF 10,000 between a private and group account. In contrast to the baseline treatment, the larger group size treatment involved increasing the number of farmers from four to eight while keeping everything else the same. The intervention of unequal endowments required farmers to choose their contribution levels based on two scenarios where they received either a high (HUF 15,000) or a low (HUF 5,000) initial endowment. The last two different treatments of the game were low threshold and high threshold, with the former requiring a lower minimum threshold of HUF 10,000 in total contributions to the group account, whereas the latter required a higher minimum threshold of HUF 25,000, and any contributions made below the threshold were gone (Nassila, 2022).

3.1.3 Netherlands

In December 2020, a virtual workshop was organized in the Netherlands through Zoom. The participants of the workshop included six farmers who were also members of AECM collectives, along with one representative from the management organization of agri-environmental collectives. To gain further insights into the discussions and outcomes of the workshop, an expert interview was conducted in January 2021 with an advisor from the national service point on the Common Agricultural Policy. Ultimately it was determined that three treatments would be implemented alongside the baseline treatment. These treatments include heterogeneous endowments, the incorporation of a threshold, and a tripled marginal per capita return (Rommel et al., 2021).

The data collection survey was done online, together with a Dutch market research institution (https://www.prosu.nl/) from March 2022 until May 2022. All players who completed the survey were rewarded with a EUR 15 gift card. Moreover, one participant out of every ten was randomly chosen to receive an additional payment based on their decisions throughout the survey. Since in the Netherlands farmers can already choose to participate in collective contracts for AECMs, the experimental design was different. In the first stage of the PGG, farmers participated in all treatments (baseline, triple, heterogeneity, or threshold) in random order. This within-subjects design allowed for direct comparisons between different treatments among the same participant. An initial endowment of EUR 50 was given to participants in the baseline treatment. In the second stage, the farmers could choose between the different treatments and played the PGG again. They were paired with others who had also chosen the same treatment. This second stage of the experiment allowed analysing farmers' preferences between different organizations (Rommel et al., 2021).

3.1.4 Poland

In April 2021, a workshop was held via Zoom. The workshop was attended by seven experts from Poland, including a representative from the Ministry of Environmental Protection, a representative from the Ministry of Agriculture, two representatives from non-governmental organizations dedicated to biodiversity protection, one researcher from Warsaw Agricultural University, and two agricultural advisors from rural advisory centres (Rommel et al., 2021).

The experiment was designed to evaluate the effectiveness of the different treatments of the PGG in Poland. The experiment was conducted through an online survey from January 2022 to February 2023. The farmers were contacted through a network of farm advisors and a list of farmers maintained by a project partner at the University of Warsaw. The treatments included baseline, larger group size, heterogeneity, and thresholds. In the baseline scenario, each player was endowed with PLN 100. In the experiment, the incentive for the players was the possibility of receiving a payment, with one out of ten participants being randomly selected for a reward. The amount of the payment was dependent on the treatments and actions of the players.

Table 1. Overview of the public goods game experiments.

	DE	**HU**	**NL**	**PL**
Setting	Online survey, Germany, December 2020 to February 2021	Online survey, Hungary, June 2021 to December 2021	Online survey, Netherlands, March 2022 to May 2022	Online survey, Poland, January 2022 to February 2023
Data collection	Agri-experts (https://www.agri-experts.de)	Kynetec (https://www.kynetec.com)	Prosu (https://www.prosu.nl)	Network of farm advisors and project partner of University of Warsaw
Financial incentives	Every tenth participant (randomly selected) received a payment based on the decisions in the game	Every tenth participant (randomly selected) received a payment based on the decisions in the game	15 Euros Gift card and every tenth participant (randomly selected) received a payment based on the decisions in the game	Every tenth participant (randomly selected) received a payment based on the decisions in the game
Treatments	Baseline, heterogeneity, leading, norms, optimum	Baseline, group size, heterogeneity, threshold	Baseline, triple, heterogeneity, threshold	Baseline, group size heterogeneity, threshold
Endowments (Baseline)	EUR 50	HUF 10,000	EUR 50	PLN 100
Number of players per group (Baseline)	4	4	4	4
Number of rounds	1	1	4 + 1 (no feedback)	1
Sample size	358	418	351	279
Sample size baseline (for NL first stage)	71	84	90	59

Source: Own calculations.

3.2 Data

The analysis of the thesis solely refers to the data of the baseline contribution. Each dataset for each of the four countries consists of different treatment variables due to different experimental designs (see Table 1). Since the baseline treatment was played in all four countries, the data of the baseline treatment is the most comparable between the countries. Note that the baseline contribution is measured in percentages from 0% to 100%. In the appendix, the summary statistics are presented for Germany (Table A1), Hungary (Table A2), Netherlands (Table A3), Poland (Table A4) and the pooled data (Table A5). In the following Table 2, the covariates included in the FMM analysis are described. The dummy variables for gender, university, full- or part time, and farm type were created based on the original data. To ensure consistency in measuring education levels across all four countries, the university dummy distinguishes between farmers having at least a university degree (= 1) or having a qualification, which is below a university degree (= 0). It should be mentioned that the university dummy includes degrees obtained from applied universities, such as those found in Germany and the Netherlands.

Table 2. Variables description.

Variable Name	Description
base	= 0% - 100%
gender_dummy	= 1 if male, = 0 if female or other
age	= age in years
university_dummy	= 1 if university degree, = 0 if no university degree
full_part_time_dummy	= 1 if participant is full time farmer, = 0 if participant is part time farmer
farm_type_livestock_dummy	= 1 if livestock farm, = 0 if other (mixed or crop)
farm_type_crop_dummy	= 1 if crop farm, = 0 if other (mixed or livestock)
cropland_owned	= owned cropland holding size in hectares
cropland_leased	= leased cropland holding size in hectares
grassland_owned	= owned grassland holding size in hectares
grassland_leased	= leased grassland holding size in hectares
other_land	= other land holding size in hectares

Source: Own calculations.

3.3 Finite mixture model

A finite mixture model (McLachlan and Peel, 2000) puts observations in different latent classes of overlapping distributions. Heterogeneity in contributions to a public goods game is driven by various motivations (Bardsley and Moffatt, 2007). The FMM is suitable for identifying the distinct types of players and estimating the probabilities of the players belonging to one of the finite types of different latent classes (Bardsley and Moffatt, 2007). Moffatt (2016) refers to the finite mixture framework by McLachlan and Peel (2000) because this framework allows for specifying distinct behaviours and ultimately analysing the motivational heterogeneity of the different contributions made in a public goods game.

Applying a finite mixture model in the statistic software R with the "mixtools"-package on the experimental data allows for categorising farmers into a finite number of different latent classes (Benaglia et al., 2009). With the finite mixture model, the probability of belonging to one of the classes and the effects of the covariates on the respective classes can be estimated. The parameters for all the models, including the mixing proportions parameter that represents the proportion of each class in the population, are estimated respectively (Moffatt, 2016).

As a first step, when deciding which covariates to include in the finite mixture model, it is important to consider the theoretical expected correlations between the available covariates and the baseline contributions. The novel research context of this thesis presents a challenge when it comes to identifying appropriate literature to reason on the covariate's selection for the FMM. According to existing literature, it is recommended to incorporate the gender variable when analysing public goods games. Studies have shown that in a PPG scenario, female participants tend to make higher contributions compared to their male counterparts (Balliet et al., 2011;

Pereda et al., 2019). It appears that age does not have a significant influence on the level of contributions made in a PGG (Hermes et al., 2020). Therefore, the age variable will not be included in the FMM. Based on the literature, lower levels of education and income may play a role in the lower levels of contributions observed in public goods games (Bekkers and Wiepking, 2010). As a result, it was decided to include the education variable in the form of a harmonised university dummy variable in the FMM. Whether a farmer works as a full time or part time farmer leads to significant differences, for example, differences in incomes or in risk attitudes. Therefore, the full time covariate will be included in the model. There is no literature available on the correlation between different farm types (livestock, crop or mixed) and the level of contributions in a PGG. Since different farm types lead to different management practices, different daily routines, and overall different farming objectives, differences in the level of contributions in a PGG are expected to occur. Therefore, the farm type variable will be incorporated into the analysis. Currently, there is no literature available exploring the potential correlation between the amount of different farmland (cropland, grassland, or other land) and the contribution levels of farmers in a PGG. As such, it was decided to incorporate the different farmland covariates into the analysis, to explore any possible effects.

Based on the theoretical reasoning above, the general FMM analysis of the baseline contribution including the covariates looks the following:

$$
\begin{aligned}
Baseline \sim\ & gender\_dummy + university\_dummy \\
& + full\_part\_time\_dummy\ + farm\_type\_livestock\_dummy \\
& + farm\_type\_crop\_dummy + cropland\_owned \\
& + cropland\_leased + grassland\_owned + grassland\_leased \\
& + other\_land
\end{aligned}
$$

As a second step, a set of representative covariates is selected for each country, based on the variability of the covariates in the summary statistics (see appendix 1-5), as it determines the extent to which the results can be generalized. For Germany, all available covariates will be included for the FMM analysis, except for the gender variable, because there is only one female farmer in the dataset. Referring to the Hungarian FMM, all available covariates will be included, except for the livestock farms (farm_type_livestock_dummy), because only 2% of farms in the Hungarian dataset are livestock farms. For the Netherlands, all available covariates will be included in the FMM, except for the crop farms (farm_type_crop_dummy), because only 17% are crop farms in the Dutch dataset. For the Polish FMM, all available covariates will be included, except the livestock farms (farm_type_livestock_dummy), because only 19% of the farms in the Polish sample are livestock farms.

4. Results

4.1 Graphical inspection of heterogeneity

Analysing the distribution of baseline contributions (dependent variable) can provide informative insights. Specifically, using graphical methods to examine different levels of contribution can be enlightening (Moffatt, 2016). As a first result, there are five histograms of the baseline contributions including a kernel smoothing of the probability density estimation presented in the next paragraph. To allow for comparability of the histograms, the scale of each y-axis is standardised.

4.1.1 Germany

Figure 2 shows the baseline contribution (from 0% to 100%) of the participating German farmers, plotted together with a kernel density function.

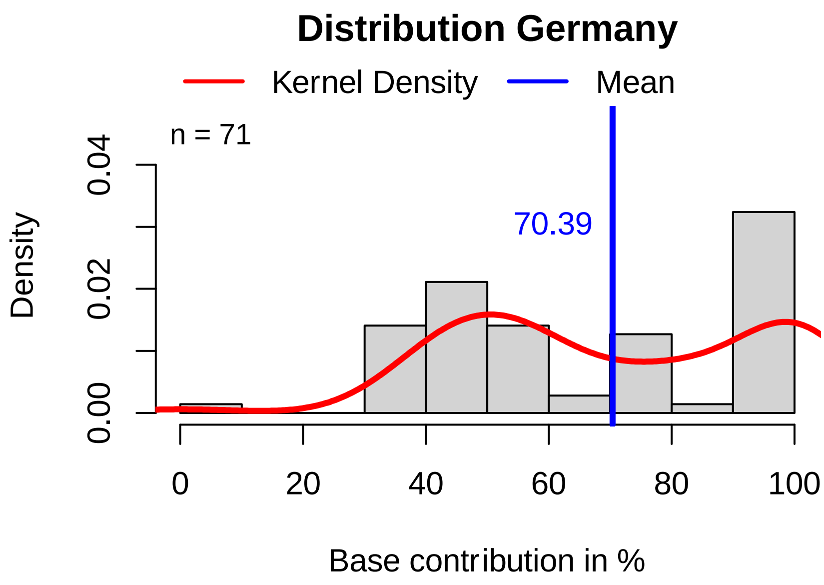

Figure 2. Histogram of baseline contribution Germany.

It seems that the baseline contribution is distributed as a combination of two bell-shaped distributions. One of the distributions has a peak at around 50%, while the other one has a peak at around 100%. If we consider the baseline contribution as the decision taken by the participants in a PGG experiment, we can approximately classify the participants into two classes. One class is approximately at 50%, and the second class is approximately at 100%. Based on the bimodality evident in the histogram, a two-component mixture model is a reasonable fit for the finite mixture model of the baseline contribution of the German dataset.

It can be noted that one player contributed 0% of the initial endowment, so there is one free-rider in the German sample (71 in total). It is as well interesting to see that 22 of the players contributed 100% of the initial endowment. On average, the participating German farmers contributed 70.39% of their initial endowment.

4.1.2 Hungary

The baseline contribution (from 0% to 100%) of participating Hungarian farmers is presented in Figure 3, with a kernel density function overlaid.

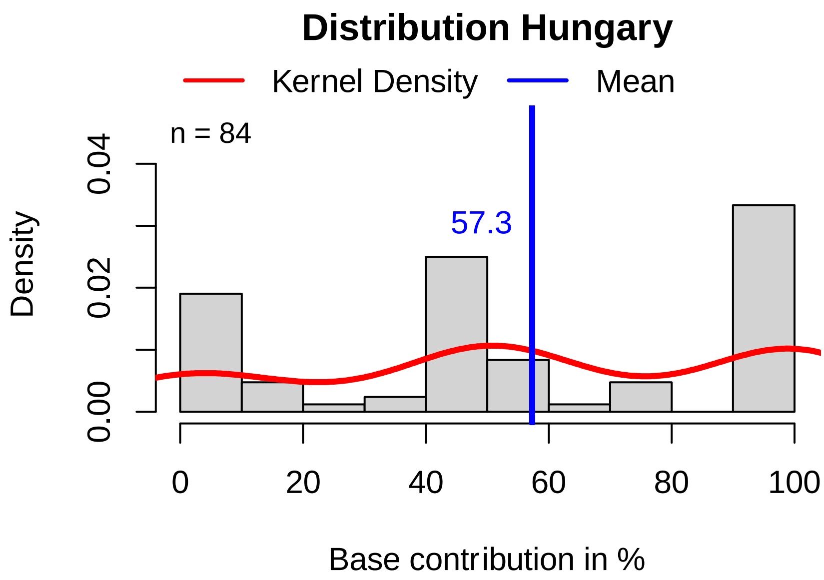

Figure 3. Histogram of baseline contribution Hungary.

It is visible that the baseline contribution is distributed as a combination of three bell-shaped distributions. One of the distributions has a peak at around 0%, the second one at around 50%, and the third one at around 100%. Therefore, we can classify the participating Hungarian farmers into three different classes. The tri-modality of the histogram indicates that a three-component mixture model would be a suitable choice for the finite mixture model of the baseline contribution in the Hungarian dataset.

In the Hungarian dataset (84 observations in total), there are 13 free-riders, because 13 farmers contributed 0% of their initial endowment. 21 farmers contributed 50% and 100% of the initial endowment was contributed by 28 participating farmers in the sample. The overall mean contribution of the involved Hungarian farmers was 57.30% of their initial endowment.

4.1.3 Netherlands

Figure 4 displays the baseline contribution (from 0% to 100%) together with the kernel density of the Dutch farmers, that played the PGG experiment.

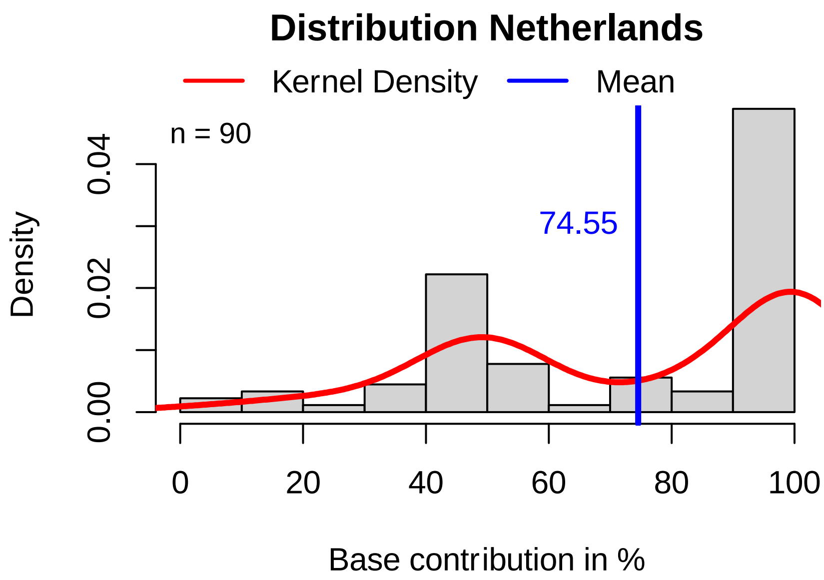

Figure 4. Histogram of baseline contribution Netherlands.

Looking at the baseline contribution of the farmers from the Netherlands, there appear to be two bell-shaped distributions in the sample. One of them has a peak at around 50%, while the other distribution has a peak at around 100%. This indicates two different classes of Dutch farmers. It is visible from the bimodal shape of the histogram that a two-component mixture model is a suitable fit for the finite mixture model to analyse the baseline contribution of the Dutch dataset.

In the Dutch dataset (90 in total), there is one farmer, who contributed 0%, so there is one free-rider. 44 farmers contributed 100% of the endowment instead. On average, Dutch farmers contributed 74.55% of their initial endowment to the group account.

4.1.4 Poland

In Figure 5 the baseline contribution of the Polish farmers is shown, plotted together with a kernel density function.

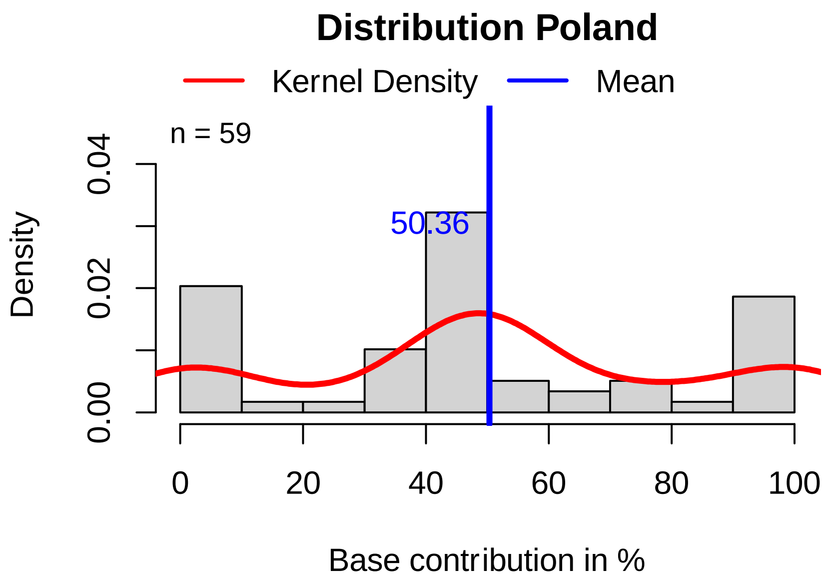

Figure 5. Histogram of baseline contribution Poland.

The histogram shows three peaks in the baseline contribution distribution. The first peak at around 0%, the second peak at around 50%, and the third peak at around 100%. It seems that the baseline contribution is distributed as a combination of three bell-shaped distributions. Consequently, we can categorize the Polish farmers who participated into three distinct classes. The presence of three peaks in the histogram indicates that a three-component mixture model would be an appropriate choice for the finite mixture model.

Looking at the Polish data of the baseline contribution (59 observations in total), eight farmers choose to completely freeride, because their contribution was 0%. 18 Polish farmers contributed 50% and eleven farmers contributed 100% of the endowment. The average baseline contribution of the Polish farmers in the experiment was 50.36%.

4.1.5 Pooled data

The baseline contribution of the farmers from all four countries pooled together is shown in Figure 6.

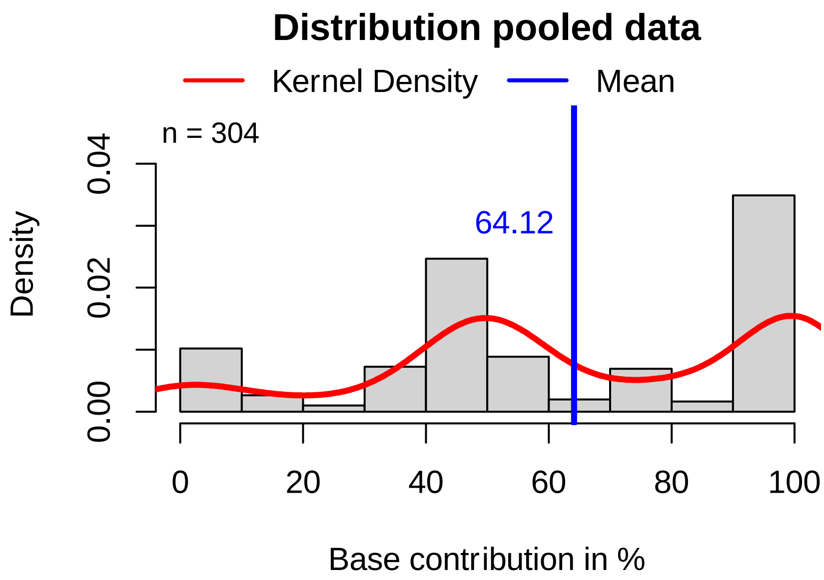

Figure 6. Histogram of baseline contribution pooled data.

The distribution of the baseline contribution from the pooled data appears to have three distinct peaks visible in the histogram. The first peak is observed at approximately 0%, the second at around 50%, and the third at roughly 100%. It emerges that the distribution of the baseline contribution is a mixture of three bell-shaped distributions, indicating three different classes of farmers. The existence of three distinct peaks in the histogram suggests that using a three-component mixture model would be a fitting approach for the FMM when examining the baseline contribution of the entire dataset.

Summarizing, looking at the dataset pooled together from all four countries, 23 farmers contributed 0% meaning that 23 farmers were freeriding. On the other side, 105 participants contributed 100%. On average, the involved European farmers contributed 64.12% of their initial endowment of the public goods game.

4.2 Finite mixture model analysis

Table 3 presents the results of the finite mixture model based solely on the baseline contribution from the farmers, both for each country individually and for the pooled data. Note that "lambda" represents the proportions of the different classes, which must add up to one, “mu” refers to estimated means, and "sigma" denotes estimated variances. For a comprehensive analysis and to observe varying levels of fits, all finite mixture models have been estimated for two (k=2) as well as three (k=3) classes. The FMM consists of three components: "Comp 1" represents the first class, "Comp 2" represents the second class, and "Comp 3" indicates the third class. For the sake of clarity, all values are rounded to two decimal points.

Table 3. Results of finite mixture model analysis.

	Germany					Hungary					Netherlands					Poland					Pooled data				
Model	(1)		(2)			(3)		(4)			(5)		(6)			(7)		(8)			(9)		(10)		
Classes	K = 2		K = 3			K = 2		K = 3			K = 2		K = 3			K = 2		K = 3			K = 2		K = 3		
Comp.	1	2	1	2	3	1	2	1	2	3	1	2	1	2	3	1	2	1	2	3	1	2	1	2	3
Baseline																									
lambda[1]	0.35	0.65	0.24	0.14	0.63	0.00	1.00	0.25	0.36	0.39	0.20	0.80	0.04	0.91	0.04	0.09	0.91	0.20	0.52	0.28	0.00	1.00	0.13	0.44	0.43
mu[2]	48.28	82.32	44.99	54.95	83.26	57.38	57.30	5.93	50.45	96.24	50.01	80.81	40.05	79.12	14.67	50.78	50.32	2.17	46.78	92.40	64.52	64.12	5.49	49.85	96.14
sigma[3]	6.88	22.27	5.27	5.42	21.98	36.48	36.49	9.14	4.07	9.06	0.07	28.40	0.08	24.78	9.48	32.34	32.32	3.70	8.57	11.24	32.44	32.22	7.96	7.96	7.98
Observations	71		71			84		84			90		90			59		59			304		304		
Loglik	-319.65		-319.26			-421.35		-371.18			-362.77		-418.71			-288.79		-263.37			-1487.03		-1357.196		
AIC	649.30		654.52			853.00		758.35			735.54		873.42			587.59		542.99			2984.06		2730.39		
BIC	660.62		672.62			864.85		777.80			748.04		853.43			597.98		559.61			3002.65		2760.13		

Source: Own calculations.

[1] Note, that "lambda" denotes the estimated proportions of the different classes.
[2] Note, that “mu” denotes estimated means.
[3] Note, that "sigma" denotes estimated variances.

The results presented in Table 3 are in line with our graphical findings. Estimating the finite mixture model with two classes leads to a better level of fit for the German Model 1 and the Dutch Model 5 compared to the three classes. And vice versa for Hungary, Poland, and the pooled data, because the three-class finite mixture models 4 and 8 and 10 get a better level of fit than the two-class finite mixture models. Looking at the Hungarian case as an example of how estimating the FMM for three classes leads to a better level of fit than two classes. Model 3 estimates, that 0% of the participating Hungarian farmers (Comp. 1) contributed on average 57.38% of their initial endowments to the group account with an estimated variance of 36.48. While 100% of the participating Hungarian farmers (Comp. 2) contributed on average 57.30% with an estimated variance of 36.49. Model 4 estimates, that 25% of the Hungarian farmers (Comp. 1) contributed on average 5.93%, 36% of the farmers (Comp. 2) contributed on average 50.45% and the last 39% of the Hungarian farmers (Comp. 3) contributed on average 96.24%. Moreover, estimating the FMM for three classes in Model 4 leads to a lower Akaike's Information Criteria (AIC) and Bayesian Information Criteria (BIC). The same logic applies to the remaining countries accordingly.

4.3 Finite mixture model analysis including covariates

In Table 4, the outcomes of the finite mixture model are presented, based upon the initial baseline contribution of farmers and the corresponding covariates for each country. "Lambda" represents the proportions of different classes that must total to one and "sigma" represents the estimated variances. FMMs were estimated for both two and three classes in all countries to analyse different levels of fit. The covariates can be interpreted as linear effects on the baseline contribution. A change in one unit of the covariates (independent variable) affects the baseline contribution (dependent variable) by the size of the corresponding estimate. The results of Table 4 were calculated with the “regmixEM” function from the “mixtools” package in the statistics software R. It is important to note that the "regmixEM" function does not provide estimates for the means of the various classes. To ensure clarity, all the values have been rounded off to two decimal points.

Table 4. Results of finite mixture model analysis including covariates.

	Germany					**Hungary**					**Netherlands**					**Poland**					**Pooled data**				
Model	(11)		(12)			(13)		(14)			(15)		(16)			(17)		(18)			(19)		(20)		
Classes	K = 2		K = 3			K = 2		K = 3			K = 2		K = 3			K = 2		K = 3			K = 2		K = 3		
Comp.	1	2	1	2	3	1	2	1	2	3	1	2	1	2	3	1	2	1	2	3	1	2	1	2	3
Baseline																									
lambda[4]	0.27	0.73	0.53	0.25	0.23	0.24	0.76	0.28	0.33	0.40	0.23	0.77	0.23	0.17	0.60	0.75	0.25	0.30	0.48	0.23	0.71	0.29	0.08	0.15	0.77
sigma[5]	1.18	30.39	33.20	1.32	0.24	6.03	22.19	10.27	2.40	8.27	10.30	28.35	1.39	4.78	15.32	25.51	3.11	3.87	9.37	8.79	30.63	0.23	0.20	0.24	31.36
gender						1.95	11.70	-8.57	-0.83	5.53	29.51	43.97	100.77	72.68	23.84	24.96	-48.38	6.52	10.94	-45.16	4.95	100.26	-0.31	100.21	21.40
university	3.13	38.78	42.16	-0.15	45.14	-3.72	-0.38	-9.96	-2.51	-1.64	-4.16	19.90	0.33	6.76	7.84	28.85	-121.05	2.23	15.37	-196.06	11.22	0.03	0.09	0.06	13.05
full_part_time	-7.03	33.57	25.22	-7.61	40.07	8.87	-2.91	9.46	-2.44	1.22	3.58	15.49	-2.02	-35.10	8.78	-15.76	-43.45	-9.57	8.90	-97.37	2.18	-0.01	-51.15	0.12	-0.84
farmtype_livestock	48.06	18.13	6.38	49.36	8.26						2.49	25.33	-53.25	-32.61	60.66						39.28	0.10	50.11	-0.14	35.94
farm_type_crop	33.35	61.78	64.39	43.74	56.73	7.69	-10.84	16.23	0.41	0.60						28.14	81.20	5.20	32.40	124.10	37.49	0.02	49.88	-99.89	44.16
cropland_owned	0.53	0.12	0.24	0.18	-0.00	-0.04	0.89	0.01	0.54	0.93	0.17	0.25	0.01	0.93	0.15	0.11	8.69	0.22	0.60	11.14	0.01	-0.00	0.12	-0.00	0.03
cropland_leased	-0.00	-0.13	-0.26	0.03	0.03	-0.07	0.68	0.03	0.54	0.94	-0.14	0.02	0.00	-0.03	0.06	0.99	10.24	7.61	-0.51	2.88	0.04	-0.00	0.52	-0.01	0.02
grassland_owned	-0.35	-0.12	0.24	1.24	0.89	-0.16	0.20	0.96	0.48	0.50	0.71	0.01	0.25	-0.12	-0.07	-0.40	11.94	0.05	5.62	17.73	0.12	-0.00	-0.01	-0.00	0.15
grassland_leased	0.48	0.22	0.92	-0.16	-0.29	-0.14	0.74	0.08	0.57	0.56	-0.68	0.34	-0.60	0.91	0.41	0.21	3.02	-0.08	0.12	0.96	0.23	-0.03	0.40	-0.02	0.19
other_land	-0.24	0.33	0.12	-0.44	-0.05	-0.02	0.68	0.11	0.55	0.89	0.15	-0.52	0.09	0.54	-0.51	-2.43	15.81	-0.17	8.51	115.60	0.06	-0.00	0.10	0.60	-0.00
Observations	64		64			84		84			87		87			55		55			290		290		
Loglik	-285.25		-251.51			-397.97		-357.34			-420.65		-369.89			-253.34		-238.99			-1161.98		-1271.20		
AIC	580.49		519.02			805.95		730.69			851.30		755.78			516.67		493.99			2333.96		2558.40		
BIC	591.29		536.29			818.10		750.13			863.63		775.51			526.71		510.05			2352.31		2587.76		

Source: Own calculations.

[4] Note, that "lambda" denotes the estimated proportions of the different classes.

[5] Note, that "sigma" denotes estimated variances.

Except for the pooled data, assuming three classes of farmers leads to a better level of fit of the models for all four different countries, because both the AIC and BIC values are lower than the FMM estimations for two classes. Generally, the estimated lambdas for the models from Table 4 go in the same direction as the estimated lambdas from Table 3. Looking at the effects of the covariates, the following aspects emerge. The gender variable has a big effect on the classes of farmers in the Netherlands, as we can see in Model 16. A male farmer contributes 100.77% more in Comp. 1, which represents 23% of the total Dutch farmers, compared to females. In Comp. 2 (17% of total Dutch farmers) it is 72.68% more, and in Comp. 3 (60% of total Dutch farmers) 23.84% more. Having a university degree or not leads to big differences on the willingness to cooperate in Poland, both among two and three estimated classes. The results show, that being a full-time farmer mostly negatively relates to the level of contributions made in the PGG, with only an exception in Germany. In Model 11 in Comp. 2 (73% of the German farmers), full time farmers contribute 33.57% more than part time farmers. In most cases, the type of farm correlates with the level of contributions in the game positively. Summarizing the covariates of the farm size, it can be noted, that except for the Polish sample (Model 17 and 18), the farm size has no big impact on the willingness to contribute.

Due to the rather small sample sizes, the results of the FMM analysis estimating the covariates need to be interpreted with caution. This is because the FMM estimates two or three classes for ten covariates, however the baseline contribution data has relatively small sample sizes (see appendix 1-5). Convergence issues were observed when estimating the standard errors. It is likely that the FMM failed to converge because there are too many parameters compared to the available sample sizes.

4.4 General robustness and additional analysis

The following questions arise when considering the robustness of the results.

Further analysis is required to examine whether there is a correlation between the speed of farmers' decision-making and the amount of their contributions. Is there a relevant difference in behaviour between farmers who make quick decisions compared to those who take more time to decide, on the amount farmers contribute to the public group account? If such a difference does exist, how might it impact the results of their decisions? These questions require further investigation to better understand the relationship between farmers’ decision-making speed and the level of contributions in the PGG. In the raw data, information on the timing of the experiments is included.

Additional analysis is needed to investigate whether control questions before the public goods game impact the results. In each of the four countries, the participating farmers were required to read an explanation of the PGG and instructions, before playing the actual PGG. Following this, the participants were given eleven control questions to assess their comprehension of the game's mechanics and implications. It is crucial that all participants successfully answered all control questions, indicating that every subject had the same level of knowledge. A question emerges as to whether the exclusion of those farmers who did not answer the control questions correctly could potentially alter the outcomes of the game and therefore the results. To investigate this matter, it is worth considering the impact of adding such participants to the dataset and assessing whether the results are significantly affected.

Further investigation is necessary to examine whether the decisions made in the PGG should be made by a single farmer alone or whether multiple actors should be involved. The OECD (2013) highlighted that in the complex decision-making process of whether to participate in collective AECMs, multiple actors are involved. Given that farms are often family-run enterprises, decision-making processes rarely involve a single individual farmer alone. As a result, when analysing the willingness of farmers to cooperate on collective AECMs, it is crucial to consider group decision-making at the farm level, going beyond individual behaviour (Dessart et al., 2019).

There are various factors that can influence the behaviour of participants in a PGG experiment, that cannot be controlled. For example, people’s prior experience, their beliefs and attitudes towards risk, and their willingness to trade off decision-making effort and accuracy for monetary rewards (Ledyard, 1994). These factors are important to consider as they may impact the level of cooperation and the overall outcomes of the experiment. Additionally, other uncontrolled phenomena such as individual differences in cognitive abilities, personal biases, and external factors like economic conditions may also impact the results of the experiment. Therefore, it is important to acknowledge and account for these variables in the further collection and analysis of data.

5. Discussion

5.1 General discussion of methodology

According to the results, farmers from all four European countries, namely Germany, Hungary, Netherlands, and Poland have different motivations when deciding the level of contribution to the public goods game and can therefore be categorised into different motivated classes. It has been shown that farmers in Germany and the Netherlands can be categorised into two different classes. The farmers from Hungary, Poland and the pooled data can be categorised into three different classes. Table 4 clearly underlines the effects of the socioeconomic variables and farm characteristics on the baseline contribution. The heterogeneity of European farmers' willingness to cooperate on collective AECMs is evident.

When estimating finite mixture models for a number of classes not aligned to the findings from the graphical inspection, the FMMs had to be forced to run in the R code employing the “maxit” and “maxrestarts” arguments from the “mixtools” package. The "maxit" argument refers to the maximum number of iterations allowed for the expectation-maximization (EM) algorithm to converge. The EM algorithm is used to estimate the parameters of the FMM. The "maxrestarts" argument determines the maximum number of restarts allowed for the EM algorithm. Restarting the algorithm involves randomly initializing the parameters and running the EM algorithm again. It helps in finding better estimates, especially when the algorithm gets stuck in local optima, which would drive the likelihood to infinity. These arguments were used to control the behaviour and performance of the EM algorithm. By setting appropriate values for "maxit" and "maxrestarts," the algorithm runs for a sufficient number of iterations, to achieve satisfactory results. The necessity to force the FMM to run for Model 2, 3, 6, 7, 9, 12, 13, 16, 17, 19. proves the findings of the graphical inspection of heterogeneity in Chapter 4.1. The bimodality evident in the histograms from Germany and Netherlands indicates a two-class mixture model. Running the model for three classes for Germany and Netherlands is contrary to those graphical findings. Findings from previous graphical inspections for the German and the Dutch sample are supported by the fact that the EM algorithm had to be forced to run for three classes. The opposite occurred for Hungary and Poland.

Evaluating the model of fit and comparing the models represents one of the most discussed challenges within the context of finite mixture models (McLachlan and

Peel, 2000). When assessing the model fits, one needs to take into account that determining the most appropriate number of classes is heavily influenced by the characteristics of the data, model specification, or a combination of both (Grimm et al., 2017). For the thesis, the Akaike's Information Criteria and Bayesian Information Criteria were used for analysing the goodness of fit for the FMM. The calculated BIC value should be always greater than the calculated AIC value, because the BIC adds a greater penalty on each of the parameters. Both for analysing the baseline contributions solely and for including the covariates, the best level of fit has been obtained for Poland (see Table 3 and Table 4). Another approach to examine the fit of the model is to visually plot the density estimate of the data along with the estimated density of the mixture model. This creates a plot that shows the histogram of the data along with the estimated density of the mixture model. The level of fit can be visually assessed by comparing the estimated density to the histogram of the data. The plotted histograms with the estimated density of the mixture models for all four countries and the pooled data can be examined in the appendix.

The method of using a public good games approach to analyse the willingness to cooperate of European farmers on collective AECMs has some limitations. Generally, successful collective action depends on multiple factors, such as group size or heterogeneity (Ostrom, 1990). Whether a subject acts selfish or unselfish can also depend on stochastic choice, censoring and motivational heterogeneity (Bardsley and Moffatt, 2007). Focusing on the participant's incentives of the experimental design, ex-post random matching of participants and ex-post payments in the PGG is not ideal. This ex-post matching restricted the analysis of farmers' cooperation over time.

Applying a FMM on public goods game data to explore the heterogeneity of European farmers is not the only way to go. It is important to have in mind, that the results of the proposed FMM framework are estimations based on rather small sample sizes. However, the more informative the original data is, the more accurate the estimations (Moffatt, 2016). Further, when assessing the goodness of fit of the FMMs, there is a trade-off between model complexity and fitting of the model. An alternative approach to explore the heterogeneity of the data is allowing the data itself to determine the number of classes, instead of graphically estimating them (Moffatt, 2016).

A critical aspect to highlight is the external validity (or parallelism) of the results, which is the link between game results from the experiments to real-world behaviours (Smith, 1976). The generalisation of the results of this thesis for realistic conclusions needs to be questioned. Experiments such as public good games aiming to analyse the willingness to cooperate of farmers on AECMs are rather abstract research scenarios, which makes it challenging to translate the results into real-world conclusions. Public good games are no silver bullets, and they are only complimentary to other research methods. Due to the SARS-CoV-19 pandemic, all the experiments were played online with farmers completing a survey, which underlines the conceptual nature of the game. The abstract experimental setting needs to be taken into account when applying the results to the specific context of collective AECMs. However, by using an experimental design of a PGG, it is possible to isolate and analyse the impact of specific covariates without the risk of any additional framing effects, even though it is not an easy task to do (Ledyard, 1994). A relevant aspect to highlight is the fact, that the participants of the experiments were actual farmers, which counterbalances the rather abstract nature of the PGG experiment.

Applying a one-shot or a repeated public goods game has considerable consequences. All data analysed in the thesis come from one-shot PGGs. The original intention for all four experiments was to play multiple rounds. However, due to the SARS-CoV-19 pandemic, this was not possible, except for the Dutch experiment. Hence, the analysis only refers to the first round of the Dutch dataset. One-shot games do not allow for analysing conditional cooperation, which in the context of the cooperative behaviour of farmers on AECMs might be a relevant aspect to consider. Although repeated games are commonly utilized to minimize errors, they can worsen the issue of elision (Bardsley and Moffatt, 2007). The literature indicates that the level of contributions in repeated PGG experiments are decreasing over time (Isaac et al., 1984; Ledyard, 1994). The reason is that players of a repeated PGG are learning, either regarding the incentive structure of the game, which involves learning to be rational, or about the behaviour of other players, which refers to social learning (Moffatt, 2016). Further, using a one-shot game does not accurately represent the decision-making process in the praxis of European farmers, since the decision to participate at the current AECMs needs to be taken repeatedly every five years.

5.2 Agricultural policy implications

Based on the results and having the general discussion of the methodology (see chapter 5.1) in mind, the following agricultural policy implications can be drawn.

The observed high level of contributions in Germany (70.39% on average) and the Netherlands (74.55% on average) indicate a high level of willingness to cooperate of the farmers on collective AECMs. This is a sign of the strong support of German and Dutch farmers for the design approach of collective AECMs. Up to now, European policymakers follow a top-down, government-led approach in the AECM design and implementation process (OECD, 2013). In the EU, the Netherlands are currently the only exception to the top-down AECM approach (Ministry of Economic Affairs, 2016). Overall, Figure 6 highlights that when considering the pooled data from multiple countries to obtain a broader European perspective, farmers' willingness to contribute is approximately two-thirds of their initial endowments. This underlines that in general European farmers are open to a new AECM design approach.

The evidence of more freeriding in Hungary and Poland also emphasises that monitoring of collective AECMs is crucial. A substantial number of the participating farmers in the PGG experiment are indeed free-riders. The prevalence of freeriding in Germany and the Netherlands was relatively low, with rates of

1.39% and 1.11%, respectively. However, in Hungary and Poland, the incidence of free-riders was considerably higher, at 15.48% and 13.56%, respectively. Note, that if collective AECMs are implemented with rather smaller groups of farmers, freeriding becomes easier to detect than with rather large groups of farmers (OECD, 2013).

The higher occurrence of freeriding in Hungary and Poland raises doubts about collective AECMs that require the participation of every farmer, such as rewetting a landscape for cooperative peatland management. If the goal of a collective AECM is to rewet a landscape, every farmer within a watershed or certain geographical region must be on board. However, this might be difficult to achieve in Hungary and Poland due to the significant gap between farmers who contributed 0% and those who contributed 100% (see Figures 3 and 5). On the other hand, bridging such gaps might be easier in Germany and Netherlands as the number of farmers who contributed 0% is low in these countries (see Figures 2 and 4). For example in the Netherlands, there is cooperative peatland management in the form of collective AECMs in place since 2016 with positive results, even though Dutch farmers have different viewpoints on cooperating on collective AECMs (Reichenspurner et al., 2023).

The numerical results (see Table 3 and 4) as well as the graphical inspection (see Figure 2, 3, 4 and 5) highlight that German and Dutch farmers can be categorised into two different classes, whereas Hungarian and Polish farmers can be categorised into three different classes. The participating farmers are heterogenous in their willingness to cooperate, which is in line with the literature (OECD, 2013). The overall heterogeneity in the willingness to cooperate shows, that holistic approaches are necessary to promote collective AECMs among farmers. This categorisation is supported by analysing the experimental data with finite mixture models.

Crucial to the success of collective AECMs is the collaboration between local governments and the European Commission, given the heterogeneity among the four countries. Table 4 shows the substantial differences in the motivation to participate in collective AECMs across countries and across socio-economic factors and farm characteristics. Additionally, most collective AECMs are dealing with specific, local environmental issues (OECD, 2013). Therefore, good cooperation and flexibility between the local authorities and European policymakers are crucial to adjust AECMs to farmers' heterogeneity and local conditions.

6. Conclusion

This thesis explored the heterogeneity of European farmers' willingness to cooperate on collective Agri-environment-climate measures, using data from PGGs played with farmers from Germany, Hungary, Netherlands, and Poland. The research aims to investigate the extent to which European farmers are willing to collaborate on AECMs, revealing significant differences in cooperative behaviour among farmers within each individual country. Based on a finite mixture model, the thesis analyses the heterogeneity of farmers' willingness to cooperate, to identify different latent classes of farmers and socioeconomic- and farm-characteristics that anticipate cooperativeness. The findings of this thesis imply that the policy issue of European farmers' cooperation on collective AECMs is complex and multifactorial.

These findings contribute to the current policy discussion on the implementation of collective Agri-environment-climate measures at European level. In general, European farmers are open to a new, collective AECM design approach. The substantial heterogeneity in farmers' motivation to participate in collective AECMs across countries spotlight the need for flexible and tailor-made approaches. Given the higher occurrence of freeriding in Hungary and Poland, it might be a low-hanging fruit, to focus in those countries on collective AECMs, where farmers just select into a group, for example participating in organic farming practices.

However, further research is needed to gain a more comprehensive understanding of the complex factors that influence farmers' willingness to cooperate on voluntary environmentally friendly practices like AECMs. Future research can help to inform European policymakers on how to tackle farmers' heterogeneity of willingness to cooperate on AECMs more coherently and holistically. The thesis stresses the importance of holistic approaches that consider the diverse characteristics of European farmers in promoting collective action across the EU.

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Lastly, my heartfelt gratitude goes to Giuditta, for always believing in me. Thank you!

Appendix 1

Table A1. Descriptive statistics Germany.

Variable	Unit of measurement	Number of observations	Mean	Standard deviation	Minimum	Maximum
Dependent variable						
Baseline contribution	Continuous variable	71	70.39	24.72	0	100
Independent variables						
Socio-economic variables						
gender_dummy	Binary variable	71	0.99			
age	Continuous variable	71	43.63	13.39	21	75
university_dummy	Binary variable	71	0.38			
Farm characteristics						
full_part_time_dummy	Binary variable	71	0.54			
farm_type_livestock_dummy	Binary variable	71	0.35			
farm_type_crop_dummy	Binary variable	71	0.44			
cropland_owned	Continuous variable	68	55.78	95.21	0	600
cropland_leased	Continuous variable	67	99.21	235.33	0	1300
grassland_owned	Continuous variable	70	12.66	27.64	0	175
grassland_leased	Continuous variable	66	20.17	64.42	0	500
other_land	Continuous variable	71	13.86	38.11	0	200

Source: Own calculations.

Appendix 2

Table A2. Descriptive statistics Hungary.

Variable	Unit of measurement	Number of observations	Mean	Standard deviation	Minimum	Maximum
Dependent variable						
Baseline contribution	Continuous variable	84	57.30	36.71	0	100
Independent variables						
Socio-economic variables						
gender_dummy	Binary variable	84	0.76			
age[6]	Continuous variable	81	52.65	13.59	19	79
university_dummy	Binary variable	84	0.51			
Farm characteristics						
full_part_time_dummy	Binary variable	84	0.54			
farm_type_livestock_dummy	Binary variable	84	0.02			
farm_type_crop_dummy	Binary variable	84	0.75			
cropland_owned	Continuous variable	84	48.10	49.42	0	300
cropland_leased	Continuous variable	84	33.40	38.81	0	100
grassland_owned	Continuous variable	84	2.13	7.80	0	50
grassland_leased	Continuous variable	84	1.75	7.32	0	50
other_land	Continuous variable	84	17.00	36.76	0	100

Source: Own calculations.

[6] Note that for the calculation of the age variable, three responses were excluded due to inaccuracies. However, these responses were retained in the dataset for all other purposes.

Appendix 3

Table A3. Descriptive statistics Netherlands.

Variable	Unit of measurement	Number of observations	Mean	Standard deviation	Minimum	Maximum
Dependent variable						
Baseline contribution	Continuous variable	90	74.55	28.37	0	100
Independent variables						
Socio-economic variables						
gender_dummy	Binary variable	90	0.88			
age[7]	Continuous variable	67	60.36	15.64	23	94
university_dummy	Binary variable	90	0.42			
Farm characteristics						
full_part_time_dummy	Binary variable	90	0.77			
farm_type_livestock_dummy	Binary variable	90	0.68			
farm_type_crop_dummy	Binary variable	90	0.17			
cropland_owned	Continuous variable	90	13.37	22.62	0	120
cropland_leased	Continuous variable	89	15.50	85.56	0	800
grassland_owned	Continuous variable	89	22.45	27.69	0	160
grassland_leased	Continuous variable	89	8.76	13.71	0	65
other_land	Continuous variable	87	3.03	14.53	0	125

Source: Own calculations.

[7] Note that for the calculation of the age variable, 23 responses were excluded due to inaccuracies. However, these responses were retained in the dataset for all other purposes.

Appendix 4

Table A4. Descriptive statistics Poland.

Variable	Unit of measurement	Number of observations	Mean	Standard deviation	Minimum	Maximum
Dependent variable						
Baseline contribution	Continuous variable	59	50.36	32.60	0	100
Independent variables						
Socio-economic variables						
gender_dummy	Binary variable	59	0.61			
age[8]	Continuous variable	56	43.04	12.30	22	66
university_dummy	Binary variable	59	0.32			
Farm characteristics						
full_part_time_dummy	Binary variable	59	0.59			
farm_type_livestock_dummy	Binary variable	59	0.19			
farm_type_crop_dummy	Binary variable	59	0.66			
cropland_owned	Continuous variable	59	15.36	5.54	1	35
cropland_leased	Continuous variable	59	2.84	3.59	1	14
grassland_owned	Continuous variable	59	5.78	5.54	1	17
grassland_leased	Continuous variable	59	2.78	3.47	1	12
other_land	Continuous variable	59	1.24	0.80	1	5

Source: Own calculations.

[8] Note that for the calculation of the age variable, three responses were excluded due to inaccuracies. However, these responses were retained in the dataset for all other purposes.

Appendix 5

Table A5. Descriptive statistics of pooled data.

Variable	Unit of measurement	Number of observations	Mean	Standard deviation	Minimum	Maximum
Dependent variable						
Baseline contribution	Continuous variable	304	64.12	32.27	0	100
Independent variables						
Socio-economic variables						
gender_dummy	Binary variable	304	0.82			
age[9]	Continuous variable	275	50.42	15.42	19	94
university_dummy	Binary variable	304	0.42			
Farm characteristics						
full_part_time_dummy	Binary variable	304	0.62			
farm_type_livestock_dummy	Binary variable	304	0.33			
farm_type_crop_dummy	Binary variable	304	0.49			
cropland_owned	Continuous variable	301	25.67	23.46	1	73
cropland_leased	Continuous variable	296	13.38	15.62	1	52
grassland_owned	Continuous variable	301	13.61	15.62	1	52
grassland_leased	Continuous variable	298	7.37	10.88	1	40
other_land	Continuous variable	301	3.95	6.38	1	25
is_Germany	Binary variable	304	0.23			
is_Hungary	Binary variable	304	0.28			

[9] Note that for the calculation of the age variable, 29 responses were excluded due to inaccuracies. However, these responses were retained in the dataset for all other purposes.

is_Netherlands	Binary variable	304	0.30
is_Poland	Binary variable	304	0.19

Source: Own calculations.

Appendix 6

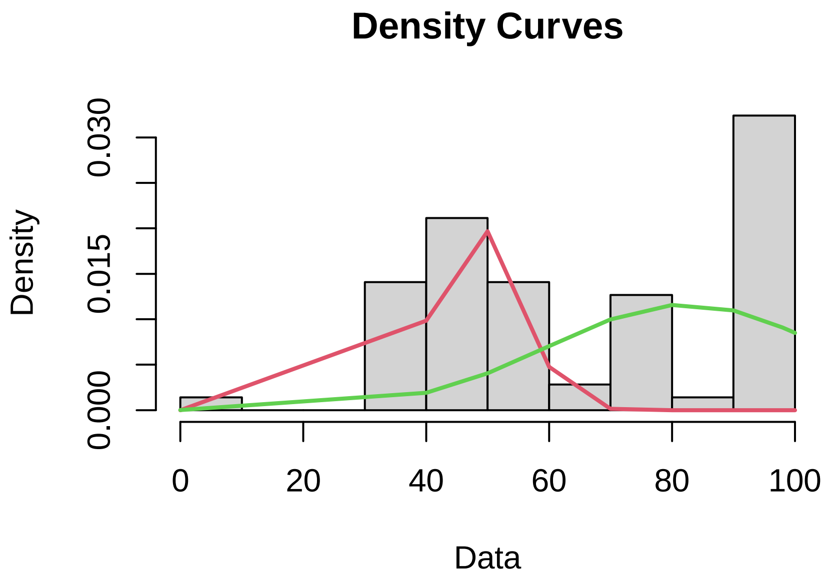

Figure A1. Histogram finite mixture model Germany (k=2).

Appendix 7

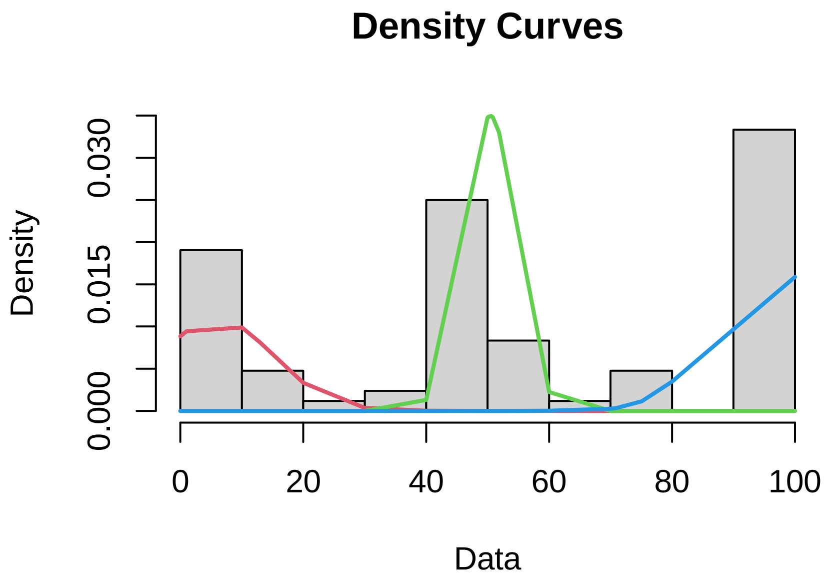

Figure A2. Histogram finite mixture model Hungary (k=3).

Appendix 8

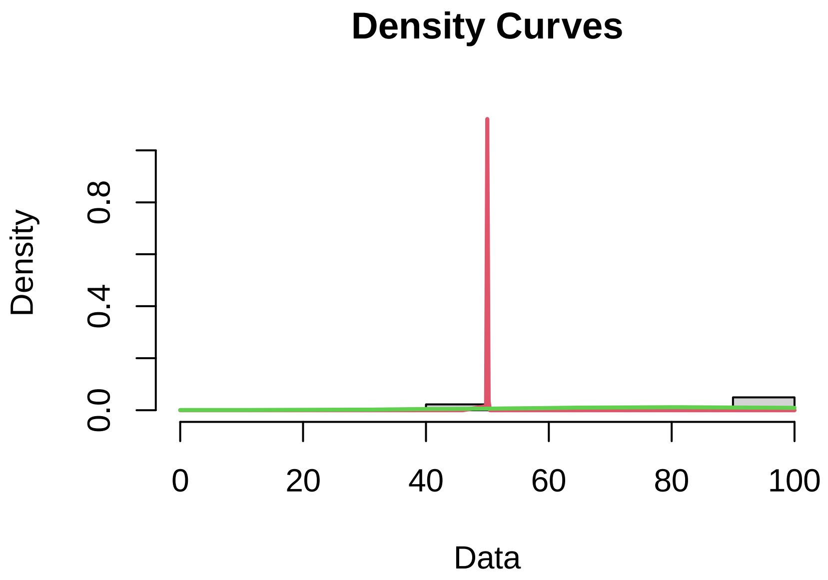

Figure A3. Histogram finite mixture model Netherlands (k=2).

Appendix 9

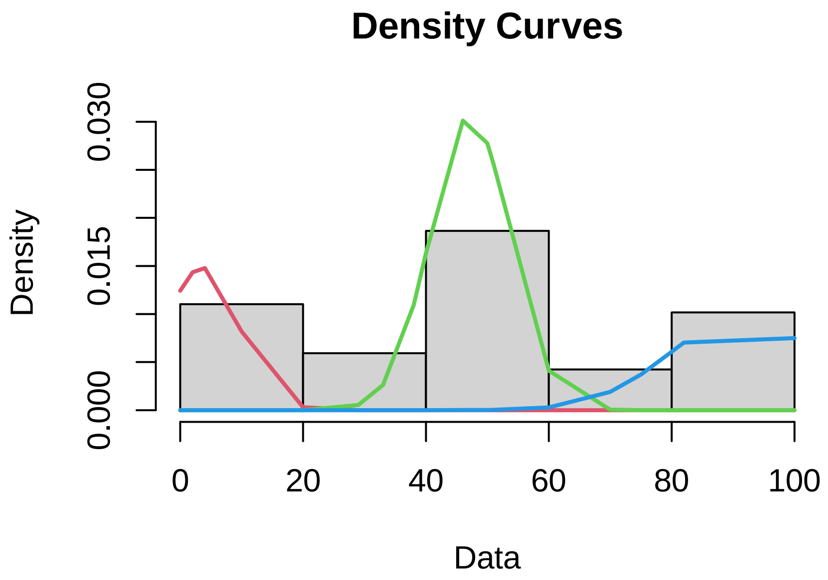

Figure A4. Histogram finite mixture model Poland (k=3).

Appendix 10

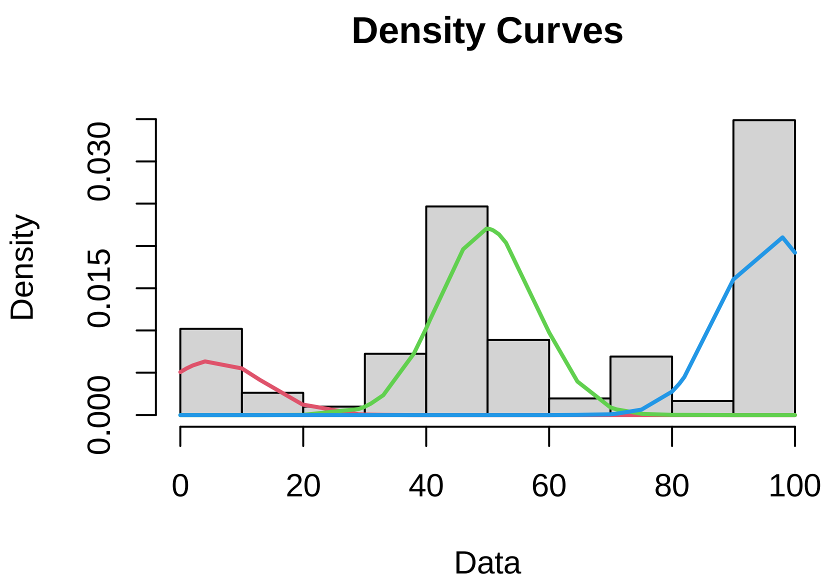

Figure A5. Histogram finite mixture model pooled data (k=3).

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