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Driving food systems into a circular economy model

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Driving food systems into a circular economy model

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“*It could work!*”

Gene Wilder, *Frankenstein Junior*

Thesis summary

The food production system has been at the core of the debate regarding the environmental sustainability of human activities since the dawn of the early ecological movements. Despite this, the road to sustainable resource management in agriculture is long and antithetical to the short timeframes required to stop various destructive phenomena enacted by humans. One promising system that reconciles human production needs and the preservation of natural resources is the Circular Economy. One promising system that reconciles human production needs and the preservation of natural resources is the Circular Economy. It fits into the sustainability discourse by proposing a reinvention of the design of current production and consumption processes. It counters the linear processes of production, where resources are ultimately turned into waste, with a circular design that, through systems of reuse, recycling and up-cycling, through the involvement to varying degrees of all the actors in the supply chain, puts resources into a virtuous circle that preserves them in the long run. The challenge carried out in this thesis is to study how to propel the production system toward such a fundamental and all-round change. This text elaborates strategies for transitioning the olive oil sector in Southern Italy towards a Circular Economy model. The choice of singling out a specific food (i.e. olive oil) as the object and subject of part of the study stems from the peculiarity that each food production system possesses, making the research results specific to that sector. In addition, the olive oil sector is of primary importance to the entire southern agrifood sector in several terms. That is, in terms of employment (more than 600,000 farms throughout Italy, most of which are South-based), production (Italy is the second largest producer in the world after Spain) and consumption (first country in the world for olive oil consumption). Despite its primary importance, the sector pours into sub-optimal conditions since, according to the sector report drawn up by ISMEA[1], more than 60 per cent of olive-oil farms fall into marginal conditions. The reasons behind this situation are many and varied, from the hobbyist nature of many small family farms to the delay in receiving technological innovations. With respect to this problem, the Circular Economy can also provide effective tools, such as innovative business models. While there are many virtuous examples, the spread of the Circular Economy is still in an unadvanced state. Again, there are different reasons for this, but undoubtedly the low propensity of farms to innovate and the lack of consumer awareness play a key role. Part of this thesis is precisely devoted to these aspects. That is, the thesis aims to clarify in a more defined way some of the limitations to the diffusion of the Circular Economy model in the South Italy olive oil sector and to indicate possible ways forward to incentivize the transition to this model. Also shown in the thesis is the work done to develop an agro-environmental simulation model whose goal is to enable socio-ecological assessments of possible transition scenarios. The model presented here is a development of ALMaSS software, a complex agent-based model system. ALMaSS is used to generate dynamic digital-twins of really existing agricultural

[1] Agricultural Food Market Services Institute - https://www.ismea.it/istituto-di-servizi-per-il-mercato-agricolo-alimentare

landscapes. From these, it is possible to make both environmental and social assessments of agronomic landscape management using hypothetical or really existing scenarios.

The thesis is divided into one chapter containing the introduction plus three chapters, each consisting of an article published in a peer-reviewed scientific journal. The first chapter sets out the work done to measure the risk attitude of Apulian olive growers and European farmers in general. It is well known in the literature that sustainable farm innovation, a crucial element of the Circular Economy, can be held back by farmers' behavioural aspects. Among these, the most cited is risk aversion (or propensity). Risk aversion influences part of the farmers' population toward more cautious and less profitable business choices and, therefore, to avoid investment in sustainable innovations that carry a certain amount of risk. In addition, several behavioural theories are tested and compared, namely the Expected Utility theory and the Cumulative Prospect Theory. The results confirm the presence of risk aversion in farmers' behaviours, both for the Apulian sub-sample and the European sample, and indicate better adherence to the data of the Cumulative Prospect Theory behavioural model. The second chapter reports the study on the relationship between consumers and initiatives pertaining to the Circular Economy in the food sector. Within a production system inspired by the Circular Economy, the role of consumers is pivotal. They are emancipated from the mere role of waste-producers and rise to users rather than consumers, actively interacting with the other phases of circular processes. This paradigm shift frequently involves the active participation of consumers, e.g., using a packaging deposit system for marketing olive oil, and thus requires a certain commitment that may be physical, mental or in terms of time use. The study's contribution is to precisely "dimensionalizing" the effort and to analyze in these terms the most frequent circular initiatives in food. The process led to the proposition of an index that measures the effort required of consumers who participate in Circular Economy initiatives. The third chapter covers the work done to develop the ALMaSS agent-based model system. With a view to proposing policies aimed at the transition to a Circular Economy model, the evaluation of possible scenarios in socioeconomic and environmental terms is a priority. This is why we wanted to invest in the sophistication of an existing model system, the ALMaSS. The contribution to the ALMaSS project, outlined in the concluding chapter, concerns the behavioural aspects of farmers within the simulations. Specifically, farmers' interactions are mediated according to the bounded rationality framework giving rise to more realistic and complex interactions within the agri-environmental simulations generated by ALMaSS.

Riassunto tesi

Il sistema di produzione di cibo è al centro del dibattito riguardo la sostenibilità ambientale delle attività antropiche fin dagli albori dei primi movimenti ambientalisti. Nonostante ciò, la strada da percorrere per arrivare ad una gestione sostenibile delle risorse in agricoltura è lunga e in antitesi agli invece brevi tempi di azione necessari per bloccare diversi fenomeni distruttivi messi in atto dall'uomo. Un sistema promettente, che concilia le necessità produttive antropiche e la salvaguardia delle risorse naturali, è l'Economia Circolare. Essa si inserisce nel discorso sulla sostenibilità proponendo una reinvenzione del design dei processi attuali produttivi e di consumo. Contrappone ai processi lineari di produzione, dove le risorse vengono in ultima istanza trasformate in rifiuti, un design circolare che attraverso sistemi di riutilizzo, riciclo e up-cycling, attraverso il coinvolgimento in diversa misura di tutti gli attori della filiera, immette le risorse in un circolo virtuoso che le preserva nel lungo periodo. La sfida che si pone la ricerca portata avanti in questa tesi è di studiare come propellere il sistema produttivo verso un tale cambiamento fondamentale e a 360°. Il presente testo elabora delle strategie di transizione del settore olivicolo oleario del Meridione d'Italia verso un modello di Economia Circolare. La scelta di individuare un alimento specifico, l'olio di oliva, come oggetto e soggetto di parte dello studio, deriva dalla peculiarità che ogni sistema produttivo alimentare possiede e che rende i risultati della ricerca specifici per tale settore. Inoltre, il settore dell'olio di oliva è di importanza primaria per tutto il comparto agroalimentare meridionale in diversi termini. Ovvero in termini occupazionali (oltre 600 mila aziende agricole in tutta Italia, la cui maggior parte nel Meridione), produttivi (l'Italia è il secondo produttore al mondo dopo la Spagna) e di consumo (primo paese al mondo per consumo di olio di oliva). Nonostante la sua importanza primaria, il settore riversa in condizioni di sub-ottimalità in quanto, secondo il report di settore redato da ISMEA[2], oltre il 60% delle aziende agricole olivicolo-olearie riversa in condizioni di marginalità. Le ragioni dietro questa situazione sono molteplici e di diversa natura, dalla natura hobbistica di numerose piccole aziende a conduzione familiare, al ritardo nella ricezione delle innovazioni tecnologiche. Anche rispetto a questo problema l'Economia Circolare può fornire strumenti efficaci, come ad esempio modelli di business innovativi. Seppur con molti esempi virtuosi, la diffusione dell'Economia Circolare è ancora in uno stato poco avanzato. Anche qui le ragioni sono differenti, ma senza dubbio la scarsa propensione all'innovazione delle aziende agricole e la mancanza di consapevolezza da parte dei consumatori giocano un ruolo fondamentale. Parte di questa tesi è proprio dedicata a questi aspetti. Ovvero la tesi si propone di chiarire in maniera più definita alcune delle limitazioni alla diffusione del modello di Economia Circolare nel settore dell'olio di oliva nel Meridione e di indicare delle possibili strade da percorrere per incentivare la transizione verso tale modello. Inoltre, nella tesi viene mostrato il lavoro fatto per lo sviluppo di un modello di simulazione agro-ambientale il quale obbiettivo è di permettere valutazioni di carattere socio-ecologico dei possibili scenari di transizione. Il modello qui presentato è uno sviluppo del software ALMaSS, un complesso sistema di

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[2] Istituto di Servizi per il Mercato Agricolo Alimentare - https://www.ismea.it/istituto-di-servizi-per-il-mercato-agricolo-alimentare

modelli agent-based. ALMaSS viene utilizzato per generare dei *digital-twin* dinamici di landscape agricoli realmente esistenti. Da questi è possibile fare valutazioni di carattere sia ambientale che sociale della gestione agronomica dei landscape, utilizzando scenari ipotetici o realmente esistenti.

Il lavoro di tesi si divide in un capitolo introduttivo seguito da tre capitoli ognuno dei quali composto da un articolo pubblicato su riviste scientifiche peer-review. Il primo capitolo espone il lavoro svolto per la misurazione dell'attitudine al rischio degli olivicoltori pugliesi e degli agricoltori europei in generale. È noto in letteratura che l'innovazione sostenibile delle aziende agricole, elemento cruciale dell'Economia Circolare, venga frenata da aspetti comportamentali degli agricoltori. Fra questi, il più citato è l'avversione (o propensione) al rischio. Essa risulta in una preferenza da parte degli agricoltori verso scelte imprenditoriali più caute e meno remunerative e, quindi, a evitare investimenti in innovazioni sostenibili che presentino una certa dose di rischio. Inoltre, diverse teorie comportamentali vengono testate e messe a confronto, ovvero la teoria dell'Utilità Attesa e la teoria del Prospetto Cumulativo. I risultati confermano la presenza di avversione al rischio nei comportamenti degli agricoltori, sia per il sottocampione pugliese che per il campione europeo ed indicano una migliore adesione ai dati del modello comportamentale della teoria del Prospetto Cumulato. Il secondo capitolo riporta lo studio effettuato sul rapporto fra consumatore e iniziative afferenti all'Economia Circolare nell'ambito del food. All'interno di un sistema produttivo ispirato all'Economia Circolare il ruolo dei consumatori è pivotale. Essi vengono emancipati dal mero ruolo di produttori di rifiuti e assurgono a utilizzatori (*users*), piuttosto che consumatori, interagenti attivamente con le altre fasi dei processi circolari. Questo cambio di paradigma prevede frequentemente la partecipazione attiva dei consumatori, ad esempio utilizzando la formula del vuoto-a-rendere per la commercializzazione dell'olio di oliva, e quindi richiede un certo impegno che può essere fisico, mentale o in termini di impiego di tempo. Il contributo dello studio è proprio quello di andare a "dimesionalizzare" l'*effort* e di analizzare in questi termini le iniziative circolari nel campo del food più frequenti. Si è giunti quindi alla proposizione di un indice che misuri l'*effort* richiesto ai consumatori che partecipano ad iniziative di Economia Circolare. Il terzo capitolo riguarda il lavoro svolto per lo sviluppo del sistema di modelli agent-based ALMaSS. In un'ottica di proposizione di politiche volte alla transizione verso un modello di Economia Circolare, la valutazione di scenari possibili in termini socio-economici ed ambientali è una priorità. Per questo si è voluto investire nella sofisticazione di un sistema di modelli già esistente, ALMaSS. Il contributo al progetto, esposto nel capitolo conclusivo, riguarda gli aspetti comportamentali degli agricoltori all'interno delle simulazioni. Nello specifico le interazioni dei farmers vengono mediate secondo il framework della *bounded rationality* dando origine ad interazioni più verosimili e complesse all'interno delle simulazioni agro-ambientali generate da ALMaSS.

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Chapter 1

Thesis Introduction

Resource depletion and overexploitation threaten ecosystem stability and their imminent consequences should worry everybody. Numerous studies (e.g., Rockström et al., 2009; Sterner et al., 2019) identify a list of planetary boundaries[3] that, if overtaken, might cause irreversible deterioration of the necessary conditions for human life on the planet. The food supply chain alone contributes to the transgression of several of those. On the other hand, a sustainability-oriented design of the food supply chain might reverse those impacts into benefits[4], returned to the environment while adding economic value. Hence, the sustainable innovation of the processes to produce, distribute and consume food is on the top priority list for the interventions needed for humanity to thrive on the planet. Since the detrimental effects of human activities on ecosystems are undoubted (Steffen et al. 2011), a continuing debate within the academia has been taking place on the possibility to sustain both production (e.g.: systems, quantity, and economic value) and natural resources preservation. However, consensus and, most important, indications on concrete, practical resolving actions are still scarce.

A promising framework developed by scientists and the industry refers to Circular Economy (CE) (EMF, 2013). CE addresses resource sustainability issues by rethinking the entire production and consumption process (Borrello, Pascucci, & Cembalo 2020). It encompasses concepts of different disciplines and uses those to create a closed-loop production system design. As the term itself explains, innovation brought by CE is in the process's design, shifting it from linear to circular. To illustrate, today's production 'end-of-life' system creates a linear chain of material, energy, and products that start from resources and end in waste, impoverishing natural resources and producing an unsustainable amount of waste with only a scant recirculation flow of materials. The CE principles oppose to this waste-producing stream of events, an innovative production design where end-consumers are thought of as users, materials are kept in the cycle of reusing, recycling, and up-cycling as long as possible, and nutrients are restored into the biosphere. The CE narrative already inspires the industries to propose innovative business models as well as policy-makers in their decisions. Moreover, the CE narrative may also promote a society-acceptable limitation to over-consumption, providing consumers with understandable coherent concepts (Borrello et al. 2022).

A path to sustainability could so emerge as a transition of the food supply chain towards a CE model. In this transition process, where more and more "loops" are formed by linear processes, researchers should drive this

[3] Those are climate change, change in biosphere integrity, nitrogen and phosphorous, ocean acidification, land-system change, freshwater, green and blue water, ozone depletion, atmospheric aerosol, and novel entities. A more detailed explanation of this concept can be found at https://www.ecologyandsociety.org/vol14/iss2/art32/

[4] An example is the implementation of biogas plant connected to food industries, like olive millers or dairy companies, where important amount of biomass is produced as by-product.

transformation by supporting entrepreneurs and policy-makers, informing the stakeholders and, perhaps most importantly, by contributing to developing the CE rooting concepts. Theory building might help to overcome some of the most cited barriers to CE diffusion (Kirchherr et al. 2018). In particular, the hesitant company culture, the lack of consumer interest and awareness, among others. The work here presented address specifically those barriers, and provide possible solutions that could assist the transition toward a more sustainable food supply chain. Tackling both company and consumers is a wide objective, so we centred the research on specific facets of these subjects. In particular, we investigated the farmers behavioural aspects that influence their decisions regarding sustainable investments and we deepened the analysis of the relation between consumers and CE. Finally, a first effort in the direction for possible socio-environmental assessment of one entire food supply chain by the implementation of a simulations model. Our analysis has a case-study approach and it applies to the olive oil supply chain in the Italy southern regions. The decision to focus on the olive oil supply chain come from different reasons, but mainly for the importance it has on the food economy of the South Italy and for the possibilities of interventions there are.

The contributions brought by this work are dedicated by the need of fostering the transition pathways towards a CE model of the olive oil supply chain in Italy's Southern regions by providing farmers, consumers, and policy-makers guidelines and indications about the viable and effective trajectories. In order to do so, different problems have been tackled and different "chain links" (or sub-systems) of the supply chain have been addressed specifically. The different chapters of the current work are divided into a logical path throughout the olive oil supply chain. In the first chapter, the problem related to olive growers' attitudes towards sustainable innovations is addressed. The approach is to focus on the farmer's psychological and personal facets and model those by empirically testing different behavioural theories where the risk attitudes towards sustainable innovations play a central role. Following, we focus on the role of consumers under the CE. CE questions the neoclassical paradigm of consumption: consumers are called to actively participate in CE activities. The intention is to explore the effort consumers experience when doing so, proposing an effort index to compare different CE initiatives. Finally, our contribution to the development of an agent-based model that will serve as the basis for future socio-environmental assessment of the olive oil supply chain. As posed by Hartley and Kirchherr (2023), models trying to incorporate CE processes need "renewed attention" and our work goes in that direction. The model presented here aims to reproduce the first part of the olive oil supply chain as a digital twin. Further developments will implement the remaining elements to incorporate into the model. The three chapters have the format of peer-review papers.

Sub-system approach

The olive oil sector in Italy counts more than 600 hundred farms with an olive oil production that makes Italy the second biggest producer in the world, right after Spain. Most of the farms, olive millers and, thus, olive oil production come from the Italian southern regions where, historically, the olive orchards are the most spread tree crop. The production of the Southern region consists of about 80% of the total production at the national level. Also, the olive oil industries, mostly olive millers, are located in the Southern regions, showing the territoriality dimension of the whole production system. Nonetheless, the interdependence with the international market reflects on the price both to the consumers and to the producers of the olive oil.

The sector is characterised by a difficult by-products management. Those by-products result from the miller's processing and are formed mostly by olive pomace. This massive amount of fresh organic substance is produced only during the winter season and can be managed in different ways. Promising innovations come from the CE and, thanks to that, the olive pomace, usually intended as a waste, now can be treated as a valuable by-product, origin of new electricity, amendments and fertilisers. Unfortunately, this CE design is far from being widely spread, but the transition towards a CE model of the olive oil supply chain should be highly prompted by both institutions and academia for sustainable olive oil production that is also economically viable.

While the sector is highly important, farms still are considered relatively undeveloped. In fact, only 11% of the olive farms are market competitive, and 63% of the farm are considered marginal by the public agency ISMEA[5]. There can be found several reasons behind this situation, but the slow innovation diffusion and a lack of investments play a central role. The farmers' and millers' propensity for innovation and the dynamic of the innovation diffusion are one of the main topics of this research and will be further analysed in the next chapters. Innovating the sector both from a managerial, technological and sustainability point of view, is a necessity on which the welfare of a broad agricultural area depends and that urges for more attention by researchers and policy-makers.

The work's main objective here is to provide guidelines for the stakeholders of the olive oil supply chain and indicate pathways to a more sustainable olive oil production and consumption by stimulating the transition towards a CE model of the supply chain in Italy's Southern regions.

In order to fulfil that objective, different fundamental components of the olive oil supply chain have been studied, and different solutions/pathways regarding different sub-systems have been provided. Specifically, most of this research attention has been dedicated to the farm side and to the consumption side of the product olive oil for reasons explained hereafter. Farmers are both the most important and the most fragile actor in the olive oil production chain. Price volatility, production fluctuations, and low bargaining power with respect to millers and wholesalers are only a few of the reasons why farmers' economic sustainability is uncertain. In fact, as highlighted by the Italian national institute of statistics (ISTAT), Italy's farm population has halved in the last twenty years. This dynamic is a consequence of several socio-economical aspects, but it should also be pointed out the recent relative job instability of farmers. This is just one of the reasons why the EU puts enormous effort into protecting farmers' income with subsidies and, more in general, with the Common

[5] Source: *ISMEA – Scheda di settore: olio d'oliva*. (Sector report: olive oil).

Agricultural Policy. Secondly, the consumer's role and consumption dynamics are pivotal in the CE transition process. The whole CE narrative creaks if consumers and consumption are not targeted and innovated in the direction of the protagonists of the food supply chains. As mentioned earlier, consumers play a central role in the CE philosophy. To illustrate, consumers are often required to participate to some extent in CE initiatives in order to be successful, changing their habits and adopting new consuming practices. From consumers to users, engaged actively in the supply chain, able to transform waste production processes into more sustainable ones, like by-product upcycling or simple recycling. Although scholars' interest in consumers' roles in the CE is growing, the analysis of the effort that consumers experience when participating in real-case CE initiatives is still relatively neglected. Different CE projects ask consumers for varying levels of involvement and the economic success of the initiatives may also come from the perceived effort people experience in participating. Already many firms belonging to the food industry and supply chain have implemented various CE practices, and analysing those in conjunction with directly identifying the possible efforts required to the consumers is critical. The last aspect covered by the thesis is the socio-environmental assessment of the supply chain. Even if rarely done, identifying possible pathways toward a CE should include an ex-ante evaluation of the hypothetical suggested scenarios, in order to avoid unpredicted results in terms of expected environmental performance of the system. The concept of evaluation of the environmental performance of a food product has gained interest worldwide primarily due to the connection it has with the pressure humans are creating on natural resources (Heller et al., 2013). Different methods exist for the scope, but each shows strengths and limitations. Our approach is to model the system with an agent-based model aimed at recreating the interactions of the system's elements and to provide prediction primarily on the farmers' behaviour.

The thesis is organized as follows. After the introduction, three peer-reviewed scientific papers form the main three chapters of the thesis. The first chapter explores the EU farmers' risk aversion attitudes and behaviour, with specific insight into the Apulian olive growers. The second chapter presents the modules add to the ALMaSS simulation system model in order to have a socio-ecological assessment of the olive oil supply chain. The third chapter explores the different dimensions of the effort experienced by the consumers participating in CE activities.

Innovation adoption

As already mentioned, the sustainable innovation of the olive oil supply chain is of primary importance. The olive producers play a central role in this process. Examples are numerous. Farmers can help reduce resource consumption with efficient water management by reusing reclaimed wastewater for irrigation. They can contribute to climate change mitigation by subtracting carbon dioxide from the atmosphere and incorporating it into the soil via organic matter coming from olive processing. The eco-innovations adoptions are often left on the shoulders of the farmers alone and the resulting diffusion is strongly influenced by the farmers' personal choices. A better understanding of the farmer's barriers and drivers of adoption practices may contribute to public policies aimed at enhancing the adoption of sustainable innovations. Drivers and barriers to eco-innovation adoption are manifold and can be found both in farms' structural aspects and environmental aspects, such as the market stability or the technologies availability, and in the farmer-entrepreneur behavioural facets. The latter is the focus of one of the three studies reported in the current work. They have been neglected by researchers and only in the last years they received the deserved attention. Among the farmer-entrepreneur behavioural facets, the attitudes toward risk constitute one of primary importance. Farmers' risk preferences are critical inputs for effective policy formulation. Policies willing to enhance sustainable innovations and investments by farmers must take into account the farmers' risk attitudes and preferences in order to be effective and to reach the expected results, especially in terms of innovation adoption. As mentioned earlier, a specific chapter is devoted to the study and measurement of European farmers risk attitudes, including a sample of Apulian olive growers. An empirical approach was implemented for measuring farmers risk attitudes by applying an experimental economics setting. To illustrate, an experiment using lotteries was applied to infer farmers' risk aversion. Moreover, different theories explaining to model farmers' risk aversion were tested, namely: the Expected Utility Theory (EUT), first proposed by Bernoulli (1954), and the Cumulative Prospect theory (CPT) (Tversky & Kahneman 1992). Both assume that farmers are risk adverse. However, CPT allows to explicitely models a different risk aversion in the gain and the loss domain, while taking into account distortions of the extreme probabilities function. The two hypotheses just stated were confirmed by our analysis, indicating a more complex dynamic of the farmers' risk aversion, in contradiction to the EUT.

Olive oil supply chain simulation

A further objective of the thesis is to model theolive-oil supply chain system to simulate the behaviour of the system subject to a modification (e.g. policy implementations, CE design adoption, supply chain organization/governance innovation, technological innovation adoption, just to name some) with the aim to evaluate hypothetical scenarios from socio-economical and environmental perspectives. Simulations models are relatively recent due to the considerable computational power needed to run. Nonetheless, various applications in the agricultural field are flourishing (e.g, Appel and Balmann, 2019; Deffuant et al., 2000; Jager and Janssen, 2012; Taghikhah et al., 2021), thanks to the promising results and machine power accessibility. The simulation system presented in the current work is built around the agent-based approach. Agent-based models start from the description of individuals' behaviour. Those agents might be insects in an agricultural field, cars in a traffic jam or, as in the current work, farmers managing their farms in an agrarian landscape. A key feature of this model is that individuals, the agents, have properties of interaction with their environment and their behaviour changes according to it. One drawback of those models is the high dependence the results have in respect of the boundaries of the system, i.e. in respect to what is modelled and what is not. Widen the boundaries involves time and effort but might seriously increase the model's realisticity and predictive power (Topping et al. 2015). For this reason, the effort was devolved into incorporating the aspects we are interested in into an already existing simulation system: the ALMaSS (Topping 2022). ALMaSS stands for Animal, Landscape, Man Simulation System and was first developed to study the wild animals population dynamics in specific landscapes of interest in northern European countries. Since then, the model has been developed significantly and now it is also used for environmental assessments related to agricultural management[6]. Compared to the plethora of other existing agent-based models, ALMaSS has the advantage of being the most sophisticated dynamic landscape simulator among the others. Such landscape is usually an agricultural landscape digital twin of really existing ones where plants grow, meteorological phenomena happen and crops are harvested. The intentions of the ALMaSS creators and modellers met our research questions and a new chapter of ALMaSS development began with the work presented in this thesis. Our contribution to the ALMaSS project is to model the farmers that will inhabit the agricultural landscape, increasing their complexity and incorporating social-economical aspects regarding the management of their farms. The aspects to include are numerous and only part of those are presented here. As already mentioned, one agent-based model peculiarity is the possibility of the agents interacting with themselves and their environment. For that reason, we have developed a model of interaction between farmers that will serve as the basis for the study of policy acceptance, adoption and diffusion of innovation and, ultimately, the assessment of both real and hypothetical scenarios from socio-economical and environmental perspectives.

Consumer effort

The circular economy (CE) advocates a system in which the concept of waste is gradually eliminated by turning it into a nutrient that circulates in endless technological and biological loops (Ellen MacArthur Foundation, 2013; Borrello et al., 2020). The adoption of CE in the agro-food industry is a great chance to change the current food system and move towards more sustainable production and consumption models (Jurgilevich, 2015; Bocken et al., 2016; Zimon et al., 2020; Bjørnbet et al., 2021; Swain and Sweet, 2021; Silvestri et al., 2022). Transitioning from linear consumption to a CE model, where practices of reuse and recycle are predominant over waste production, calls for new consumers' involvement, shifting from a passive role to a more active one, protagonist of the circular flows producing food, where their involvement is crucial to the CE initiatives' success. Commonly, the CE activities that involve consumers focus on minimising food waste. However, different ideas and practices involving consumers' behavior and consumption patterns are also emerging. Most of the attention is put on the production side: only about 20% of the CE-related scientific publications discuss the role of consumers in the CE transition, posing the necessity of a more in-depth analysis of consumer engagement in CE activities. While the factors influencing the participation in CE initiatives of consumers have been studied (Camacho Otero et al., 2018), their specific role and the effort related to participation in CE activities still lack a thorough investigation. Firms that work according to CE principles

[6] For further information go to https://www.ecostack-h2020.eu/

often require different levels of consumer engagement in their circular business models. This engagement can be represented by diverse types of practices made by consumers and, so, different levels of consumer effort. Besides the already mentioned food waste-preventing initiatives, new practices of participation and sharing, new recycling loops and new taking-back systems are being implemented. These innovative initiatives clearly involve consumers' active engagement. Moreover, a certain level of effort is required to consumers in order to accomplish most of the CE initiatives (Sijtsema et al., 2020; Georgantzis Garcia et al., 2021). Although its presence in many CE initiatives, the consumer effort still lacks in-depth analysis. The contribution to this topic, hereafter presented, is to fill this gap by delving into the topic and highlighting the core parameters of consumer effort in existing CE initiatives, using a qualitative research methodology with a multiple-case study approach. These parameters "dimensionalized" effort and will serve as a component of a proposed "effort index" of consumer engagement in CE initiatives.

Chapter 2

Farmers' risk preferences in 11 European farming systems: A multi-country replication of Bocquého et al. (2014)

Abstract

We replicate Bocquého et al. (2014), who used multiple price lists to investigate risk preferences of 107 French farmers. We collect new data from 1,430 participants in eleven European farming systems. In agreement with the original study, farmers' risk preferences are best described by Cumulative Prospect Theory. Structural model estimates show that farmers in the new samples are, on average, less loss averse and more susceptible to probability distortion than in the original study. Explorative analyses indicate differences between estimation approaches, as well as heterogeneity between and within samples. We discuss challenges in replications of economic experiments with farmers across farming contexts.

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2.1 Introduction

Risk and uncertainty are at the core of many questions in agricultural economics, and researchers have long been interested in estimating farmers' risk preferences (e.g., Binswanger 1980; Collins et al. 1991). Risk preferences are an important modelling input of broad interest to policy-makers and insurance companies. There is a large diversity of approaches to studying farmers' risk preferences, but the literature is scattered (Iyer et al. 2020). Few studies systematically investigate differences in risk preferences across countries and farming systems to capture heterogeneity and assess the distributional effects of risk-related policies. Large multi-country datasets collected under consistent protocols are mostly unavailable, and some geographical regions and farming systems in Europe are underrepresented in the literature on risk preferences (Iyer et al., 2020).

To reveal risk preferences in controlled environments, researchers have often used experiments with incentivized gambles (e.g., Holt & Laury 2002). Such gambles, as part of multiple price lists, have been widely applied to investigate farmers' risk preferences in the gain domain (Iyer et al., 2020). A widely cited study in the field of agricultural economics is Bocquého et al. (2014), who used the multiple price lists developed by Tanaka et al. (2010) to investigate risk preferences of a sample of French farmers. The authors compared two major theories of decision-making under risk: (1) Expected Utility Theory (EUT, von Neumann & Morgenstern 1947), which captures risk tolerance through the curvature of the utility function and (2) Cumulative Prospect Theory (CPT, Tversky & Kahneman 1992), which is based on reference dependence, leading to gain-loss asymmetry in behavior towards risk and probability weighting. Bocquého et al. (2014) used structural models to estimate EUT and CPT parameters, including models that adjust for socio-demographic heterogeneity. The authors found that farmers are risk averse in the gain domain under EUT and exhibit loss aversion and probability distortion under CPT. CPT provided a better overall fit to the data.

The main objective of this paper is to explore the robustness of the results by Bocquého et al. (2014) based on data gathered under a similar protocol on new populations from 11 Euro- pean farming systems. We cover a wide range of farming systems and national contexts, namely arable farmers in Austria, Germany, the Netherlands, and Sweden; wine growers in Croatia; potato farmers in Northern France; organic farmers in the North-West of France; olive growers in Apulia (Southern Italy); young farmers in Slovenia; members of two olive oil cooperatives in Andalusia (Spain); and farmers of different specializations in Poland. Our study is a conceptual replication of an experiment (i.e., the same protocol is broadly followed, but applied to a different context or sample), but we also engage in verification and reanalysis of the original data (see Christensen et al. 2019 for a discussion of different forms of replication and Rahwan et al. 2019 for an example of a conceptual replication of an artefactual field experiment). We focus on the same questions as in the original study: Are farmers' risk preferences better described by EUT or CPT? And, what are the parameters for standard specifications of structural models under these theories? Hence, our study also contributes to a better understanding of farmers' decision-making under behavioral biases (F. J. Dessart et al. 2019) and the broader debate on the replicability of prospect theory across different study populations (Ruggeri et al. 2020).

2.2 Theory, experimental design, data, and estimation strategy

2.2.1 Utility functions and weighting function

Bocquého et al. (2014) estimated three structural models: (1) an EUT power function model with a reflected utility function at zero with parameter r, (2) an EUT expo-power function model with a reflected utility function at zero with parameters α and β, and (3) a CPT model with parameters σ, λ, and γ. The authors also estimated the impact of socio-economic covariates on the size of these parameters. In the following, we briefly introduce the utility and weighting functions underlying the structural models.

Under the EUT power model, 1 - r is the Constant Relative Risk Aversion parameter (i.e., r is an anti-index of risk aversion for positive payoffs). The utility over payoffs y from a risky prospect $u(y)$ is defined as follows:

$$u(y) = \begin{cases} y^r if\ y \geq 0 \\ -(-y)^r if\ y < 0 \end{cases}$$

For gains ($y \geq 0$), $r < 1$ implies concavity and risk aversion. Because the function is reflected for losses, concavity and convexity reverse for $y < 0$. Note that this specification also implies reference dependence (but no loss aversion) due to the reflection of the function.

The EUT power model implies constant relative risk aversion. In contrast, the EUT expo-power function model allows for varying degrees of absolute and relative risk aversion (Saha 1993). In expression (2), parameters α and β capture risk aversion for gains ($y \geq 0$), assuming the following utility function:

$$u(y) = \begin{cases} \dfrac{1 - e^{(-\beta y^{\alpha})}}{\beta} if\ y \geq 0 \\ \dfrac{1 - e^{\beta(-y)^{\alpha}}}{\beta} if\ y < 0 \end{cases}$$

CPT has three parameters: (1) σ is an anti-index of concavity for gains, where values of $\sigma < 1$ indicate risk aversion in the gain domain; (2) λ is an index of loss aversion, where values of $\lambda > 1$ imply that the utility function is steeper in the loss domain (loss aversion); and (3) γ is an anti-index of probability distortion towards overweighting of small probabilities, where, for binary prospects, values of $\gamma < 1$ imply probability distortion (overweighting of small probabilities and underweighting of large probabilities)[7]. Here, we assume the status quo as the only reference point, although there has been a long debate on the identification of different (endogenous) reference points in prospect theory (Barberis 2013; Koszegi & Rabin 2007) or the possibility of more than one reference point (Koop & Johnson 2012). The utility function of CPT is defined as follows:

$$\begin{cases} y^{\sigma} if\ y > 0 \\ 0\ if\ y = 0 \\ -\lambda(-y)^{\sigma} if\ y < 0 \end{cases}$$

[7] Note that Kahneman and Tversky allowed for σ to differ in the gain and loss domains. The same applies to γ in Prelec's probability weighting function.

Under CPT, probabilities of all gambles are weighted, and here, we use the one-parameter weighting function of Prelec (1998), which is strictly increasing from the unit interval into itself, that is, for any two probabilities $pa > pb$, it maintains the order for the assigned weights such that $\omega\ (pa) > \omega\ (pb)$. By defining $\omega\ (0) = p0 = 0$ and $\omega\ (1) = p1 = 1$, the start and end points of the weighted and unweighted probabilities are the same. For any $p > 0$ and $p \leq 1$ the probability weights ω are defined as follows:

$$\omega(p) = e^{-(-\ln p)^{\gamma}}$$

Bocquého et al. (2014) used maximum likelihood for the estimation of all three structural models, which we also followed in our analysis[8].2 This estimation strategy uses a latent choice index, which is the difference between the expected and prospect utilities for the gambles. Note that for λ = γ = 1, ω (p) = p and σ = r, that is, the CPT model becomes the EUT power model. This feature allows for a direct comparison of model fit between the EUT and CPT specifications. For all models that reject the null of λ = γ = 1, CPT provides a better fit than EUT. Because CPT has more parameters, we will follow Bocquého et al. (2014) and also use the Bayesian information criterion (BIC) to decide on the better model fit.

2.3 Experimental design and sample of Bocquého et al. (2014)

The experiment of Bocquého et al. (2014) was based on a modification of the three multiple price lists designed by Tanaka et al. (2010) to approximate parameters for CPT in a three-parameter specification in rural Vietnam. The modification of Bocquého et al. (2014) consisted of multiplying the lottery stakes by 10 and deleting two rows from the first price list. The Tanaka et al. (2010) task has been used in other studies with farmers (e.g., Bougherara et al. 2017; Liu 2013; Sagemüller & Mußhoff 2020; Villacis et al. 2021), but Bocquého et al. (2014) is one of the few studies dealing with CPT in European agriculture (see Bonjean 2022 or Kreft et al. 2021 Bonjean, 2022 or Kreft et al., 2021 for other European examples). In each of the three multiple price lists (cf. Table 1), participants had to choose the row at which they preferred to switch from the *safer lottery* (Option A) to the *riskier lottery* (Option B). The task of choosing the switching row, rather than picking a lottery row by row as in Holt and Laury (2002), prevents multiple switches. Therefore, without having to discard inconsistent responses, the task enforces mono- tonicity, which allows us to approximate CPT parameters per respondent based on their switching points by the so-called mid-point approach (Tanaka et al., 2010). Bocquého et al. (2014) used a stratified random sampling strategy to build a representative sample of 107 farmers in the Burgundy Region in France. Their experiment was conducted face-to-face from February to June 2010 as part of a 2.5-h long survey. Participating farmers were told that they all would receive a fraction of Euro amounts displayed in the lotteries and that this fraction was predetermined and hidden in a closed

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[8] The original code was written for Stata. We estimated all models in R, using the maxLik package for maximizing the likelihood functions of the structural models (Henningsen & Toomet 2011).

envelope. Payments were calculated with an exchange rate of 2% of the amounts displayed as points (Euro) in Table 1. The exchange rate of 2% was revealed after farmers completed their decisions.

Table 1 - Multiple price lists used in this study

Row	Option A		Option B		Expected payoff diff.
Series 1	*Probability 30%*	*Probability 70%*	*Probability 10%*	*Probability 90%*	*Option A - Option B*
1	400	100	680	50	77
2	400	100	750	50	70
3	400	100	830	50	60
4	400	100	930	50	52
5	400	100	1060	50	39
6	400	100	1250	50	20
7	400	100	1500	50	-5
8	400	100	1850	50	-40
9	400	100	2200	50	-75
10	400	100	3000	50	-155
11	400	100	4000	50	-255
12	400	100	6000	50	-455
Series 2	*Probability 90%*	*Probability 10%*	*Probability 70%*	*Probability 30%*	*Option A - Option B*
1	400	300	540	50	3
2	400	300	560	50	17
3	400	300	580	50	31
4	400	300	600	50	45
5	400	300	620	50	59
6	400	300	650	50	80
7	400	300	680	50	101
8	400	300	720	50	129
9	400	300	770	50	164
10	400	300	830	50	206
11	400	300	900	50	255
12	400	300	1000	50	325
13	400	300	1100	50	395
14	400	300	1300	50	535
Series 3	*Probability 50%*	*Probability 50%*	*Probability 50%*	*Probability 50%*	*Option A - Option B*
1	250	40	300	210	60
2	40	40	300	210	45
3	10	40	300	210	60
4	10	40	300	160	85
5	10	80	300	160	105
6	10	80	300	140	115
7	10	80	300	110	130

Note: Adapted from Tanaka et al., 2010; Displayed units are points. Note that in accordance with the original study, the expected payoff difference was not shown to participants.

2.4 Protocol and adjustments of the replication

The replication idea emerged from discussions in the "Research Network on Economic Experiments for the Common Agricultural Policy", a group of researchers using and promoting experiments for the evaluation of agricultural policy[9]. The idea was shared with researchers who had experience in data collection with farmers and could reasonably offer a sample of participants. These researchers were invited to a series of joint meetings in which the experimental protocols were developed and discussed. Eventually, 11 teams joined the effort and were involved in designing the experiment and data collection in different farming populations.

A few adjustments to Bocquého et al.'s (2014) protocol were agreed upon. First, we only included the survey parts that were relevant to the study of risk preferences to reduce response time. Second, we modified incentives in the experiment. We used a common point system to display rewards consistently across all samples and currencies. This allowed us to share materials and videos more easily across multiple samples, also enhancing experimental control. We adjusted exchange rates between points and monetary rewards to account for variations in opportunity costs of participation time in the respective samples. The goal was to achieve 150% to 200% of a typical participant's opportunity costs for 20 min (see Supplementary Material for more details per sample). We also allowed paying out higher amounts to only a fraction of participants to limit administrative costs without losing the incentive effect (as for instance in for a general discussion).

Third, in contrast to Bocquého et al. (2014), in all instances, we revealed the exchange rate from points to monetary rewards before the experiment started. We believe that this is a more transparent procedure, beneficial in terms of experimental control and unobserved het- erogeneity, because respondents are less likely to form heterogeneous beliefs about their lottery payments[10]. Revealing the exchange rate only ex-post can be perceived as even more intransparent in online studies than in face-to-face studies, and we wanted to remove this additional confound.

Fourth, due to the pandemic and to lower the cost of data collection, we chose to allow both face-to-face (as in the original study) and web-based experiments, as the option of a lab-in-the- field experiment was unavailable in many instances. Note that in many instances, farm population data for probabilistic sampling and the application of survey weights was not available or accessible to the researchers. For instance, in the Spanish case, the research team's inquiry to the regional government about making available an anonymized list of the Andalusian olive growers and the corresponding email accounts was rejected due to concerns about

[9] For more information on the network, the reader is referred to www.reecap.org. For a discussion on experiments for agricultural policy-making see Colen et al. (2016).

[10] Suppose there are two types of respondents: optimists (believing in a high payment) and pessimists (believing in a low payment). If the assumed size of the payment affects choices or noise, unobserved heterogeneity increases (because we do not know respondents' beliefs). While there is some evidence of stake size effects in ultimatum games (e.g., Andersen et al. 2011), the main concern with choices in risky gambles is noise (Camerer & Hogarth 1999; Mechera-Ostrovsky et al. 2022).

personal data protection. Hence, we decided to accept convenience samples to allow for a broader coverage of more diverse farming systems and a larger total sample size.

Finally, we agreed on a set of key covariates, in common with Bocquého et al. (2014) as explanatory of risk preferences. These covariates are (1) the age of the respondent in years, (2) the number of children, (3) education beyond secondary school (dummy), (4) (self-stated) general trust towards other people (dummy), (5) the total arable area of the farm, (6) the proportion of land owned, and (7) whether the farm is a sole proprietorship or a society with only one associate (dummy). Whenever we refer to covariates in the models, we mean these seven variables that were also part of the original study. All teams followed the same procedure when gathering the data[11].

A questionnaire was developed in English and then translated into national languages[12]. A jointly produced, approximately 4 min long, instruction video explaining the task and payment procedures was offered to all online respondents. The video used one of the examples, and the instructions used the same examples as in the original study. The video was also publicly screened in the Spanish and Austrian face-to-face data collections. Note that in some cases (e.g., France I), additional data were gathered after the experiment, serving other research purposes. We also asked about the respondents' comprehension[13]. All instructions and other materials are available online (see data availability statement).

According to national regulations, no ethical approval was required for the study, nevertheless expedite ethical approval was obtained from the German Association of Experimental Economics as a joint commitment of the group to ethical research practices (see data availability statement). The study design was pre-registered as a replication under the open science framework (see data availability statement).

We obtained informed consent from all respondents. The consent form, which had to be actively accepted by participants, explained the broad purpose, data treatment, and payment procedures, as well as an indication of the range of the variable component of the payment. It also contained contact information. No deception was used, and no personal data were recorded without consent. A debrief in the form of a summary of the results was offered to interested participants by email.

[11] In addition to these covariates, Bocquého et al. (2014) included the proportion of the household income coming from another profession than farming, a dummy for deferred payments, a dummy for livestock, the proportion of idle land out of the arable area in 2009, a dummy if the farm has no successor despite looking for one, a dummy for farms located in the Northern part of the study area, and the importance of risk faced on soft wheat (1–5 score). We did not include these covariates, because they did not fit the more diverse farming contexts we were dealing with.

[12] Due to time constraints, we did not back-translate the instructions and videos. The involved researchers were all experienced in field work with farmers and familiar with the used terminology. In all instances, multiple team members reviewed the texts for clarity and to closely match the English master version. In several instances, pre-tests were run with colleagues or farmers (e.g., a small pilot was conducted with five farmers in the Netherlands).

[13] Respondents could indicate their agreement with the three statements “It was difficult to understand the task.”, “My choices were random.”, and “There were too many different lotteries.” on a five-point scale (see Appendix S1 for more details).

2.5 Samples and recruitment across countries and farming systems

There are few attempts to elicit risk preferences across a large number of countries in incentivized experiments with students (Vieider et al. 2015) or surveys of the general population (Falk et al. 2018; Meissner et al. 2022). Overall, these studies find large within and between-sample heterogeneity, highlighting the need to investigate risk preferences in many different contexts and generally rejecting the idea of homogeneous preferences.

The original Bocquého et al. (2014) study was aimed at a probabilistic sample of a small area in Burgundy. In the replication, we had three types of sampling strategies: (1) targeting specific farming systems with homogeneous production (e.g., potato growers in Northern France or olive growers in Apulia, Italy), (2) randomly or non-randomly sampling the overall population of farmers at national (Sweden) or regional levels (Slovenia), or (3) targeting a specific type of farming practice within a smaller region (e.g., organic farmers in North-West France, members of two olive grower cooperatives in Spain). Note that these strategies limit the comparability with the original study. All data were collected in the summer and fall of 2021. We provide a short narrative with more details for each of our samples in section 3 of the Appendix S1. An overview of all samples is provided in Table 2.

Table 3 gives an overview of respondent farm characteristics pooled across all newly collected samples. Note that we include only covariates that were common across all samples and the original study. Disaggregated and additional summary statistics for each sample are presented in section 1 of the Appendix S1. We also discuss how representative of the underlying populations the samples are in section 2 of the Appendix S1.

2.6 Analysis for replication

The analysis combined the estimation of three pre-registered structural models with further explorative analysis. We obtained the data and code from the authors of the original study (for Stata), and we successfully verified all the analyses (in Stata and R). The original study weighted responses by population level statistics (survey weights in Stata, see footnote 15, page 147 in Bocquého et al., 2014). Because we did not use probabilistic sampling, we also did not apply survey weights in our analysis. The original data and code for additional verification is available online.

2.7 Results

2.7.1 Structural models

Tables 4, 5, and 6 present coefficient estimates and 95 percent confidence intervals in brackets for all structural models without covariates. We include the original study's estimates (denoted as BJR2014) with and without survey weights for better comparison. We also report statistics of model fit: the log-likelihood of a model without parameters (LL null), the log-likelihood of the reported conversion (LL converge), and the Bayesian information criterion (BIC).

Table 2 - Overview on study samples

Sample name	Target population	Sampling and survey mode	Payments	Sample size for analysis
Original study, BJR2014	Farms from 64 towns in Burgundy, France	Probabilistic ample from registry; face-to-face lab-in-the-field experiment	Cash payments to all participants (19 Euro on average, p.145)	107
Austria	Arable farmers in Austria (region: Lower Austria)	Convenience ample; face-to-face experiment in group meetings which were held in cooperation with the Chamber of Agriculture	Payments as vouchers for local farm shop to all participants (average of 11.87 Euro, ranging from 2.90 Euro to 65 Euro)	128
Croatia	Winegrowers and wine producers from Croatia	Convenience sample from web-scraped contact information; online survey	One in 10 participants received a voucher (average of 11 Euro, ranging from 7 Euro to 19 Euro)	104
France I	Potato farmers mainly located in Northern France (Hauts de France, Grand Est and Normandie)	Convenience sample of farmers contacted through various networks, newsletters, and emails; online survey	Payments with vouchers to all participants (average of 26.36 Euro, ranging from 8.70 Euro to 195 Euro)	96
France II	Organic farmers (vegetable growers, Livestock and crops) of North-West of France	Convenience sample of farmers contacted through agricultural chambers and networks of organic farmers via newsletters and a mailing list; online survey	Payments with vouchers to all participants (average of 20 Euro, ranging from 13 Euro to 27 Euro)	28
Germany	Arable farmers in Germany	Randomly selected farmers from database of a market research company; online survey	Bank transfer to all participants (average of 8.83 Euro, ranging from 2.90 Euro to 65 Euro)	153
Italy	Olive growers of Apulia region (Southern Italy)	Convenience sample; individual face-to-face interviews	Cash payments to all participants (average of 10.02 Euro, ranging from 2.90 Euro to 65 Euro)	130
Netherlands	Arable farmers in the Netherlands	Randomly selected farmers from database of a market research company; online survey	Bank transfer to all participants (average of 16.09 Euro, ranging from 4.35 Euro to 97.50 Euro)	160
Poland	Various farmers in Poland	Mixed convenience sample of online participants from market research company and face-to-face interviews (recruited by farm advisors)	Bank transfer to 94 eligible participants (average of 9.34 Euro, ranging from 4.24 Euro to 19.56 Euro)	169
Slovenia	Young farmers, members of the Slovenian rural youth association	Mixed convenience sample of online participants and face-to-face interviews during farmer events	Payments with vouchers to all participants (average of 9.15 Euro, ranging from 2.90 Euro to 45 Euro)	114
Spain	Members of two olive oil cooperatives in Andalusia	Self-selected sample of members invited to the meetings at the premises; survey filled online on individual mobile devices	Voucher payment to all to be used to purchase olive oil in the cooperative's shop (average of 15.70 Euro, ranging from 5.80 Euro to 36 Euro)	130
Sweeden	All registered farming businesses with an email address	Simple random sample; personalized link to online survey	Bank transfer to one in 10 participants (average of 132 Euro, ranging from 66 Euro to 202 Euro)	218

Note: Where applicable, local currencies were converted to Euro (1 Euro were approximately 4.60 Polish Złoty and approximately 10.30 Swedish Crowns at the time of the study). All newly collected samples can be classified as lab-in-the-field experiments.

Recall that in the EUT power specification with a reflected utility function at zero, parameter *r* is an anti-index of risk aversion (in the gain domain). In the gain domain, for $r < 1$, the utility function is concave, i.e. participants are risk averse on average (r = 1 indicates risk neutrality, r > 1 indicates risk seeking behavior).

Table 3 - Summary statistics of pooled data

Variable	Description	N	Missing (%)	Mean	SD
Age	Age in years	1371	4.13	45.96	13.9
Nb children	Number of children	1298	9.23	0.92	1.15
Educ sup	= 1 if more than secondary education	1402	1.96	0.42	
Trust	=1 if self-reported as trusting other people	1368	4.34	0.37	
Farm size	Arable land area in 100 ha	1317	7.9	0.81	2.33
Land owned	Proportion of land owned	1357	5.1	0.66	0.35
Indiv owner	= 1 if sole legal owner of the farm	1383	3.29	0.73	

Under the EUT power model, responding farmers, in all samples, are risk averse in the gain domain, on average. All estimates of r are in a rather narrow range. The point estimates of r in five samples (Austria, Croatia, Germany, Netherlands, Sweden) are slightly higher than in the original study (BJR2014 unweighted), whereas six samples (France I, France II, Italy, Poland, Slovenia, and Spain) show lower r estimates, i.e., a higher degree of risk aversion in the gain domain and risk seeking in losses.

The EUT expo–power model estimates two parameters to allow for varying degrees of absolute and relative risk aversion. Compared with the original study, point estimates of α are lower for all samples, whereas point estimates of β are lower in all but one sample (Spain), in which they are higher. Note that the EUT expo–power model must satisfy $\alpha \times \beta > 0$. Although this is not the case for all point estimates (Austria, Italy, Sweden), it holds true in most instances for combinations of values in the 95 percent confidence intervals. We refrain from additional constraints on the model specification to avoid poor convergence of the demanding computation of the maximum likelihood models.

Under CPT, most samples show values above .3 for point estimates of σ. The two French, the Spanish, and the Italian samples are below this value and slightly below the estimates based on data from the original study. For the newly added samples, all point estimates for λ are below two and show smaller values than the data

Table 4 - Structural estimates of EUT model

	New samples pooled	BJR2014	BJR.2014 weighted	Austria	Croatia	France 1	France 11	Germany	Italy	Netherlands	Poland	Slovenia	Spain	Sweden
r	0.214 [0.206; 0.223]	0.227 [0.201; 0.254]	0.212 [0.173; 0.251]	0.232 [0.202; 0.261]	0.29 [0.202; 0.257]	0.183 [0.137; 0.229]	0.187 [0.119; 0.256]	0.229 [0.208; 0.251]	0.193 [0.164; 0.223]	0.24 [0.218; 0.261]	0.212 [0.187; 0.237]	0.206 [0.173; 0.239]	0.14 [0.089; 0.192]	0.232 [0.214; 0249]
LL null	-32492.8	-2397.47	-2397.47	-2831.23	-2377.75	-2165.52	-638.889	-3483.44	-2909.46	-3594.94	-3865.61	-2604.86	-2949.75	-4968.97
LL converge	-31304.5	-2294.78	-7462.75	-2782.02	-242.197	-2146.95	-623.35	-3299.21	-2891.25	-3420.29	-3694.14	-2513.16	-2945.38	-4674464
N choices	47,190	3531	3531	4224	3432	3168	924	5049	4290	5280	5577	3762	4290	7194
N respondents	1430	107	107	128	104	96	28	153	130	160	169	114	130	218
BIC	62619.74	4597.723	14933.67	5572.383	4492.535	4301.954	1253.529	6606.956	5790.868	6849.16	7396.907	5034.548	5899.125	9357.81

Table 5 - Structural estimates of EUT expo-power function model.

	New samples pooled	BJR2014	BJR.2014 weighted	Austria	Croatia	France 1	France 11	Germany	Italy	Netherlands	Poland	Slovenia	Spain	Sweden
a	0.217 [0.207; 0.227]	0.293 [0.265; 0.321]	0.288 [0.252; 0.324]	0.213 [0.184; 0.241]	0.254 [0.224; 0.283]	0.193 [0.151; 0.235]	0.206 [0.133; 0.280]	0.23 [0.205; 0.256]	0.18 [0.138; 0.222]	0.199 [0.176; 0.223]	0.24 [0.216; 0.265]	0.232 [0.200; 0.263]	0.195 [0.153; 0.237]	0.213 [0.186; 0.240]
beta	0.01 [-0.016; 0.037]	0.107 [0.078; 0.135]	0.119 [0.076; 0.161]	-0.081 [-0.187; 0.026]	0.063 [0.014; 0.111]	0.041 [-0.097; 0.180]	0.068 [-0.130; 0.265]	0.003 [-0.067; 0.072]	-0.064 [-0.219; 0.090]	-0.164 [-0.255; -0.072]	0.076 [0.027; 0.125]	0.08 [0.010; 0.150]	0.206 [0.094; 0.319]	-0.062 [-0.147; 0.022]
LL null	-32492.8	-2397.47	-2397.47	-2831.23	-2377.75	-2165.52	-638.889	-3483.44	-2909.46	-3594.94	-3865.61	-2604.86	-2949.75	-4968.97
LL converge	-31303.4	-2226.73	-7218.56	-2776.62	-2234.56	-2146.31	-622.629	-3299.2	-2889.65	-3395.31	-3680.58	-2505.22	-2920.95	-4668.52
N choices	94380	7062	7062	8448	6864	6336	1848	10098	8580	10560	11154	7524	8580	14388
N respondents	1430	107	107	128	104	96	28	153	130	160	169	114	130	218
BIC	62629.62	4471.184	14454.84	5571.323	4486.795	4310.123	1260.302	6616.849	5797.41	6809.147	7379.803	5028.283	5860.012	9356.178

Table 6 - Structural estimates of CPT model

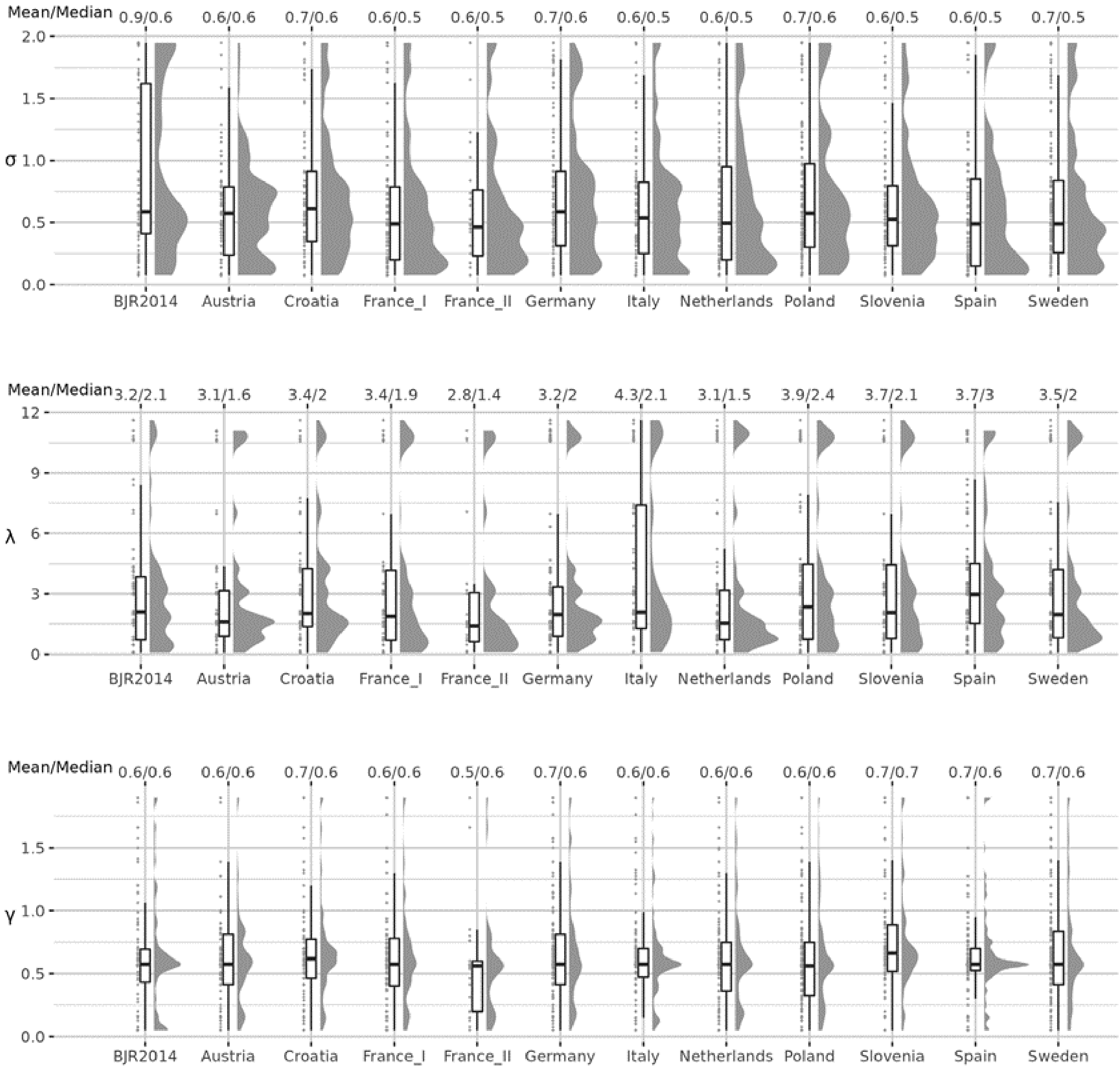
	New samples pooled	BJR 2014	BJR. 2014 weighted	Austria	Croatia	France 1	France 11	Germany	Italy	Netherlands	Poland	Slovenia	Spain	Sweden
sigma	0.314 [0.307; 0.320]	0.297 [0.276; 0.318]	0.28 [0.255; 0.306]	0.322 [0.297; 0.348]	0.333 [0.313; 0.354]	0.289 [0.254; 0.325]	0.284 [0.232; 0.337]	0.334 [0.318; 0.350]	0.297 [0.269; 0.324]	0.314 [0.294; 0.333]	0.304 [0.286; 0.3221	0.322 [0.298; 0.345]	0.284 [0.253; 0.315]	0.329 [0.315; 0.342]
lambda	1.601 [1.529; 0.674]	2.174 [1.852; 2.497]	2.274 [1.804; 2.744]	1.531 [1.316; 1.747]	1.817 [1.575; 2.059]	1.701 [1.358; 2.044]	1.751 [1.074; 2.428]	1.574 [1.386; 1.763]	1.457 [1.181; 1.733]	1.187 [0.979; 1.396]	1.807[1.563;2.051]	1.848[1.577;2.120]	2.162[1.843;2.480]	1.352 [1.185; 1.520]
gamma	0.574 [0.555; 0.594]	0.681 [0. 580; 0.781]	0.657 [0.507; 0.806]	0.643 [0.579; 0. 707]	0.595 [0.535; 0.655]	0.563 [0.464; 0.661]	0.562 [0.401; 0.723]	0.571 [0.516; 0.625]	0.546 [0.485; 0.607]	0.627 [0.566; 0.689]	0.591 [0.527; 0.656]	0.562 [0.498; 0.625]	0.487 [0.404; 0.570]	0.552 [0.506; 0.597]
LL nuli	-32492.8	-2397.47	-2397.47	-2831.23	-2377.75	-2165.52	-638.889	-3483.44	-2909.46	-3594.94	-3865.61	-2604.86	-2949.75	-4968.97
LL converge	-29400.7	-2148.74	-7027.9	-2664.9	-2037.32	-2064.86	-597.967	-3004.13	-2762.96	-3276.82	-3474.95	-2306.62	-2768.93	-4254.94
N choices	141570	10593	10593	12672	10296	9504	2772	15147	12870	15840	16731	11286	12870	21582
BIC	58837.08	4325.28	14083.61	5358.137	4102.351	4157.207	1219.715	6037.133	5554.315	6582.658	6979.076	4641.227	5566.243	8539.814

from the original study, with only the exception of the Spanish sample, which is slightly above two. The Dutch and the Swedish samples have particularly low point estimates for λ; and in the Dutch case the null hypothesis of no loss aversion ($\lambda = 1$) is included in the confidence interval. Point estimates for γ are below the estimates for the original data in all samples, implying a greater distortion of probabilities across all samples compared to the original data. For all samples, we reject the null hypothesis of $\lambda = \gamma = 1$, i.e., risk preferences are better explained by CPT than by EUT. All BIC values for the three-parameter specification of the CPT model are lower than for the nested one-parameter EUT model, indicating a better fit of CPT even if model complexity is taken into account.

2.7.2 CPT mid-point approach

Figure 1 presents kernel density distribution estimates, mean and median values (on top of each figure) for the three CPT parameters σ, λ, and γ for all samples and the original study denoted as BJR2014 obtained by the mid-point approach. Additional summary statistics and high-resolution figures per country for the mid-point approach approximations are presented in sections 5.1 and 5.2 in the Appendix S1.

Figure 1 - Kernel density estimates of the distribution of CPT parameters, using the mid-point approach.



2.7.3 Additional robustness tests

In the appendix, we report and discuss additional analysis and robustness tests. First, we re-estimated all structural models with covariates whenever the sample size allowed us to do so (appendix section 4). Similar to Tanaka et al. (2010) and Bocquého et al. (2014), we include covariates in a regression with each of the parameters as the dependent variable to explore heterogeneity in the CPT parameters for the mid-point approach (Appendix S1, section 5.3). Both approaches indicate that observed heterogeneity in the selected common farm and individual characteristics do not have a high predictive power. Risk preferences were not strongly related to any of the covariates. Second, we re-estimated the structural models using only respondents who took at least six minutes to respond to the survey in online samples (Appendix S1, section 6.2). Third, we re-estimated the structural models removing respondents who indicated poor understanding or random choices (Appendix S1, section 6.3). Fourth, as in Bocquého et al. (2014), we re-estimated the structural models, using a reduced set of observations per respondent by including only the one or two rows per multiple price list at which the switch occurs (Appendix S1, section 6.1). Note that the results for all models are generally robust to the re-estimation.

2.8 Discussion

2.8.1 Summary and general discussion

In the upper panel of Table 7, we compare the models and results in Bocquého et al. (2014) with the models and results in the newly collected samples. The first column presents an overview of the estimated models in Bocquého et al. (2014), the second column presents how we have dealt with this analysis, and the third column summarizes our main conclusions from the comparison. In the lower panel, we also present additional analysis (beyond the scope of Bocquého et al., 2014). We verified all the analysis using the original code from the authors. We also replicated the original study results in 11 additional samples. Although our results are not substantially different, we noted some deviations in our estimates from the original study, as described in the Table 7. However, we can also confirm the original study's main conclusion that farmers' risk preferences, on average, are substantially better described by CPT than by EUT, as under all approaches and for all samples, λ was consistently estimated as greater than one and γ was consistently estimated as smaller than one. In addition, the overall model statistics (and BIC in particular) also indicated a better fit of the data to CPT.

There was considerable heterogeneity both between and within samples. For example, in the structural models without covariates, the parameter for loss aversion λ ranged from a point estimate of more than two in the Spanish sample to less than 1.2 in the Dutch case. Using the mid-point technique, the same parameter λ had minimum, median, and maximum values of 0.08, 1.54, and 11.62 in the Netherlands, whereas the respective values were 0.08, 2.97, and 11.1 in Spain.

Table 7 - Comparison of original study and replication results

Bocquého et al. (2014)	Approach in the study	Comparison
Structural modeling of EUT (power and expo-power) and CPT utility functions with Maximum Likelihood without covariates	Verified using original code with survey weights; replicated with and without survey weights on original and newly collected data (pre-registered analysis) (Tables 4, 5, 6)	Similar results in all new samples; point estimates of λ and γ are slightly lower for CPT than in Bocquého et al. (2014)
Deriving individual parameters for CPT with mid-point approach	Verified using original code (Figure 1 and Appendix S1, section 5.1); models conceptually replicated	Overall patterns and order of structural models are mostly maintained between samples, but similar to the original study, mean and medians differ rather substantially from structural models (especially for λ)
Structural modeling of EUT (power and expo-power) and CPT utility functions with Maximum Likelihood with covariates	Verified using original code; slightly adapted models conceptually replicated for consistency due to non-applicable covariates (Appendix S1, section 4)	Adapted model parameter estimates following from small differences in the samples due to list-wise missing covariates are not qualitatively different from models without covariates, similar to the original study, low explanatory power of covariates within samples and pooled data
Estimating the impact of covariates on CPT parameters derived from mid-point technique	Verified using original code; slightly adapted models conceptually replicated for consistency due to non-applicable covariates (Appendix S1, section 5.3)	Similar to the original study, low explanatory power of covariates within sample and pooled data
Robustness checks with reduced observations per respondent	Verified analysis in original code and applied to new samples (Appendix S1, section 6.1)	Results are robust
Robustness checks with different reference points in CPT	Verified analysis in original code, but not applied due to difficulty of defining alternative reference points coherently across samples	Not applicable
Robustness checks with varying exchange rates	Verified analysis in original code, but not applicable (because no exchange rate ambiguity in new samples as described above)	Not applicable
Further robustness checks, not applied in the original study		
	Removal of respondents taking less Results are robust than 6 min in online samples (Appendix S1, section 6.2)	Results are robust
	Removal of respondents who self-reported to have poor understanding of or random decisions in the task (Appendix S1, section 6.3)	Results are robust

The mid-point technique can yield high values of λ for some respondents, which resulted in average values for λ of 3.09 and 3.66 in the Netherlands and Spain, respectively (see section 5.1 in the Appendix S1). In other words, not only are the estimates heterogeneous within and across samples, but substantially different conclusions may also arise from using different estimation strategies on the same data. While the structural models offer a point estimate for the whole sample using an error term that accounts for individual choice errors, the mid- point technique can give direct insights into the distribution of parameters for CPT based on raw choices. Because different estimation approaches can yield different results, we suggest the estimation of a large number of plausible models. This enables readers to assess the robustness and uncertainty associated with an estimate. More importantly, an open science approach is pivotal: the sharing of data and code allows the community to run further robustness tests and to integrate results in meta-analysis.

Our findings have important implications for policy. As stated by Colen et al. (2016), "behavioral findings (such as evidence of loss aversion), replicated over time and across domains, can safely be assumed to be valid everywhere and at any time and can therefore help understand reactions to policy of a large share of the EU farming population." Here, our estimates provide plausible ranges of parameters, which can be included in agricultural policy models.

Many agricultural measures are based on farmers' voluntary enrolment. Ex-ante evaluations are set up to predict the expected uptake of such voluntary measures. This requires that behavioral drivers of far-reaching economic decisions or technology adoption, including risk and loss aversion, are better anticipated (F. J. Dessart et al. 2019; Spiegel et al. 2021). This type of ex-ante information can help to fine-tune policies so as to obtain the desired level of participation or to optimize the outcome for a given budget. For instance, under the assumption that new measures involve greater risks, the high prevalence of risk and loss aversion signals the need to increase the compensation for agri-environmental measures or other green farm practices beyond the cost forgone for risk-averse and loss-averse decision-makers, which can pose a main barrier for transformational shifts in farming (Koetse & Bouma 2022). Likewise, risk aversion and loss aversion have welfare and policy implications for insurance design. For instance, Dalhaus et al. (2020) show how taking into account loss aversion in insurance design may increase farmers' uptake of well-designed insurance.

2.8.2 Challenges in multi-country replications of experiments with farmers

Conventional laboratory experiments with students are typically replicated under the exact same conditions, with only the timing and subjects being different. Uniform recruitment software and sampling, underlying population, localities, as well as experimental protocols and payment procedures can be used (e.g., Camerer et al. 2016). In contrast, artefactual field experiments, that is, experiments with non-standard subjects (Harrison & List 2004), such as farmers and other professionals, can create challenges for replication. For instance, in the replication attempt on dishonesty in the banking sector, Rahwan et al. (2019) had to work with a distinctive sample, which hampered a direct comparison of results with the original study, not least because of selection effects.

University laboratories typically work with long-term and experienced staff, whereas field experiments (outside of the laboratory) often build upon diverse teams, involving newly trained assistants. As a result, there are likely more confounds in such replications, such as small changes in wording, gestures, and other cues from field staff, or even changes in the sampling frame and payment procedures. These many changes will almost inevitably differ across multiple samples, affecting experimental control and, hence, causal interpretations of differences in outcomes. One could be very strict in enforcing the exact same protocol across multiple countries (e.g., as in Dessart et al. 2021 or Vieider et al. 2015). However, in this study, we have chosen a more flexible approach of building a strong network of collaborators with a good mutual understanding of the case at hand, but also open to small adjustments in the experimental procedures. Thanks to this flexibility, we could include several research teams with different constraints for data collection and obtain a large dataset. Although crucial materials to replicate are not always accessible (Palm-Forster et al. 2019; Palm-Forster & Messer 2021), luckily, we could build on the well-documented instructions, codes, datasets, and other material provided in Bocquého et al. (2014) and in later communication with the authors.

Harmonizing and improving infrastructures for social science research with farmers is an important task, also for obtaining higher quality samples. For instance, some collaborators of this project could collect data through third-party farmer panels (Netherlands, Germany) or a general registry of all farming businesses (Sweden). Others (e.g., Spain or Italy), in contrast, had to work with convenience and snowball samples. A stronger grouping of cases and further harmonization of samples within these sub-groups (e.g., by farming system, region, or sampling procedure) could lead to better benchmarks for comparison by the removal of additional con- founds. Although additional challenges, such as different legal treatments and taxation of cash rewards will likely remain, a coordinated effort to build social science research infrastructures and networks for primary data collection with farmers could facilitate cross-national research (see Lefebvre et al. 2021 for more discussion on this). As a first step in this direction, farmers who are part of the European Union's Farm Accountancy Data Network could be invited to voluntarily commit to participate in experiments with high cash rewards on a regular basis.

Recruitment of and access to farmers representing a target population is a hard task (Weigel et al. 2021), and the sampling procedures likely affects options for statistical inference. While a snowballing approach and the use of convenience samples recruited by advertising the link to the online experiment in farmers' networks were successful for some subsamples (e.g., France), we would like to note that such open links must be used with caution for incentivized online experiments. Indeed, in the first attempt at data collection in Scotland, the survey link was hijacked and bots generated multiple successive answers until fully filling the maximum number of respondents set for the survey, probably to scam payments. The problem was early identified, and consequently unique links to the online experiment were shared with verified farmers, which we recommend for future online experiments. However, one should also be aware that this form of recruitment takes a lot of time and resources. Eventually, the final sample size was not large enough to be included in this study.

Online panel providers (Germany, Netherlands) or official farm registry data (Sweden) have the advantage that access is more restricted and individual invitation links to the survey instrument can be used. One can also more plausibly apply probabilistic sampling. However, with panel provider or registry data, response rates were well below ten percent, raising concerns about selection biases. The Swedish team received several inquiries from invited farmers asking about the seriousness of the study, because the described payments seemed dubious to many. However, our recruitment efforts through email have been generally more successful than in the study of Weigel et al. (2021) who sent email invitations to more than 4,700 respondents in two experiments and – in spite of substantial monetary compensation for taking part – did not receive a single response. One can only speculate that the high levels of trust towards research institutions and the familiarity with being contacted and dealing with errands online in Sweden may have led to this greater success rate. For future recruitments, one may also consider sending paper mail invitations which in in the United Kingdom has led to a response rate of more than seven percent (Howley & Ocean, 2021).

The costs of collecting data for one respondent differed substantially between countries. Research teams who used market research companies, paid approximately 50 Euro per farmer response, whereas those recruiting through their own networks often paid less than 20 Euros per response (including incentives). However, in the latter case, the additional transaction costs (meeting and convincing partners to invite farmer participants) can be substantial. Overall, our experiences confirm that consistent data collection for social science research with farmers across Europe remains a challenge (Lefebvre et al., 2021).

Farmers complained in some instances about the experimental task being tedious, abstract, or difficult to understand. However, according to a self-assessment, problems with comprehension and poorly motivated responses were not severe (Appendix S1, section 7). Notably, two samples that used face-to-face data collection (Austria and Spain) were at the opposite ends of the assessments for most of the questions (Appendix S1, section 7). Self-assessed comprehension and response quality were very high in Austria, whereas participants in Spain faced more difficulties with the task. Finally, Italy (who also used face-to-face data collection) was close to the overall mean for these questions. Hence, we cannot draw very strong conclusions regarding the use of online vs. face-to-face data collection, but we note less between-sample heterogeneity on these aspects for online data collection. It is an open question as to how far adjusting tasks for improved simplicity and comprehension, as well as realism and engagement (e.g., Charness et al. 2016; Menapace et al. 2016; Meraner et al. 2018; Villacis et al. 2021) could have improved these scores.

2.8.3 Model extensions and future research

Our analysis can be extended with the available data in many ways. Unlike the original study, we have not applied survey weights in the analysis. This could be included in further robustness tests, based on known or assumed information of key covariates in the underlying farmer populations, although this might not be possible in all cases. The use of survey weights is also hampered by the fact that we have not used probabilistic sampling.

One could also test for other reference points in the CPT models. Here, we have focused on the standard assumption of the utility function being kinked at the status quo, but other or more reference points could apply. We have also assumed that σ and γ do not differ between the loss and gain domains. One could use different lotteries to estimate a five-parameter CPT specification (with parameters σ+, σ-, λ, γ+, and γ-) and test for differences of the σ and γ parameters in relation to the reference point (as for instance in Bocquého et al. 2022).

We have followed the original and other studies in the application of the mid-point approach (Tanaka et al., 2010; Bocquého et al., 2014; Villacis et al., 2021), but the mid-point approach can only provide an approximation of the CPT parameters because it elicits intervals. Cameron and Huppert (1989) have used interval regression to correct biases that may arise from using mid-points rather than interval limits for payment card data in contingent valuation. In the same fashion, an interval regression could be applied to better account for covariates. The data also offer additional potential to explore how predictive elicited parameters are of real-world behavior under risk, such as the purchase of insurance or the use of irrigation (Charness et al. 2020). More can also be done to further explore observed and unobserved heterogeneity. By using a finite mixture model, for example, one could estimate propensities of respondents to either belonging to a EUT or a CPT group (Harrison & Rutström 2009).

Our data and results are also useful for the integration with farm-level models. Although such models rarely consider risk and uncertainty (Huber et al. 2018), there is a growing trend towards a more realistic representation of economic agents in these models, including an increasing openness towards the behavioral economics and prospect theory literature in farm-level modeling (e.g., Appel & Balmann 2019; Huber et al. 2022). Our study provides a rich data source for modelers to parametrize such models, including an overview of the distribution of these parameters and how key farm characteristics may correlate with them.

2.9 Conclusion

The objective of this study was to verify the analysis of Bocquého et al. (2014) and to test the robustness of their results in a replication in eleven European farming systems. Provided with the original code and data from the authors, we succeeded in verifying all parameters drawn from the original study. In line with the original study and the broader social science literature (Ruggeri et al. 2020), we confirmed that CPT provides a better fit to describe farmers' risk attitudes than EUT. This conclusion holds in all additional samples, albeit we also found considerable heterogeneity within and across samples. Similar to the original study, we faced the challenge of different methods yielding substantially different results for the CPT parameters. We conclude that pre-registration of a preferred specification, a wide range of additional robustness tests, and open methods and data are the best way to deal with these challenges.

2.10 Supporting information

Supporting information can be found on-line in the Supporting information section at the end of this article at https://doi.org/10.1002/aepp.13330

Chapter 3

GeSoN: A Geo-Social Network model applying ecological rationality to farmers in socio-ecological simulations.

Abstract:

Agri-ecological environment management is a valuable tool for reducing agricultural impacts on ecosystems. Socio-ecological simulations can support these tools to find better solutions for managing natural resources. Nonetheless, these models are still few and scattered, often stand-alone, and usually applicable to a specific context. Here, we present a Formal Model for reproducing the farmer opinion dynamic in a multi-layer geospatial network, focusing on the influence farmers embedded in the same landscape have on each other. The study aims to provide a new tool to integrate complex socio-ecological system simulations incorporating human behaviour and decision-making components, specifically focused on the farmer's social networks and opinion diffusion modelling. The farmers are modelled following the bounded rationality framework and applying the concept of ecological rationality, and a bounded confidence opinion dynamic model governs the interaction between agents. The interaction between the agents is governed by an asymmetrical function and involves an explicit role of uncertainty. The model generates a connection between farmers using different criteria and developing a multilayer system where geographical, economic, and social aspects are considered. The **Ge**o-**So**cial **N**etwork model (GeSoN) shows promising dynamics and behaviours, mainly attributable to the formation of consensus, polarisation, and fragmentation among the agents' opinions. Moreover, the GeSoN model presents flexibility and adaptability to be incorporated into more complex simulation systems.

Publishing info:

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3.1 Introduction

Agricultural systems are examples of socio-ecological systems (SESs) (Filatova et al. 2013), inheriting their peculiar characteristics. Specifically, the coexistence of social and environmental factors and the inherent complexity (Levin et al. 2013). Thus, when modelling agricultural systems, farmers' behaviour is of paramount importance (Gotts et al. 2019). Crop choice, application of certain agricultural practices, and innovation adoption are some of the actions carried out by farmers that affect the economy (Timmer 2002), social sustainability (Janker et al. 2020), and environmental sustainability (Sabiha et al. 2016) of an agricultural landscape.

In the last decades, a relatively new class of model, the agent-based models (ABMs), has been widely used in modelling SESs (e.g., Holtz & Pahl-Wostl 2012; Kaufmann et al. 2009; Troost et al. 2015). ABMs are computational models that represent reality, focusing on the atomistic parts of a system (i.e., agents), describing their behaviour and the interactions between them and the environment in a "bottom-up" approach (Murray-Rust et al. 2014). They were first developed for complex theory research (Holland 1996; Lewin 1993), and their popularity throughout academia has increased since then (Macal 2016). When approaching complex socio-ecological systems, such as the agricultural landscape, ABMs can give unique insights thanks to their ability to model complex emerging phenomena (Kiesling et al. 2012). Nowadays, models that involve farmers' behaviour are quite numerous (e.g., Guillem et al. 2015; Troost et al. 2015; van Duinen et al. 2016). Among the different facets of farmers' behaviour, studies usually focus on innovation adoption (e.g., Berger 2001; Deffuant et al. 2002; Kaufmann et al. 2009; Schwarz & Ernst 2009; Sorda et al. 2013) and land use changes (Murray-Rust et al. 2014; Synes et al. 2019). Usually, these models apply a behavioural framework to farmers; depending on the chosen framework, they can define a decision-making rule applied to every agent (Schlüter et al. 2019). Well-known examples of behavioural frameworks are the Expected Utility Theory (EUT) (Frank 1989; Monroe 2001; Simon 1978), the Prospect Theory framework (Kahneman & Tversky 1979; Tversky & Kahneman 1992), and the Theory of Planned Behaviour (TPB) (Ajzen 1991). The behavioural framework influences the set of information that every farmer needs to handle to take a decision. For example, agents' risk aversion may be relevant under the Prospect Theory framework and irrelevant if the theory of planned behaviour framework is applied. Application of the same behavioural framework may also lead to substantially different models.

In most of the frameworks reviewed by Schlüter et al. (2019), the agents' decisions are influenced by their context to a variable extent. This context involves the bio-physical and social environments, including the other agents embedded in the simulation. As clearly pointed out by Heckbert et al. (2010), in complex systems, interactions matter. Hence, in the model regarding the agricultural socio-ecological system, a sophisticated and evolved representation of those interactions, particularly the interactions among human agents, should be implemented. Moreover, there is empirical evidence of the influence networks have over farmers' decision-making (Moschitz et al. 2015; Schneider et al. 2012; Sol et al. 2013).

While many agricultural systems models have been developed, relatively few studies explicitly account for social interactions (Huber et al., 2018). This study aims to fill this gap by developing a farmers' social networks and opinion diffusion model. This model involves elements of farmers' behaviour and decision-making, focusing on interactions between farmers and their influence on each other. The objective is to formulate a model in the context of SESs that recreates the farmers' social context relevant to the farmers' decision-making process. The model is planned to be part of an ABM of farmers' decision-making; therefore, it is a sub-model, but it can also be used independently to explore network properties.

3.2 Theoretical framework

The decision to apply a behavioural framework that exists already and is grounded in theory is generally recommended (Groeneveld et al. 2017; Schlüter et al. 2017). In particular, it facilitates the comparison and re-use of models (Groeneveld et al. 2017), leading to consolidation and improvements of the results (Bell et al. 2015). Moreover, it fosters communication between modellers and enhances theory development. When modelling human behaviour, the most commonly used behavioural framework derives from the Expected Utility Theory (EUT), initially proposed by Bernoulli (1954). This framework's fundamental assumptions are that humans are selfish, have stable and transitive preferences, have an unlimited cognitive capacity to evaluate every behavioural option available, and base their decisions exclusively on the utility deriving from those. Being the standard in the economics discipline and being easily formulated mathematically, this framework is prevalent (Schlüter et al. 2017). In contrast, numerous empirical studies refuted the critical assumptions of the EUT in different domains (e.g., Bocquého et al. 2014; Levine et al. 2015; Siebenhuner 2000; van den Bergh & Gowdy 2000). Consequentially, many other frameworks, mainly from psychology, have been proposed to fill the gap between the EUT and observed human behaviour. Groeneveld et al. (2017) and Schlüter et al. (2017) comprehensively describe these frameworks.

Here, the approach to modelling the farmer's behaviour follows the Bounded Rationality framework (Simon 1955, 1997). Bounded rationality states that, when making decisions, humans (or farmers, in our case) do not set out complex optimisation procedures; instead, they mediate between constraints regarding time, knowledge, and cognitive abilities. More specifically, as Jones (2003) explained, four distinct facets concerning the human-decision making must be considered. These are: 1) humans encounter difficulties in evaluating and planning long behavioural sequences, given by their limited, or "bounded", cognitive capacity and the inherent complexity of their environment; 2) people tend to set aspirational levels related to specific goals; 3) they work on goals sequentially and not simultaneously; 4) Their search strategy is aimed at satisfaction rather than optimisation.

A vital aspect of the bounded rationality framework is called "ecological rationality" (Gigerenzer & Selten 2001). This concept underlines how decisions are strongly influenced by the environment, intended as the parts of the context, both physical and social, relevant to agents' goals and needs. According to the bounded rationality framework, the definition of ecological rationality and environment both account for the agent's context when defining the system's boundaries in a bottom-up modelling approach aimed at replicating realistic human decision-making. The environment becomes part of the limitations to human-comprehensive rationality (Simon, 1997). From another perspective, the ability of individuals to understand and adapt to the environment could determine their success in satisfying their goals (Gigerenzer and Selten, 2001).

3.3 Modelling approaches

The approach used to model the interaction among farmers in this model is the opinion dynamic. This specific branch of the more general social network analysis framework (B. D. O. Anderson & Ye 2019) has gained attention for its potential application in social and political science (Sun & Müller 2013). The opinion dynamic studies the evolution of individuals' views as the result of the interactions between a network of individuals. In other words, it assumes people influence each other, describes the interaction process from an individual point of view, and produces results emergent from those interactions, pooled for the population. The seminal works of this discipline are the study conducted by (French Jr. 1956) and its revision and formal elaboration by (Degroot 1974). Their model, also known as the French-DeGroot model, focuses on consensus and the conditions that lead to a consensus amongst individuals. Since then, many other opinion dynamic models have been developed (e.g., Düring & Wolfram 2015; Tian & Wang 2018).

The opinion dynamic approach focuses on the individual elements of the network and requires the specification of several key elements. These are the network identification, the opinions definition, and the formulation of an interaction mechanism. The first step in defining the network is to determine whether the network has a specific topology or is completely random and, ultimately, determine who interacts with whom and in which order. The opinions definition involves its mathematical representation; there are two main types. The first type represents opinions as discrete variables; examples are the voter model (Clifford & Sudbury 1973) and the Snajzd model (Sznajd-Weron & Sznajd 2000). The second type models the opinions as continuous variables; usually, the opinion range values lie between 0 and 1. This type includes the Deffuant model (Deffuant 2000) and the French-DeGroot model (French-DeGroot). The present study belongs to the second type. The interaction mechanism describes how agents respond to the interaction with others. This involves the formula determining the magnitude of the influence and any constraints added to the interaction. The major constraint used in the model presented here is bounded confidence. Models developed applying this constraint assume that influence among interacting agents does not always occur. This means there is influence during an interaction only when a specific condition regarding the opinions (usually similarity between opinions) is met. Thus, the assumption underlying bounded confidence is that opposite opinions have little or no influence on each other.

The concept of geographical specificity (Namatame & Chen 2016) has been applied to model the links enabling the connection between agents. The geographical specificity must be considered an attribute of the agents that creates higher levels of heterogeneity in the population and ultimately affects the interaction rules by explicitly defining the possible interactions among agents. As a result, a multi-layer network was defined following the geographical specificity. Different network configurations were defined with different linking properties, each influencing the same explicit structure where the opinion dynamic takes place. This allows feedback mechanisms to alter the overall network dynamics due to inter- and intra-network interactions. The criteria behind the multi-layer network formation are different. Examples are the physical location and agents' economic attributes. This approach evolves from the random connection formation rule, used in the seminal models of Watts-Stogatz and French-DeGroot, that is a purely mathematical network. Instead, applying economic and social criteria to agents' connections forms a socio-economical network (Namatame and Chen, 2016). Other examples of this approach can be found in Chen et al. (2006) and Yang et al. (2022). A detailed explanation of this process is given in the *Overview of the processes* section.

3.4 Framing the model

Decisions about what to include or not to include influence the model's flexibility, results, and predictive power (Topping et al. 2015). In the modellers' opinion, the processes included in GeSoN were the most relevant in capturing the essential dynamics emerging from the social interaction among farmers. Nonetheless, some processes were intentionally left outside the model's system boundaries to maintain an adequate level of model parsimony, simplicity, and feasibility. At this stage of development, farmers are the only type of agent represented in the model. In real scenarios, some other entities, like agricultural advisors, food processing industries, or institutions, may mediate the interaction among farmers and influence the diffusion of innovation. The inclusion of those actors is planned for future developments of the model. Second, although the theoretical approach used in the model accounts for the socio-psychological characteristics of the farmers, the inclusion of every personal psychological sphere is outside the scope of the model. Notably, farmers' emotions were intentionally left outside of the system boundaries. As pointed out by (Huber et al., 2018), emotions are rarely included in farmer behaviour models, and a more consistent inclusion of these aspects should be considered in future works. Third, the agricultural land market is not taken into consideration. The decision to keep the land market outside the model was taken so as not to over-complicate the model and because of its relatively small effect on determining farmers' social interaction. Fourth, the farmers' position in the landscape is assumed to be located in their farm centre. The location has a major influence on the farmers' social network. Still, farmers' physical movements are not reasonably predicted; therefore, the assumption of the same location between farms and farmers has been made.

An important aspect left outside the model's system boundaries is the other sources of influence affecting farmers' opinions. At this stage of the development of the model, a focus on only the endogenous influence of farmers' opinions best fits the study's aim. Nonetheless, the model structure allows the integration of other sources of influence, like economic and environmental shocks causing a generalised shift in the farmers' opinions, such as their risk aversion.

3.5 Overview of the processes

3.5.1 Overview of the components and the connections

The GeSoN model has two main components that are strictly related and work together while representing different aspects of the social context of farmers. These are the farmers' social network and the interaction among farmers. The former is the structure that represents the connections between farmers. The latter is the process of interaction between farmers. In the following sections, both components are described in detail. The farmer social network is the process of forming connections between farmers. Different factors, such as the geographical distance between farms, regulate the formation of ties. The Network structure is composed of three distinct layers, forming a multi-criteria web of channels through which farmers interact. The interaction between farmers generates the model influence farmers have on each other when interacting. The influence considers farmers' opinions, like risk aversion or sustainability concerns. The farmer network forms the structure over which the interaction between farmers occurs. Those interactions are not random but based on neighbourhood. The specific morphology of the landscape and the farmers' characteristics strongly influence the outcome of these interactions and the results of applying the network structure.

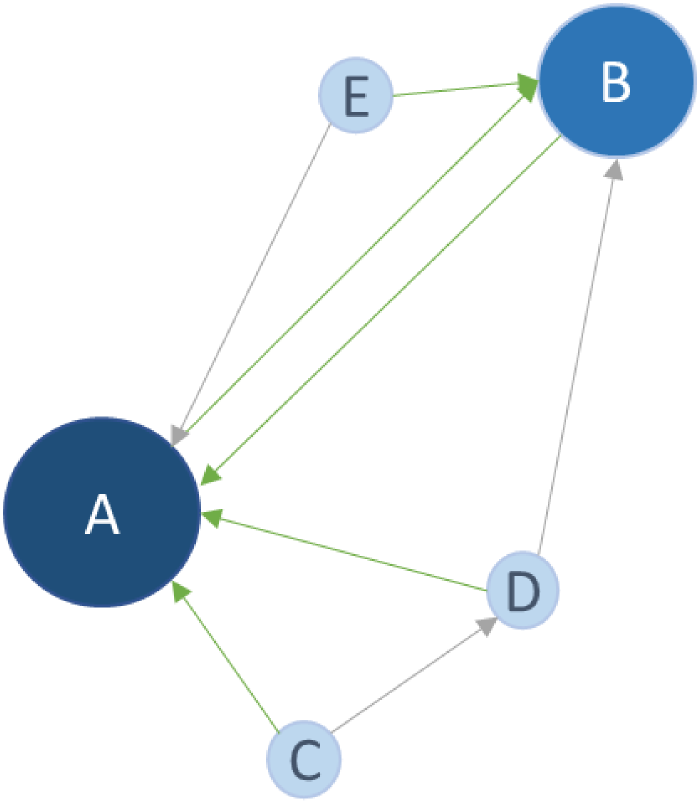
3.5.2 Process description

To better describe the GeSoN structure, the connections between agents are mapped using the network science's concepts of nodes and links. For example, in Figure 1, the basic features of the GeSoN structure are shown. Farmers and other agents (note that in the current version of the GeSoN, only farmers are considered) form the nodes distribution. Arrows represent the links between nodes and indicate the connections between agents. Both nodes and links have attributes (or features, characteristics). Nodes' attributes are size, position, and the number of connections with other nodes. Links' attributes are direction and strength.

3.5.3 Network structure

The network represents the sum of relevant ties connecting farmers in the same agricultural landscape. These connections resemble the channels through which communication takes place. Among all the possible and only partially predictable relationships between farmers, only a few of those are modelled here.

Figure 1 - Example of network elements. Coloured dots represent nodes, and arrows represent links. The dots' colour, size, and position represent the nodes' attributes. The colour and direction of the arrows indicate the strength and direction of the connections



Although the farmers' social context involves numerous actors (e.g., their family, agricultural advisors operating in the area, and local food industries), in this first development of the GeSoN, the connections between farmers are made only between farmers. In other words, GeSoN does not consider the influence of those actors directly but leaves the possibility to involve those in future developments. In the past, the network's topology (i.e., the position of the nodes and links between those) was most often separated from sociological questions (Will et al. 2020). Examples are the random network (Erdös & Rényi 1959), the small-world networks (Watts & Strogatz 1998), and scale-free networks (Albert-László & Réka 1999). On the other hand, the network's topology reflects socio-economics phenomena and is highly dependent on the agricultural landscape. Nonetheless, a certain level of stochasticity is incorporated in the formation of the ties. The different criteria forming the links between agents are intended to be separate and interacting layers, each shaping the individuals' social network. Hereafter, the specification of the rationale behind the connection between farmers is given.

3.5.4 Ties formation rationale

The ties formation process involves different features, each forming a specific sub-section of the GeSoN. In the first instance (Geographical Network), the geospatial configuration of the landscape is what most influences the network's structure. Farmer agents' primary connections are based on the farms' specific location across the landscape. The basic concept is that, as demonstrated by literature (Neal & Neal 2014; Will et al. 2020), farmers are highly influenced by their peers' behaviour. Physical distance, or proximity, between farmers partially determines their connection. Moreover, the economic size of the farmer also affects the possibility of creating links, and bigger farms are assumed to influence more frequently than others. Innovative and more influential farms are usually economically significant (Daberkow & McBride 2003; Just & Zilberman 1983; Sunding & Zilberman 2001). As a second connected parallel network, a set of links is formed to simulate the presence, in a landscape, of groups of cooperating farmers (the Associative network). These can be members of the same cooperative, members of a producer organisation, or only similar farmers in terms of agricultural production. The third network set of ties is generated to capture the non-agricultural connections between farmers. These can be various, like friendship or parenthood (the Virtual network). The sub-model section describes these three sets of links in more detail.

3.5.5 Geographical network

The Geographical Network is the major component of the GeSoN; it represents the influence over the landscape of "nodal" farmers. As described by Poudel et al. (2015), nodal farmers create the highest number of connections with others and, hence, significantly influence the agricultural landscape. The Geographical Network uses a modified gravity model to shape farmer connections. The gravity model is a well-known empirical economic model, originally developed by Newton's law of gravitation (J. E. Anderson 2011), first used by Isard (1954), and primarily applied to international trade studies (e.g., Brun et al. 2005). A modified gravity model has been used for three reasons. First, although there is a lack of connection with the economic theory, the gravity model has been proven to have an important explicatory predictive power (J. E. Anderson 2011); second, it is a parsimonious model; third has already been applied to ABM regarding farmers network (Yang et al. 2022). The two main assumptions behind the application of this model are: 1) closer farmers are more likely to interact, and 2) bigger farmers (in terms of farm size) have more influence over their neighbours than smaller farmers. In the Geographical Network, the links between agents are weighted and directional. This means that Farmer *i* can be linked strongly or weakly with Farmer *j*, independent of how Farmer *j* is linked with Farmer *i*.

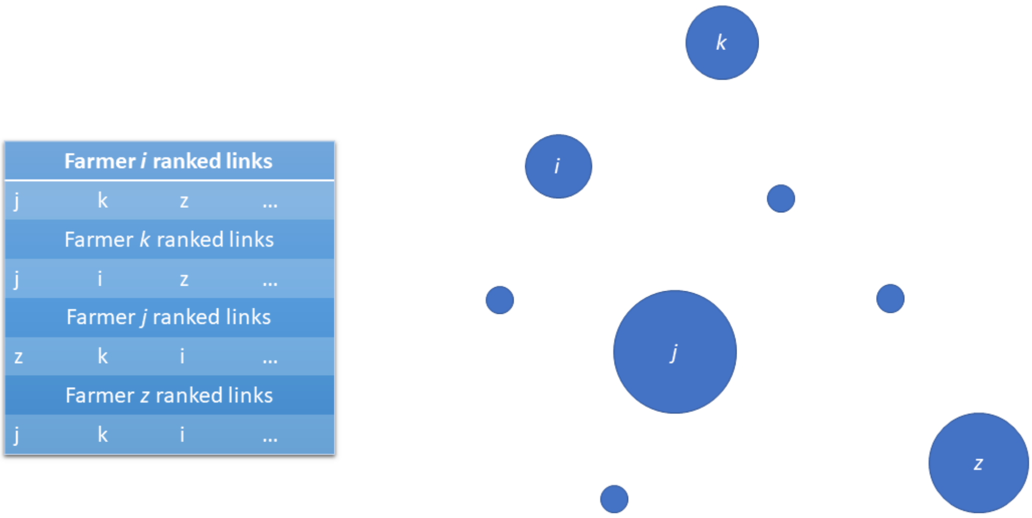
The resulting formula behind the formation of links between farmers under de Geographical Network is:

$$F_{ij} = \frac{M_j}{D_{ij}}$$

Where F_{ij} is the strength of the link that connects Farmer *i* with Farmer *j*. M_j is the farmer *j* size (note that only the size of farmer *j* is taken into consideration) and D_{ij} is the physical distance between Farmer *i* and Farmer *j*, i.e., between the two farms.

After computing the force connecting them, all farmers have a ranked list of all the other farmers in the landscape, ordered by the force. A graphical example is given in Figure 2. Note that the ordered list varies among farmers; in the example farmer *i* has its strongest link with farmer *j*, while farmer *j* is linked primarily with farmer *z*. When the interactions take place, farmers will choose a predetermined number of neighbours from the top part of the ranked list in the same order they are listed. The number of neighbours is one of the state variables of the model.

Figure 2 - Graphical example of the spatial distribution of farmers and their ranked list of neighbours under the geographical network



3.5.6 Associative and virtual network

The concept governing the Associative network's formation of ties between farmers is the potential to incorporate information about the farmer's membership of cooperatives, corporations or producer organisations. It is important to add the influence of these types of organisations on the network since farmers are strongly affected in their decision-making by being part of one of these groups . The Associative network is exogenous and predetermined at the beginning of the simulation. If information about farmers' membership to cooperative-like associations is available, scenarios with cooperatives associating similar farmers may give interesting results.

The Virtual Network's primary purpose is to incorporate unpredictable connections between farmers. Those can be of various types, like normal friendships, family relationships, or social network friendships. This additional layer completes the network structure involving a determined level of stochasticity. As with the Associative network, the Virtual network is exogenous.

3.5.7 Interaction among farmers

Once the link between agents is formed, different kinds of information can travel through it. Here we focus on the diffusion of opinions. These are risk aversion and sustainability concerns, and form parameters in the farmers' decision-making process. Opinions have been modelled as continuous variables ranging from 0 to 1, with 1 excluded, as proposed by Deffuant et al. (2000) and Hegselmann & Krause (2002). As underlined by Weisbuch et al. (2002), an explicit role of the actor-uncertainty regarding personal opinions is fundamental. Hence, every farmer has their personal opinion and a certain level of uncertainty. Uncertainty is modelled as a continuous variable, ranging from 0 to 0.6. A graphical example is given in Figure 3. The farmer's opinion is the uncertainty's central point, or mean value. 0 and 1 are the opposite extreme opinions. During the simulation, farmers interact with their neighbours and adjust their opinion according to the neighbours' one. The interaction follows the principle of bounded confidence, which implies that an agent is not influenced by distant positions (Xia et al. 2011). The rationale is that people with similar attitudes are more likely to interact (Neal and Neal 2014), and that there is a lack of understanding between persons with substantially different opinions (Deffuant et al. 2002). The minimum distance, or threshold, to enable the influence of one opinion over the other is represented by the uncertainty associated with the influenced agent's opinion (Weisbuch et al. 2002). Figure 4 and Figure 5 show when an influence of opinions occurs and when it does not, accordingly to the distance of opinions between agents. In the model, time is discrete and divided into time steps in which the farmers can interact. Every farmer has a list of neighbours, ranked by the force of the link under the geographical network. A certain number of neighbours is taken from this list. To these, other neighbours coming from the other networks may be added. Each farmer then interacts with the chosen neighbours and updates their opinion after interacting with all the selected neighbours. It is important to underly that farmers upload their opinions after every other farmer has interacted with their respective neighbours. In this way, it is avoided that the starting order of farmers makes a difference in the results. The magnitude of the influence is controlled by the *mobility* parameter. The *mobility* value is fixed for all agents at the beginning of the simulation. The resulting formula controlling the influence is:

$$x_{A,t+1} = x_{A,t} * (1 - u_A/(u_A + u_B) * q) + m_{u_{overlap}} * (u_A/(u_A + u_B) * q)$$

where $x_{A,t}$ = farmer *A* opinion at time *t*; $x_{B,t}$ = farmer *B* opinion at time *t*; u_A = farmer *A* uncertainty; u_B = farmer *B* uncertainty; ; $u_{overlap}$ = overlapping between u_A and u_B; $m\_u_{overlap}$ = central point of $u_{overlap}$; q = mobility. The formula is a weighted mean of the influenced farmer's opinion and the central part of the influencing farmer's shared opinion. The weights given to the two elements are the *mobility* parameter and its inverse, both scaled by a factor indicating the difference in the farmers' uncertainties. This factor results in the influence between farmers with unequal uncertainties being asymmetrical. Thus, when two farmers with high and low uncertainty respectively influence each other, the effect is stronger on the farmer with high uncertainty.

Figure 3 - Representation of farmers' personal opinions

Figure 4 - Example of similar opinions producing an interaction

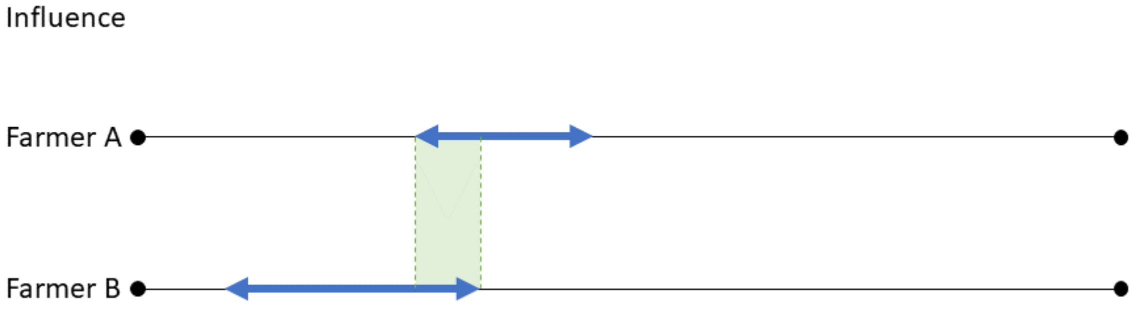
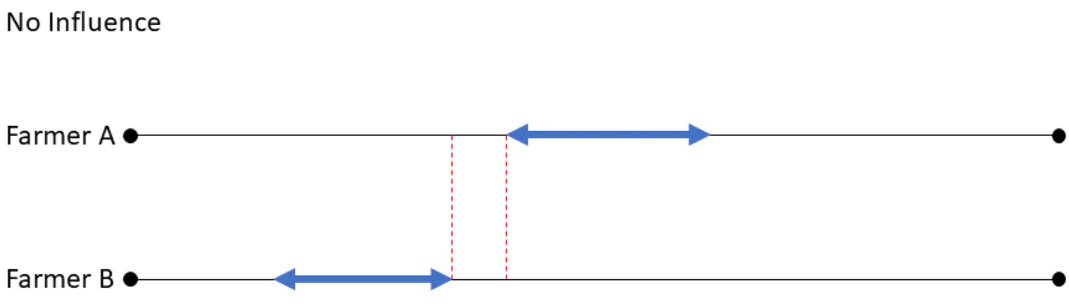


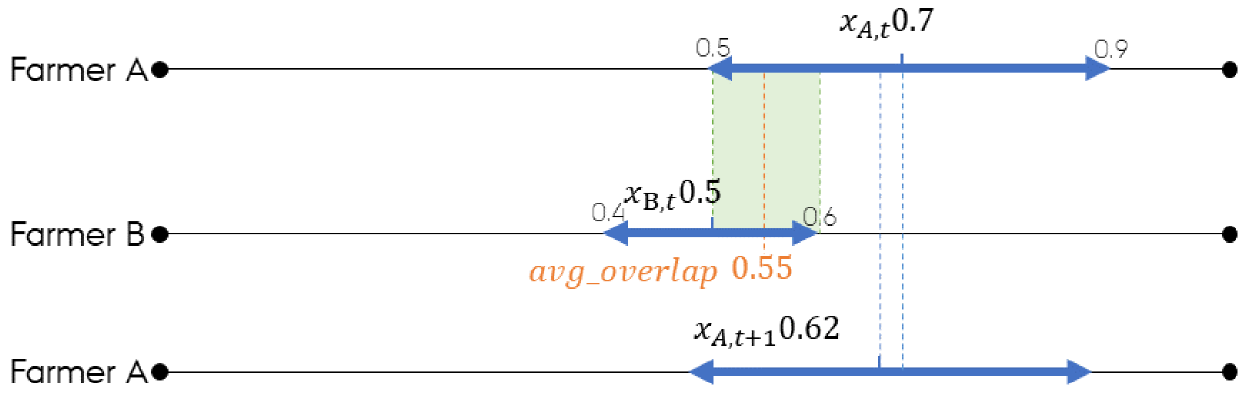
Figure 5 - Example of different opinions not producing an interaction



3.5.8 Numerical example

Here we give a numerical example of the interaction between two farmers, say A and B, whose initial opinions are 0.7 and 0.5. Uncertainty is set to 0.4 for farmer A and 0.2 for farmer B. Finally, the *mobility "q"* parameter is set to 0.8. A graphical representation of this specific interaction is given in Figure 6.

Figure 6 - A numerical and graphical representation of the interaction between agents. Farmer A and Farmer B have different opinions (A = 0.7 and B = 0.5). Nonetheless, their uncertainties overlap (green part), so the interaction occurs. Where: Farmer At = 0.7, Farmer Bt = 0.5. Farmer A uncertainty = 0.4, Farmer B uncertainty = 0.2, Mobility q = 0.8. Farmer At+1 = 0.62



3.6 State variables and scales

State Variable	Description
Neighbours from the Geographical network	In every round of interaction, the farmers will choose this discrete number of other agents from the ranked list of neighbours given by the Geographical Network.
Neighbours from the Associative Network	In every round of interaction, the farmers will choose this discrete number of other agents from the list of co-associates held by the Associative Network.
Neighbours from the Virtual Network	Every round of interaction, the farmers will choose this discrete number of other agents from the list of friends given by the Virtual Network.
Landscape	The simulated space where farms exist. List of cartesian coordinates associated with the information about the farms' size.
Mobility	A parameter that regulates the convergence of opinions during an interaction. It is a continuous variable bounded between 0 and 1. 0 means no convergence, and 1 indicates maximum convergence.
Neighbours from the Geographical network	In every round of interaction, the farmers will choose this discrete number of other agents from the ranked list of neighbours given by the Geographical Network.
Neighbours from the Associative Network	In every round of interaction, the farmers will choose this discrete number of other agents from the list of co-associates held by the Associative Network.

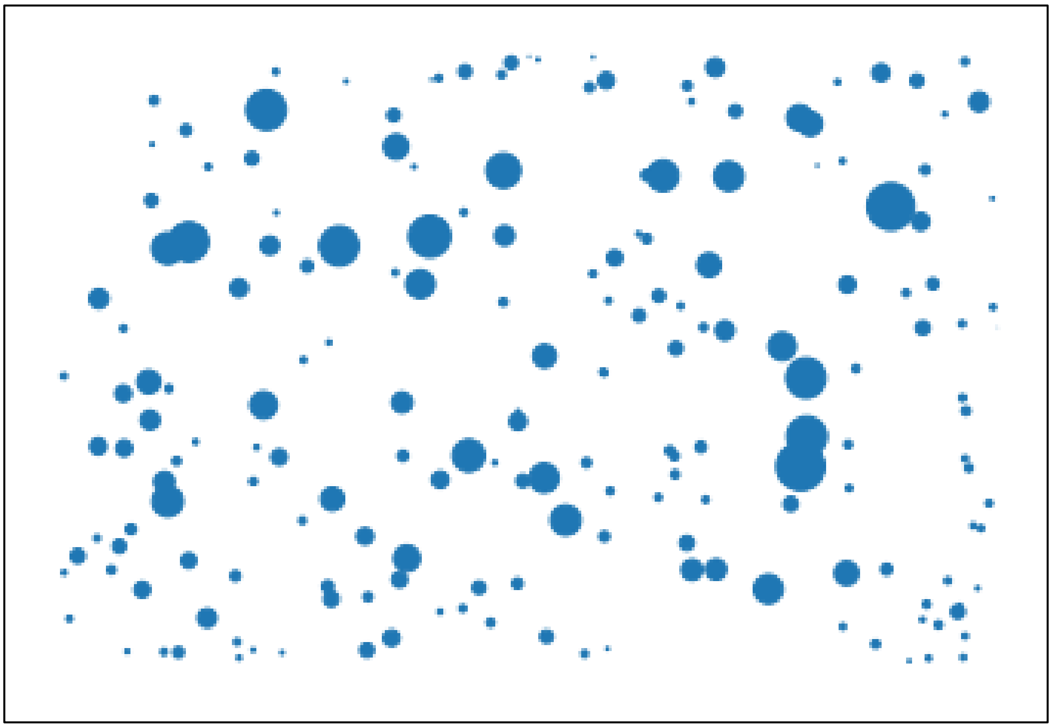
3.7 Network properties and behaviour

A rigorous mathematical analysis and a complete application of the model to a real case scenario are outside the scope of this paper. Nonetheless, some results from the model implementation are shown below to unravel some of its interesting properties.

3.7.1 Visualising the network

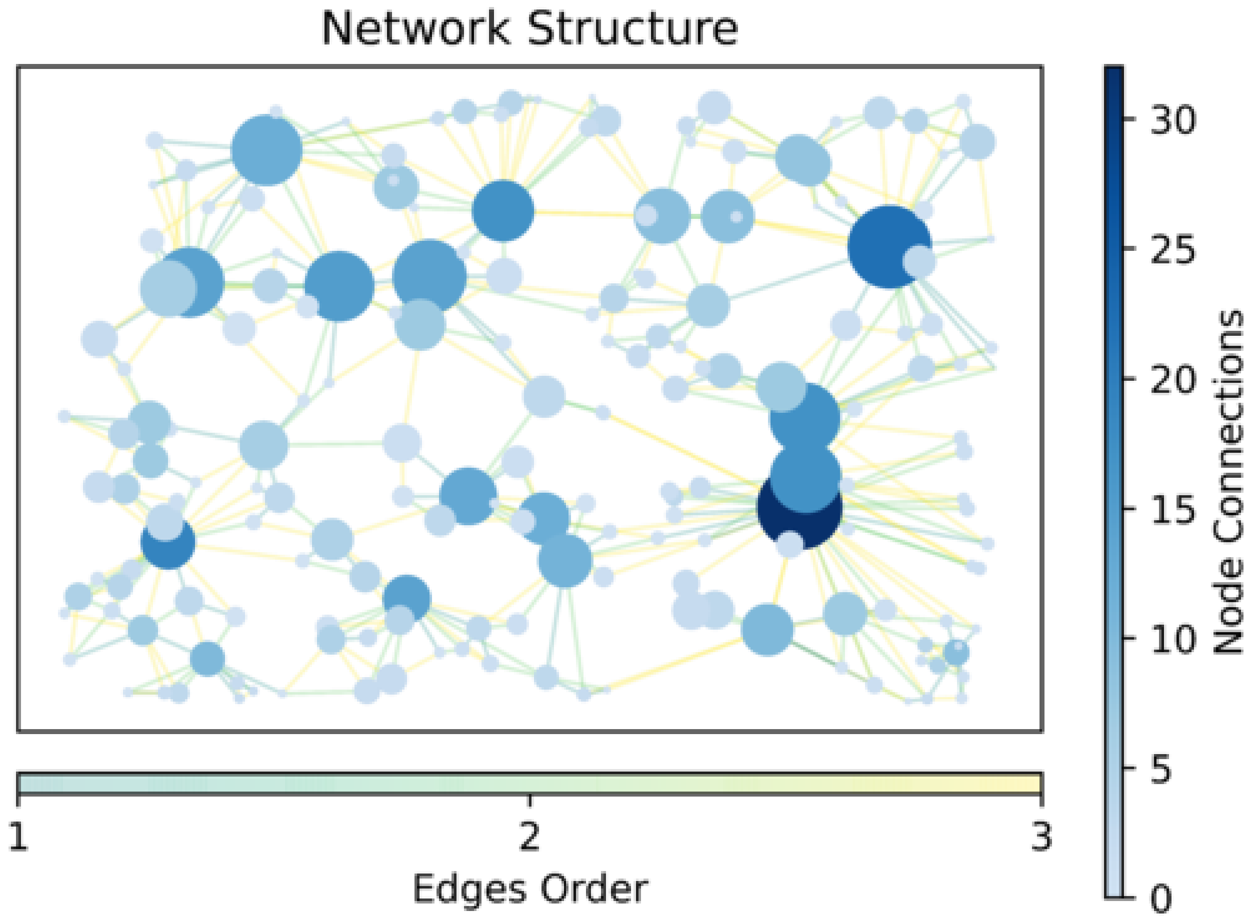
In Figure 7, a real configuration of farms from a Danish landscape is shown, Himmerland (DK). The dots represent the farms, and the size of the dots represents the area covered by each farm. In this landscape, the farms are distributed relatively evenly across the space, and there are no particular clusters of big or small farms. Data regarding the farms’ location and size have been extracted from the Land Parcel Identification System (LPIS)[14] database for Denmark. LPIS is an IT system based on satellite orthophoto used by the EU to monitor land use and provide farmers with the proper income support. This database is managed at the regional level, making the availability and quality of those data highly region-dependent. The actualisation of the Geographical Network is shown in Figure 8. Again, the position of the dots represents the actual position of the farms in the landscape, and their size represents the actual farm size. The links between the nodes indicate the strongest connections a farmer has. The colour of the dots indicates the number of connections. Hence, dark blue dots indicate farmers strongly embedded in the network, eventually influencing numerous other farmers.

Figure 7 - The spatial distribution and size of farms from the Himmerland landscape in Denmark. The dots represent the farms, and the size of the dots represents the area covered by each farm.



[14] The Land Parcel Identification System - https://op.europa.eu/en/publication-detail/-/publication/11049e0e-9a82-11e6-9bca-01aa75ed71a1

Figure 8 - The network structure for the Himmerland (DK) landscape. The links between the nodes indicate the strongest connections a farmer has. Only the top three edges are shown. Edges are coloured differently to indicate the edges' order in strength.



To provide a less balanced example in terms of farm size and location, we have generated hypothetical landscapes where this information was simulated. Figure 9, 10 and 11 show three different examples of the Network implementation over simulated landscapes. The landscapes were produced by forming clusters of farms and with a degree of correlation between farm size and farm location. The resulting network of links differs substantially and, as shown in the next section, will produce different emerging system dynamics.

Figure 9 - Implementation of the network over a simulated landscape. Here, farms are centred on one cluster and farm size and location are positively correlated. Hence, bigger farms are more likely to occupy a central position.

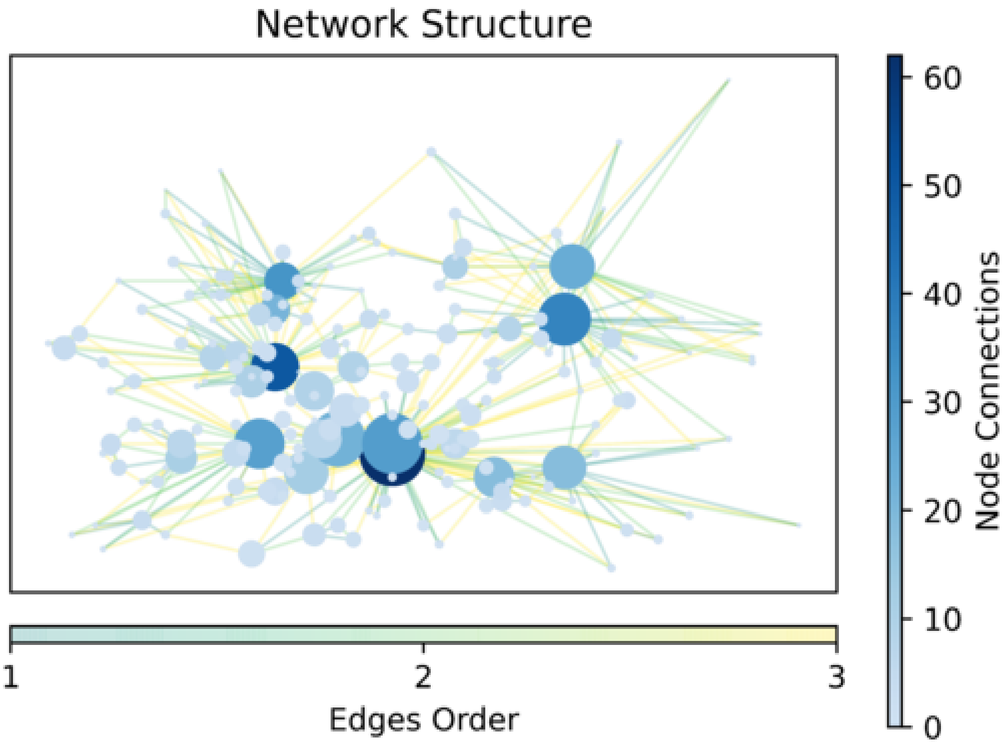


Figure 10 - Implementation of the network over a simulated landscape. Here, farms are centred on two clusters, and farm size and location are positively correlated. Hence, bigger farms are more likely to occupy a central position.

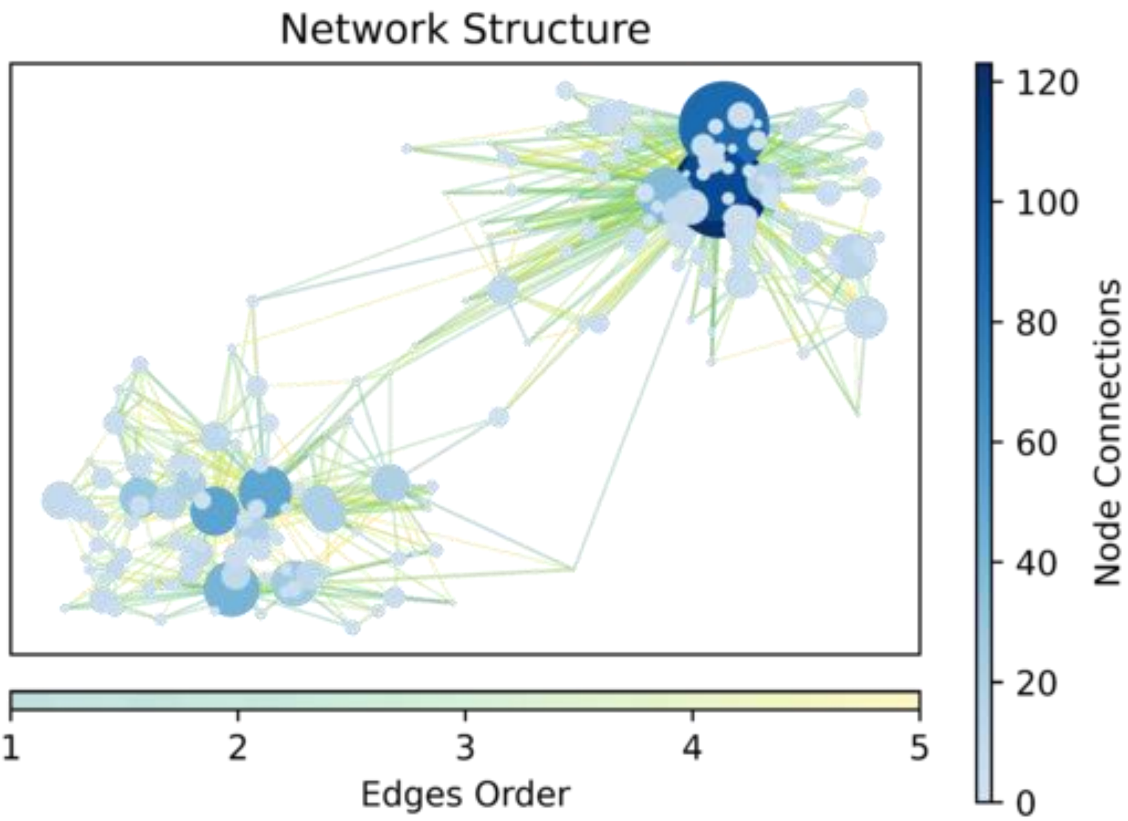
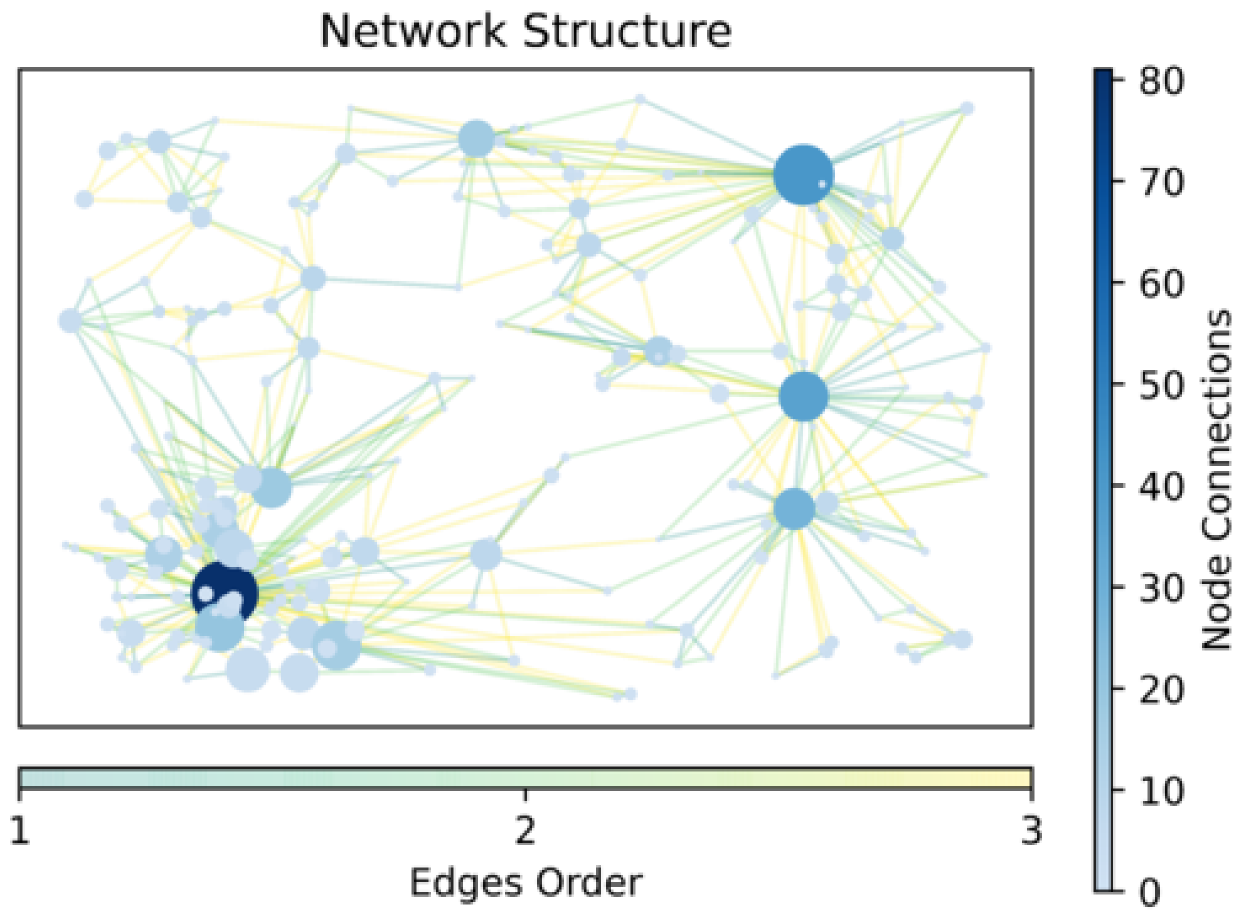


Figure 11 - Implementation of the network over a simulated landscape. Here, farms are centred on four clusters of different sizes. Farm size and location are independent.



3.7.2 Visualising the opinion dynamics: consensus, polarisation, and fragmentation

We created a prototype implementation of the model in Python to demonstrate its behavioural capabilities. The results below are derived from simulations of real and simulated landscapes and using different network structures.

3.7.3 Himmerland (DK) scenario

In this scenario, the simulation runs over the Himmerland (DK) real landscape with 190 farmers. The initial opinions are randomly selected from a uniform distribution between the extremes and the mobility parameter is set to 0.5. On the left size of Figure 12, the opinions' initial distribution and the network structure, the colour of the dots represent the farmers' initial opinions. On the right side of Figure 12, the resulting final condition after 100 time steps. Lastly, Figure 13 shows the evolution of the opinions throughout the simulation. Here, individuals interact with five neighbours at each time step, all selected from the geographical network.

As we can see, the relatively even initial distribution is replaced by a double peak distribution. The more prominent peak is slowly formed during the simulation and is evident from the 60th time step. The smaller peaks are formed early in the simulation and remain stable.

In this next example shown in Figure 14, there is a comparison of two simulations where the input values are held constant except for the network structure. In one, as the above, all neighbours come from the Geographical Network; in the other, all three networks were integrated into the test. Substantially different results emerge from the simulations. The results generated by applying all three networks showed a situation of polarisation of opinions around two values (~0.3 and ~0.7). In contrast, the results of the application of just the Geographical Network showed consensus around the mean opinion value (~0.5). This indicates that the single simple network would give erroneous results if the other networks were active in the real world. It also highlights the importance of considering the limitation of the theoretical representation.

Figure 12 - Opinion distribution histogram and network structure. The colour of the dots represents the farmers' initial opinion. On the left side, the initial condition. On the right side, the resulting final condition after 100 time steps.

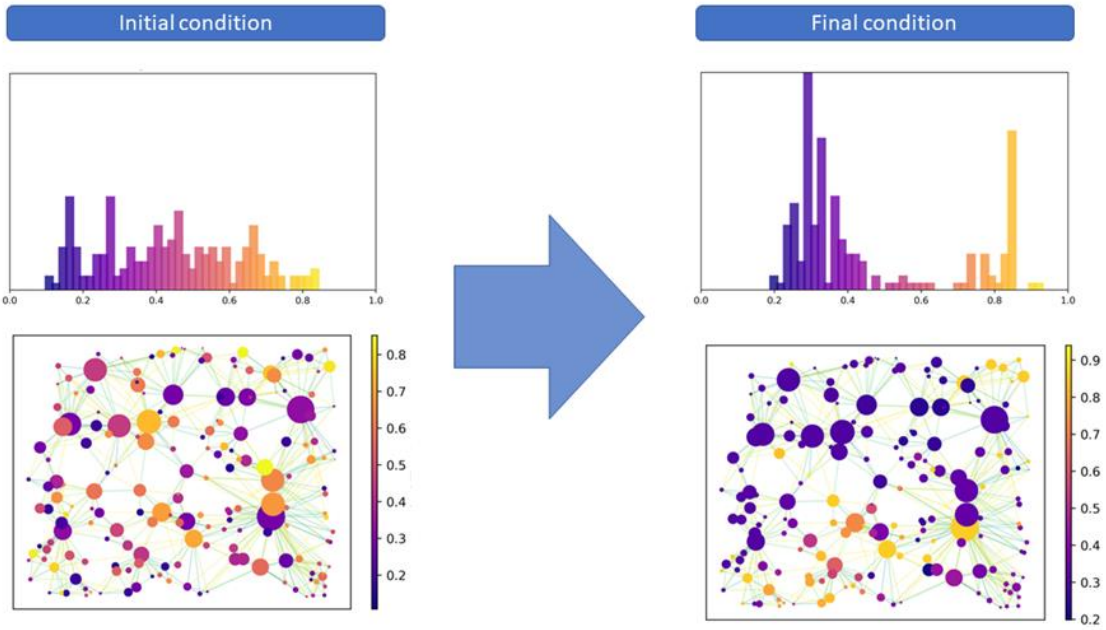


Figure 13 - The evolution of opinions during a 100-time-step simulation. The opinions in each time step are shown in pin, and the standard deviation of the opinion distribution over time is in blue.

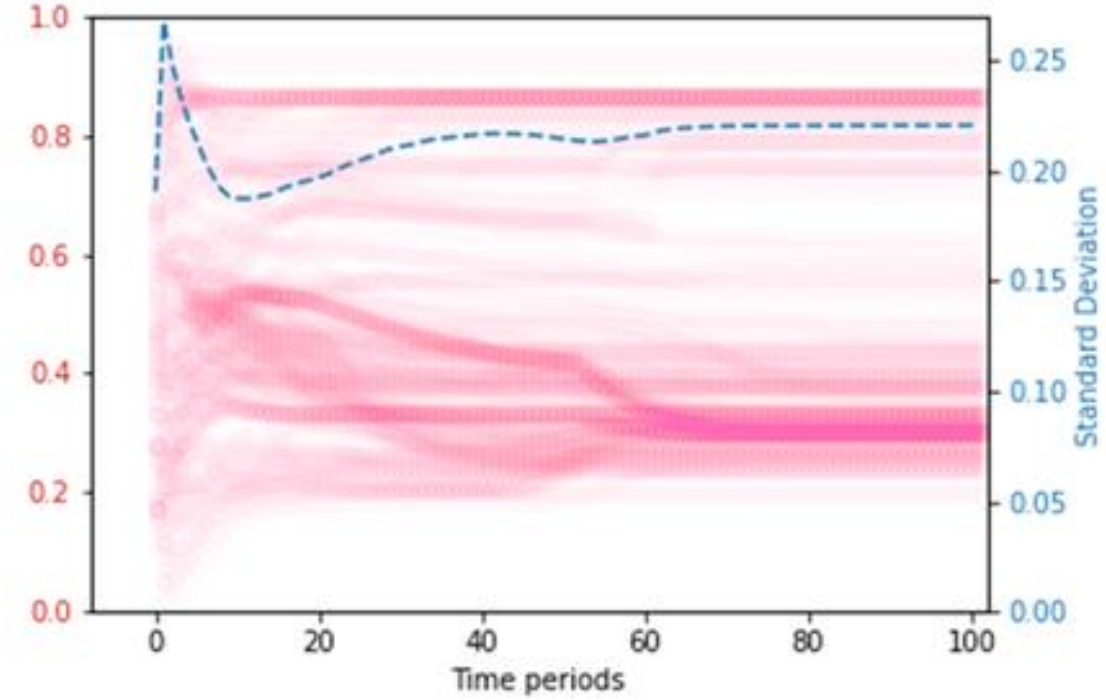
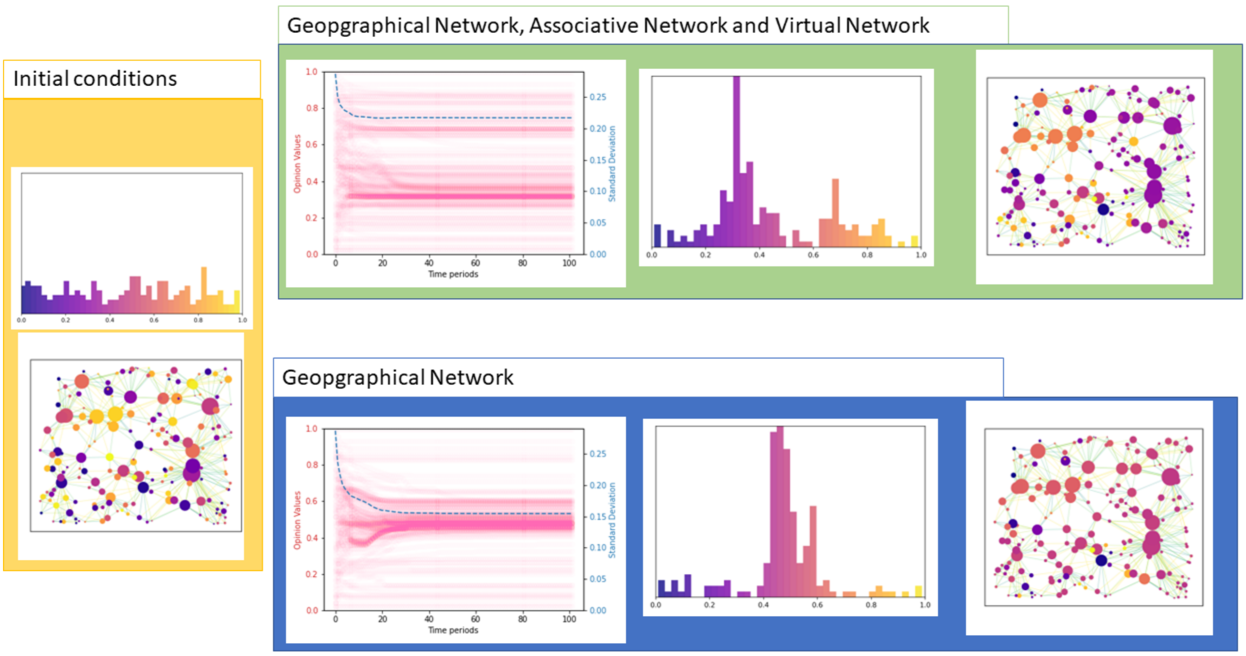


Figure 14 - Comparison of two simulations with the same initial conditions and different network structures. In the upper green highlighted result, the result of all three networks. In the lower blue highlighted, the result of only the geographical network.



3.7.4 Simulated landscape

Here, the simulation is carried out with a simulated landscape formed by 214 farmers. The initial opinions were randomly selected from a normal distribution with a mean of 0.5 and a standard deviation of 0.15. The mobility parameter is set to 1, the maximum value. The opinions' initial distribution and the network structure are shown on the left side of the Figure 15, while the final distribution is shown on the right side of Figure 15. Figure 16 shows the evolution of the opinions throughout the simulation. This second example shows different emerging dynamics. In the first time steps, two peaks were formed rapidly. The bigger peak was around 0.3 opinion value and the smaller is about 0.8 opinion value. Surprisingly, the small peak remains throughout the experiment, but the larger peak drifts towards higher values. This interesting behaviour is given by the peculiar initial value where the spatial configuration plays an important role, as seen by the final spatial distribution of opinions in Figure 15. The remaining blue cluster in the lower left corner is formed by small farms that likely do not influence surrounding farms and have a too different opinion from the neighbours to be influenced themselves.

Figure 15 - Opinion distribution histogram and network structure. The colour of the dots represents the farmers' initial opinion. On the left side, the initial condition. On the right side, the resulting condition after 100 time steps.

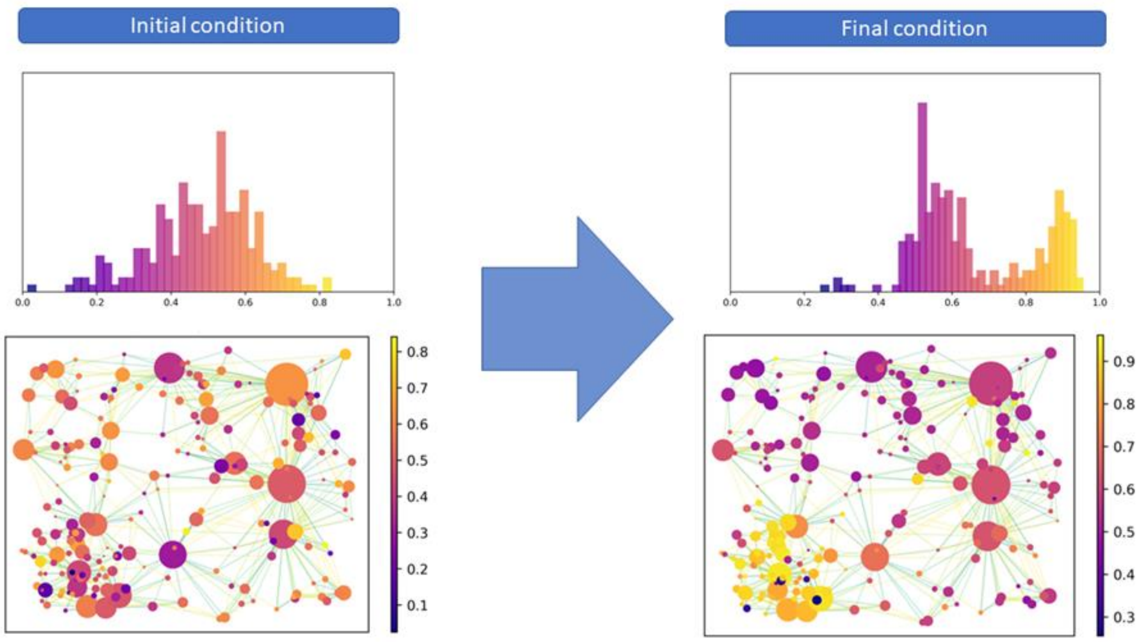
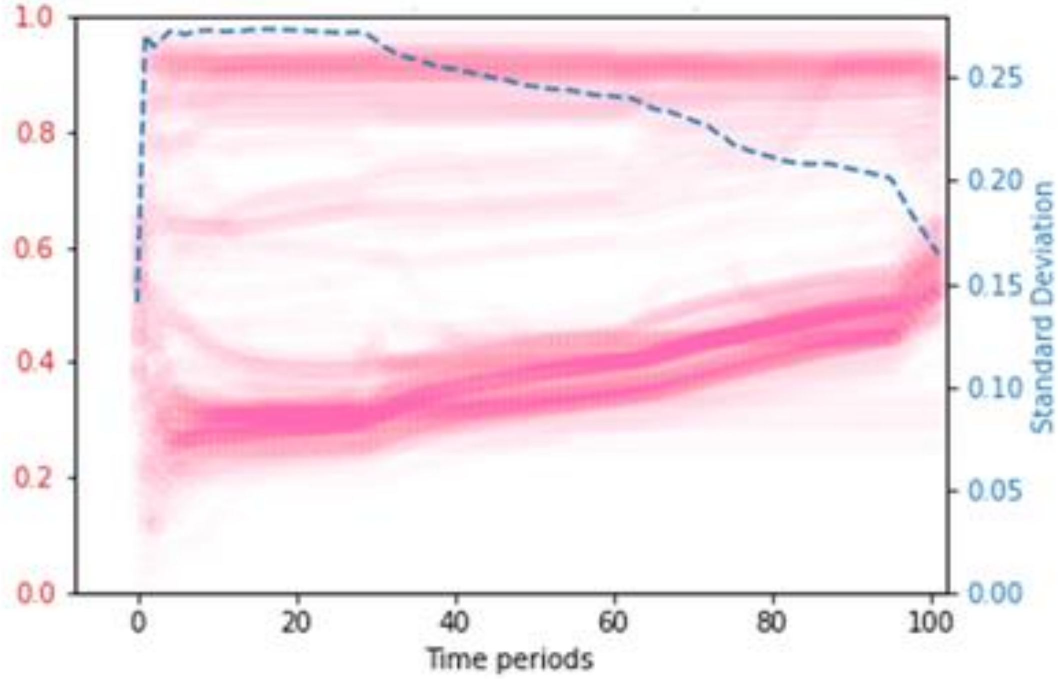


Figure 16 - evolution of opinions during a 100-time-step simulation The opinions in each time step are shown in pin, and the standard deviation of the opinion distribution over time is in blue.



3.8 Discussion

Here, we have presented the Formal model of the GeSoN aimed at reproducing the social context that affects farmers' opinions. The model's peculiarity is the conjunction of theoretical aspects regarding the social simulation, mainly based on the opinion dynamics models of bounded confidence (Deffuant, 2002), with the bounded rationality behavioural framework (Simon, 1999), and the geographical specificity (Namatame and Chen, 2016). Moreover, unique to this model is the specification of the equation governing the interaction between farmers through a multifactorial asymmetrical function. Other models apply similar equations, particularly the seminal work of the bounded confidence approach, the Deffuant–Weisbuch model. But in the case of the Deffuant–Weisbuch model, the formula governing the interaction results is symmetrical. In fact, in their model the uncertainty is not taken directly into consideration.

The multifactorial asymmetrical function has a double consequence. First, farmer interactions are independent, so exchanges are not guaranteed to be mutual. Second, when two farmers interact, the influence one farmer has on the other may have a different magnitude. The asymmetrical function not only allows for the incorporation of actor-uncertainty into the model but also allows for the possibility of the formation of different "roles" during the simulation in a particular landscape. As already mentioned, farmers with the most connections and low uncertainty will play the role of leaders or "nodal" farmers.

The GeSoN shows, since its prototype applications, promising dynamics and behaviours. These are mostly attributable to the usual final states reached by the diffusion models, namely consensus, polarization, and fragmentation (Zha et al. 2020). Other models have been tested and showed similar dynamics. Nonetheless, the prototype nature of the dynamics showed by the GeSoN makes it impossible to evaluate the effective similarity, or difference, with other models. Moreover, based on the results of a thorough implementation of the Deffuant model (Gómez-Serrano et al. 2012), models of bounded confidence are demonstrated to be Independent and identically distributed. d. nonlinear Markov processes, where, as time goes to infinity, opinions converge to a set of clusters. Finally, the results from the prototype of the GeSoN are characterized by non-linearities in the formation of typical consensus and polarization, indicating the emergence of interesting, complex dynamics.

The GeSoN has several limitations. First, the simplicity in the representation of the opinions. Opinions were originally modelled as binary options (e.g., Arthur, 1994, Degroot, 1974). With time and during the development of the discipline, this representation has been replaced by continuous variables representing opinions (Deffuant et al. 2000). Nonetheless, this representation ignores the intricacies related to one's personal opinion. Second, individual opinions are influenced only by neighbours' opinions. In real scenarios, personal opinions are formed as the sum of different contextual factors (Chacoma & Zanette 2015). To try to overcome this limitation, the GeSoN will be incorporated into a more sophisticated agent-based model. The GeSoN primarily aims at integrating the social network and opinion diffusion in an agent-based model regarding the agricultural socio-ecological system. This will be done using GeSoN as a module of ALMaSS (Topping et al., 2003; Topping, 2022). In ALMaSS, various other aspects regarding the farmers' behaviour and decision-making are modelled using the CONSUMAT as the conceptual framework (Jager and Janssen, 2012; Malawska and Topping, 2018). Finally, a limitation frequently found in this kind of model is to be unable to incorporate, at the same time, social, economic and political unpredictable changes that could strongly influence the farmers' behaviour, like financial crises, unexpectedly volatile markets, and wars.

Despite the limitations and the overall simplicity of the GeSoN, implementing it into a more sophisticated agent-based model will lead to rich output, where the different configurations of inputs, the diverse populations of farmers, and the different agricultural landscapes will generate complex emergent properties that can inform the real world.

Chapter 4

Measuring consumer effort in Circular Economy initiatives in the food domain: an explorative analysis.

Abstract

The transition towards a Circular Economy (CE) system requires a change in consumers' behavioural pattern that implies a certain level of effort which, in turn, could affect initiatives' success. Although consumers' role in CE is increasingly drawing the attention of scholars, limited knowledge is available on the evaluation of consumer's effort in CE initiatives. The current research provides an identification and measurement of the core parameters affecting consumer effort, offering a comprehensive Effort Index applied to 20 CE companies operating in food domain. Companies were classified in 5 categories (Quantity of food, Appearance of food, Edibility of food, Living with food and Local and sustainable food); the analysis of the companies revealed 14 parameters building the Effort Index. Results showed that initiatives ascribable to the category "Local and sustainable food" require higher levels of consumer effort; in contrast, case studies belonging to "Edibility of food" group are less effort-requiring.

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4.1 Introduction

Circular economy (CE) promotes a model in which the concept of waste is phased out by transforming it as nutrients circulating within infinite technical and biological loops (Borrello, Pascucci, Caracciolo, et al. 2020; Ellen MacArthur Foundation & McKinsey 2013). Put differently, CE takes inspiration from natural processes where biological and organic materials complete continuously their cycles: what an organism or process wastes becomes a nutrient for another one (Borrello et al. 2017).

The implementation of CE in the agro-food sector represents a great opportunity for transitioning into a food system that may help to achieve sustainable models of production and consumption (Bali Swain & Sweet 2021; Bjørnbet et al. 2021; Bocken et al. 2016; Jurgilevich et al. 2016; Silvestri et al. 2022; Zimon et al. 2020). As for the latter, the most frequent circular initiatives in the food sector are those aiming at reducing the amount of waste by recycling food as nutrients, and making by-products out of them (Ghisellini & Ulgiati 2020; Jurgilevich et al. 2016). To illustrate, a recent stream of literature is mostly focusing on topics investigating food waste in food supply chains (Hamam et al. 2021; Jurgilevich et al. 2016; Zucchella & Previtali 2019). The issue of food waste is at the centre of the scientific debate because data reveals that an amount between 30 and 50 per cent of food intended for human consumption is wasted, with a global cost that is estimated to be around a trillion US dollars (do Canto et al. 2021; Jurgilevich et al. 2016; Moschini et al. 2005; Silvestri et al. 2022).

Even though the interest in CE in the food sector has upsurged recently, most of the attention has been focused on the production side (Camacho-Otero et al. 2020). According to Kirchherr and colleagues (Kirchherr et al. 2017), less than 20% of scientific publications tackle consumer role in CE transition, highlighting the urgent need for a deep understanding of consumers' engagement in circular initiatives (Camacho-Otero et al. 2018; Caracciolo et al. 2013; Georgantzis Garcia et al. 2021; Gomes et al. 2022). Previous literature on consumer's side, in fact, has been focusing the attention mainly on the understanding of factors influencing individuals' participation in CE initiatives instead of analysing how consumers are practically involved in circular processes, what is their role, and what is requested to them in these processes. Specifically, a detailed review conducted by Camacho Otero and colleagues (Camacho-Otero et al. 2018) classified studies on consumers showing that the themes mainly investigated by researchers were: *barriers, drivers and motivation of consumers participation in CE* (Abbey et al. 2015; Lutz et al. 2018); *consumers attitudes towards circular solutions* (Atlason et al. 2017; Guo et al. 2017); *consumers typology* (showing typologies of consumers linked circular solutions) (Decrop et al. 2018) and *incentives for acceptance* (external strategies aiming to improve consumers acceptance of CE) (Mugge et al. 2017). Gomes and colleagues (Gomes et al. 2022), in a more recent literature review, analyzed consumers' circular mindsets, circular behaviour (the realization of circular mindset), and influencing factors emerging when consumers decide to be involved in circular consumption systems. Results showed that, driving by mindset as starting point and pre-disposition, consumers make their circular behaviour (*e.g.* acquire recycled products, maintenance of products, tacking back products, reusing goods[…]) which can be affected by several factors (political, economic, demographic[...]). The outcome is a comprehensive investigation on circular consumption system. However, what is still unclear is the perceptions of practical involvement and effort required to individuals when they decide to embrace circular behaviours. The transition towards a CE system and the success of related initiatives, indeed, depends on consumers' willingness to change their routinized behaviour at different stages of their everyday life, such as decision-making at purchase and/or end of life management moments (Georgantzis Garcia et al. 2021; Hobson & Lynch 2016; Parajuly et al. 2020; Planing 2015). Consequently, the theoretical precepts of circular economy have brought to light an innovative image of consumers strongly involved in new practices, such as participation and sharing practices, new ways of recycling, taking back systems or returning products that clearly imply an active engagement and a certain level of effort (Georgantzis Garcia et al. 2021; Migliore et al. 2012; Sijtsema, Snoek, van Haaster-de Winter, et al. 2020). Nevertheless, how to explore and measure this effort, and understand what kind of companies/organizations - following circular principles - require higher levels of consumer effort are relevant aspects that, to the best of our knowledge, are scantly investigated in the scientific literature.

Tunn and colleagues (2019) defined consumer effort in CE as one of the four business model elements relevant for the achievement of CE and sustainable consumption patterns, together with resource strategy, revenue model and objective at consumption level. Moreover, when a new system of supply is developed, it is crucial to consider the level of effort required by consumers, as they compare "the new with the old way" in terms of effort required (Camacho-Otero et al. 2020).

The relevance of consumers effort in the CE debate is already highlighted in recent literature. Hoffman and colleagues (2020) stressed how the evaluation of effort required in CE initiatives could determine the failure of circular practices. Authors highlighted that, at consumption level, business models, that have the ability to reduce the amount of effort required to consumers, are evaluated as the most promising for transitioning towards CE models. To illustrate, CE solutions push consumers to move away from traditional habits bringing them in a new and different experience that require, almost always, more involvement. A more recent work conducted by Guyader et al. (2022) tried to analyse consumers' evaluation when involved in a CE experience; results have underlined the main role of effort, indicating that consumers' assessment was negatively influenced by the superior level of effort required compared to the traditional one. This aspect reinforces the trade-off between consumers' acceptance of CE initiatives and the "amount of extra effort required" that may compromise the success of circular business initiatives (Guyader et al. 2022; Hoffmann et al. 2020). Another relevant issue relates with the wide range of literature that has focused the attention mainly on recycling activities as the core CE practice conducted by consumers, not considering that there are an extensive range of circular sustainable behaviors proposed by circular initiatives that, in turn, require extensive time and effort. Therefore, evaluating consumer effort starting from the analysis of CE initiatives operating in the market is clearly a core concern for practitioners and policy makers interested in fostering CE. Nevertheless, to the best of our knowledge, no research has attempted to define effort considering real-world business initiatives.

The objective of current research is to fill the gap regarding the analysis of effort in circular initiatives and provide a broad definition of the core parameters of consumer effort in CE companies operating in the food domain. These parameters, declare or "*dimensionalize*" effort and seek to generate, for the first time, an effort index throughout an inductive process starting from a set of observations of CE real enterprises. The innovative contribution of the current research, as compared to previous scientific studies, is the "*case studies centric approach*" adopted, that tries to define how consumers embrace CE practices and how to decompose the effort spent (Bekin et al. 2007; Guyader et al. 2022). To do so, several recently born circular companies have been analysed; in detail, we selected twenty western companies mainly operating in tackling food waste issues and applying CE principles. Using the method validated by Narvanen et al. (2021), we classified the case studies in five groups according to the circular practices they developed. For the analysis of effort, we took the classification provided by Howie and colleagues (2018) according to whom cost associated with personal effort can be examined in terms of four dimensions: *physical energy, distress, money, and time*. Throughout the deep analysis of the twenty case studies in terms of their organization, the way they operate and, especially, how the organization involves consumers in the process, we have extrapolated 14 core parameters necessary to measure the amount of effort required to consumers; each of the 14 parameters describe and represent a peculiar aspect related to one of the four effort categories. The novel result of current research lies in providing, for the first time, a measure of consumer's effort to be used as a tool to classify circular initiatives and companies according to the level of effort required to consumers. Findings could foster these circular initiatives development and promote their up-scaling. As for the latter, it is important to reiterate that, the understanding of consumers' effort is relevant because it also impacts individuals' evaluation of the underlining product (Franke et al. 2009, 2010; Kivetz & Simonson 2002; Troye & Supphellen 2012).

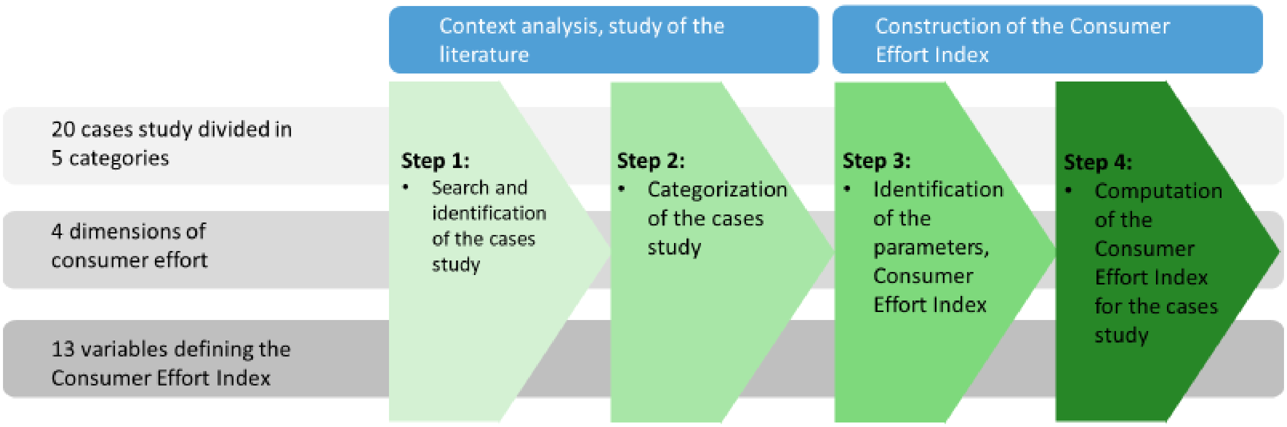
Current study is based on a qualitative research methodology with multiple-case study approach (Dubois & Gibbert 2010). Case study research is well suited in the attempt of digging into a phenomenon rather than in the context of testing established frameworks (Närvänen et al. 2021).

The paper is organized as follows. In the next paragraph each step of analysis is described together with the methodology applied for the measurement of consumer effort. In paragraph 3 the concept of consumer effort is defined, and how it is operationalized in the academic debate. Moreover, the classification of effort dimensions according to Howie and colleagues (2018) are depicted. Paragraph 4 is dedicated to the description of the origin of the parameters, that measure the level of effort in our case studies. Subsequently, results are presented and discussed; finally, concluding remarks and future research avenues are provided.

4.2 Analysis development

In this paragraph we illustrate each step of analysis of the present study from the beginning of the data generating process to the application of the methodology applied to build and measure the effort index proposed (Figure 1).

Figure 1 - Graphical representation of each step of analysis



In the first step the selection of case studies was performed. Recently a growing number of sustainable and circular companies have flourished. Most of them act considering the CE principles according to which, what is perceived as waste for one firm may become a resource by another (Perey et al. 2018). Therefore, in this phase we were continuously concentrated on monitoring and observing several sources of information such as online websites and media/social sources, to find active circular businesses in the food sector. Particularly, we focused our attention on the search of companies operating in Western Countries with the objective of preventing food waste as well as fostering the reuse of it for human consumption, and more in general of companies that operate within circular economy principles. Moreover, we referred to recent literature reviews to retrieve scientific papers that have presented circular real case studies (Närvänen et al. 2021; Sijtsema, Snoek, Winter, et al. 2020). Results of this search provided 20 circular companies which constitute our sample of case studies; through their websites, web news and scientific papers we understood how companies operate, the rules of their organization, how they addressed the issue of circular practices and how the organization involved consumers in the process or put differently, which are the set of activities, decisions, and behaviours required to consumers. Table 1 briefly describes the 20 case studies analysed.

In the second step of analysis each case study was categorized applying a method adapted from Narvanen et al. (2021); authors defined four categories capable to classify all circular food case studies according to circular practices developed: *i. quantity of food, ii. appearance of food, iii. edibility of food and iv. living with food.* To increase the scope of initiatives to these categories we added a fifth category, named *local and sustainable food* that includes initiatives of Alternative Food Networks or sharing local food communities. Practice of food provisioning participating in Alternative Food Networks, such as Community Supported Agriculture or Short food chains (*e.g.* farmers markets), have been defined in recent literature as examples of circular food initiatives due to the benefits that implementation of these peculiar organizations of food production and consumption generate in defining patterns of sustainable development (Canto et al. 2021; Jurgilevich et al.

2016; Pascucci 2020; Sijtsema, Snoek, van Haaster-de Winter, et al. 2020). Hereafter we shortly describe each of the five identified categories.

Quantity of food: in this category we insert companies that induce the circular behaviour of "purchasing innovative products or up cycled food products", "digital platforms and e-commerce fighting food waste" and "purchasing waste to value food" (Canto et al. 2021; Coderoni & Perito 2020). More specifically, companies in this group use surplus of food and food waste at different stages to sell them and to create new products. Some of them also use digital platforms to connect different stakeholders in the process (Mattila et al. 2020; Närvänen et al. 2021).

Appearance of food: the aim of these initiatives is to address the circular practice of "purchasing food with a non-standard aesthetics or surplus food" (Canto et al. 2021). The scope is to sell products rejected by retailers due to the anaesthetic aspect of foods (for example misshapen fruits and vegetables).

Edibility of food: this category is devoted to reducing waste by extending the life of food products through technological devices. Initiatives in this group specify the edibility of products to manage rationally stocks at home. An example of circular practice conducted by consumers in this group of companies is "the monitoring/storing food in specific and particular container" (Otles et al. 2021); the scope is related to the need of redesigning some food provisioning practices that lead to high food waste, such as storing and serving food (Borrello, Pascucci, & Cembalo 2020; Moser 2020).

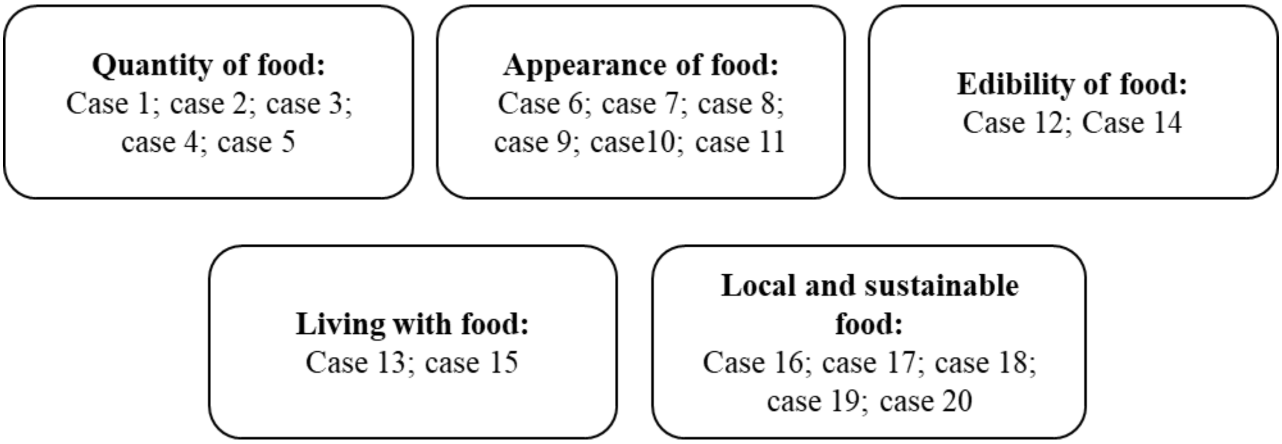
Living with food: companies included in this group act considering consumers' circular food practice of "purchasing soon- to-expire food" (Otles et al. 2021) helping retailers to collect potential food waste and products that are near to expiration date, to resell them to final consumers.

Local and sustainable food: the last group of companies include examples of CSA, community of food sharing, farmers market that represent approaches to stimulate the transition towards CE. Circular practices carrying out by case studies in this group are "purchasing local and seasonable food", "participating in alternative food network or Short supply chain" and "sharing food and in excess food within a community" (Canto et al. 2021; Otles et al. 2021). Reconnecting the place of production and the place of consumption, these companies present several advantages including reduced packaging, reduced waste, enhanced product freshness and a shorter supply chain (Jurgilevich et al. 2016). The categorization applied allows each case study to fit only into one of the five categories of circular food initiatives (Figure 2).

Table 1 - Country of operation - Year of establishment and description of case studies

N° Cases	Description
Case Study 1	(Denmark -2015) it is an on line app that connect costumers to restaurant and shops to sell leftover of food products.
Case Study 2	(Finland - 2015) A start-up company, born in 2015 that to sell on line food services leftovers meals to consumers at a discount.
Case Study 3	(UK- 2015) This company, established in 2015, allow shops to offer, throughout a mobile application, their surplus food that is redistributed to consumers. Consumers could be active in the process using the same app to share their leftover food.
Case Study 4	(Finland – 2016) Online discount selling packaged groceries at waste risk from other Finnish food industries, importers and wholesalers.
Case Study 5	(the Netherlands – 2014) A company that use surplus food from local supermarkets and other producers to cook dishes to serve in their restaurants or food truck.
Case Study 6	(Portugal –Not available) This company delivers fresh fruit and vegetable boxes containing surplus and out-of-spec produce that is rescued directly from farms via a weekly subscription service.
Case Study 7	(The Netherlands – 2012) A social company that produces soups from misshapen vegetables collected from growers.
Case Study 8	(Germany – 2014) This company use 'deformed' organic fruit and vegetables from farmers to resell them to business customers.
Case Study 9	(France – 2015) A start-up that produces jams from surplus fruits and vegetables from shops.
Case Study 10	(Italy – 2000) A start- up with an on line platform that redistribute leftover and misshapen veggies and fruits to costumers. The initiative works with a subscription of big or small boxes that are delivered directly to home.
Case Study 11	(The Netherlands -Not available) A company that produces veggie soup with leftovers of producers and wholesalers.
Case Study 12	(United States – 2018) This start-up, this company offers a Smarterware' system, a stock management app for the home, that help consumers to avert food waste.
Case Study 13	(Italy – 2015) application for sellers to offers products about to expire. Also, the company offer a waste management system to monitor their stock.
Case Study 14	(Bulgaria – 2017) A mobile application that helps consumers to manage their shopping and stocks.
Case Study 15	(Germany -Not available) The company sells food that can be visually unappealing, mislabelled, or close to the best-before date. Products are sold on line and in dedicated supermarkets.
Case Study 16	(Italy -Not available) the initiative has the scope of promoting a different model respectful of biodiversity and health. The work condition of farmers, the rights of consumers have a leading role in the initiative, indeed consumers are considered as co-producers and are involved in the certification of products and in the projects.
Case Study 17	(The Netherlands -Not available) A CSA with approximately 200 families members. Members decide what they want to eat from their farm; they employ a farm and, in case the families want to help with harvesting, this is possible.
Case Study 18	(The Netherlands -Not available) A farm near to or in a city where pigs are fed with residuals products from breweries. Pigs eat (food) waste from the city (bakeries, supermarkets and cheese farmers). Local residents also help to keep the pigs. In the end, when the pigs are slaughtered, the pig meat could be eaten during activity.
Case Study 19	(Canada - 2011) It is a local urban farm that delivers directly to customers thousands of food baskets filled with our rooftop-grown veggies. The vision is to create a better food system, promoting rooftop farms and local agriculture (farmers and food makers) in all shapes and sizes and creating a community of pick-up points to deliver all this food as directly as possible.
Case Study 20	(Germany – 2012) Initiative against food waste. The scope is to save "unwanted" food and in excess food from families and firms. The sharing of food works throughout an on line platform and members are volunteers and for free.

Figure 2 - Categorization of cases studies (adapted from Närvänen et al. (2021)



The third step of research represents the core of the present study with the construction of the Consumer Effort Index (CEI) throughout the identification of the parameters that better describe and decline effort in our circular case studies. The fourth step consists in the data analysis with the evaluation of the CEI for each case study.

4.3 Consumer effort: definition and classification of components

Consumer effort is a broad concept, and it is subject of several fields of scientific research. In order to better define, and size to our scope the concept of consumer effort, we focused on scientific literature coming primarily from economics. Nonetheless, notably important insights regarding the same concept have been brought also from psychology (Kurzban 2016), and neuroscience (Hernandez Lallement et al. 2014). The first of the two disciplines in particular, provided an initial, general definition of effort. In accordance with Eisenberger (1992), effort can be seen as an intensification of activity, that individuals apply toward some outcomes. In our case, we intend consumer effort as the intensity of work that consumers, apply to engage in circular initiatives in the agro-food sector. Different studies specifically focused on consumers, have shown the negative reflection effort has in terms of willingness to buy or to participate in consumer-related activities (Hull 1943; Inzlicht et al. 2018). For instance, Howie et al. (2018) illustrate how consumers may apply defensive denial, a psychological defence, in order to avoid effort. However, to some extent, consumers' effort can also be perceived as a value, and not as a cost. An example of this unusual case is documented by Norton et al.(2012), where the "*Ikea effect*" is described. This underlines how coproduction, hence effort required by the consumers, has become one of the peculiar and extensively accepted characteristics of the company Ikea in which consumers often need to complete the assembly of their goods. Consumer effort, related to CE activities, can arise in different moments and distinct situations. Consumers can be asked to recollect their product from the producer or to acquire second-choice food. These are only two examples of how consumers may experience very different types of effort. In the first case, effort can be intended as the consumption of time and fatigue deriving from the transfer to the producer. In the latter, consumers are faced with the intangible effort of renouncing the first-choice food. Thus, consumer effort can be further described by identifying all the important dimensions that jointly compose it. We, therefore, will use these to "*dimensionalize*" the consumer effort. Several researchers have already identified these dimensions leading to similar results. While there is a certain agreement on the physical dimension of effort (Cardozo 1965; Piliavin et al. 1975), Cardozo (1965) included a financial (money) dimension. Finally, Piliavin and colleagues (1975) identified other two dimensions: time and distress. Howie and colleagues (2018) used the four dimensions of effort jointly: physical, time, money, and distress.

These dimensions can be seen as the principal resources invested by consumers in participating in CE activities in the food sector. We choose to consider the four dimensions of effort together (physical, time, money and distress), as suggested by Howie and colleagues (2018), with the aim to better classify the effort required to consumers in the circular businesses of the sample. Going into details of each dimension, the physical dimension includes physical actions needed to participate in a specific CE activity, such as transfer to a specific place or simply cleaning vegetables. The time dimension encloses all the necessary amount of time spent in the CE activity, this can be due to taking part in the organization of the CE activity or just due to participate in the activity, such as time spent in the learning processes. The money dimension, instead, refers to the monetary expenditure required by individuals besides the purchase, as the subscription cost; often these expenditures are meant as consumers' risk sharing. Finally, the distress dimension includes all the uncertainty and anxiety that can be caused by the CE activity, for example in some CE activity participants do not precisely know the quality and quantity of the product purchased. Each of these dimensions of effort has been investigate using a list of parameters emerging from the analysis of the set of activities, decisions, and behaviours required to consumers in the case studies (more deeply explained in the next paragraph).

4.4 Methodology: the construction of a Consumer Effort Index and its measurement in CE initiatives in the food sector

The lack of a validated direct measure of consumer effort in CE initiatives in the food sector highlights the need of an exploration of the concept. For that reason, a conceptual thinking and theory-building approach fits best the aim of the current study. Our analysis led primarily to the construction of a CEI and, subsequently, to a first assessment of it. The formulation of the CEI followed two consequential, complementary paths. The first led to the identification of statements, parameters that contained all the important facets concerning consumer effort in participating in circular economy initiatives, emerging from the analysis of the initiatives themselves. The second path involved the application of this statement-formed index to the cases study identified, to verify whether the parameters effectively described all the selected initiatives. The identification of the statements involved the group of researchers' authors of the current paper who, independently, analysed the cases study selected and proposed, for each of the four dimensions of the consumer effort, a list of sentences that described the effort-producing factors characterizing the case studies. Researchers, in this step, worked individually to produce a personal list of parameters. Subsequently, these parameters were discussed collegially, grouped, and cleaned from redundancies. Moreover, the sentences were rewritten in order to obtain dichotomous possible answers, i.e.: every sentence could (or could not) apply completely to each case study. Then, a second round, in which researchers reviewed the group of sentences, was performed. This first path ended with a list of 14 parameters divided throughout the consumer effort dimensions as follows: 3 parameters regarding the physical dimension, 2 the time dimension, 2 the money dimension, 6 the distress dimension. The full list of parameters is reported in Table 2.

The sub-categories are differently represented, 3 parameters are sub-categorized as Physical, 2 as Time, 2 as Money, and 7 as Distress. Given the innovative and explorative nature of the present study, the authors decided not to assign specific weights to single parameters, excluding an order of importance or differentiation in the level of effort required per each. Therefore, all the parameters are dichotomous; the majority of these indicate an increase of effort, while three of these (i.e., Incentives such as discounts or promotions and discounted prices, Possibility of obtaining complete information about the purchased product and Possibility to decide the exact quantity of the product) have an opposite direction in terms of required effort. Hence, while for the latter three parameters, the CEI increases by one point if these are not applicable to the activity being studied, for all the remaining parameters, the CEI increases by one point if these are applicable. A first assessment of the CEI was the subsequent step. Researchers evaluated the case studies through the list of effort parameters previously identified (Table 2). Authors once again worked independently from each other and produced a personal evaluation of the case studies. This step led to evaluate whether or not the constructs were easily applicable, comprehensible and if it led to consistent results if applied by different individuals.

Finally, parameters that do not apply to any case studies, were removed leaving only those that apply at least to one case study. The definitive CEI applicable to Circular Economy initiatives in the food sector goes from 0 to 14 (where 0 means minimum effort, and 14 maximum effort) and is divided into four sub-categories, according to Physical, Time, Money and Distress dimensions.

Table 2 – Parameters building the CEI.

Parameter	Dimension	Description
A transfer is necessary to take the product / use the service.	Physical	Product delivery is not organized, hence physical movement is required. This could end up being time and money consuming e.g. farmer's market in a particular place far from the house.
A transfer is necessary to return part of the product.	Physical	Once the product is consumed, or used, part of it has to be taken back to the seller. e.g. Reusable packaging such as cans.
Product cleaning, washing or inspection required.	Physical	Before use, food products may need an inspection to remove non-edible part, for example when dealing with raw food or second choice vegetables.
Time dedicated to the project, besides purchasing.	Time	Total time consumed in activities related to the product (e.g., harvesting vegetables in community-supported agriculture.
Moments of sharing, lessons involved in the project.	Time	Time consumed in cooperating with other partners of the project, or time consumed in learning processes.
Money invested in the activity besides the purchase – Risk sharing.	Money	Besides the money spent for purchasing the product, a common practice sustains a cash fund to minimize the business risk.
Incentives such discounted prices.	Money	This parameter could apply to general promotions offered and also to product sold at a low price compared to the market. e.g.: Food sold near to the expired date at a lower price
Possibility of obtaining complete information about the purchased product.	Distress	In some case studies, the offered products may not be known at the time of purchase. For example, several case studies sell box of mixed vegetables where the buyer knows just partially the content of it.
Possibility to decide the exact quantity of the product.	Distress	This parameter describes the situation where the consumers could not decide the exact quantity of the product to purchase. This could happen for several reasons, e.g.: food near to expired date usually has a limited quantity, or food acquired in mixed box of different weights.
Limited variety of choices.	Distress	In several case studies, consumer may not have a large variety of products to choose from.
Purchase only on specific days.	Distress	Purchase is limited to specific, usually predefined, days.
Long waiting time to obtain the product.	Distress	Particular delivery services and time needed to prepare the product may result in a long waiting time by the consumers
The product may be close to deterioration.	Distress	Some case studies, for environmental reasons, sell food that may me close to deterioration or partially deteriorated.
The product comes from waste, by-products or unsold.	Distress	Selling, or encouraging the consumption, of food that otherwise would be waste

4.5 Results and Discussion

New consumption practices falling inside the circular economy expect consumers to adapt their behaviors towards a more sustainable act of consumption that involves extensive time and effort (Guyader et al. 2022). As stated by Hoffman and colleagues (2020), consumers' evaluation of effort in CE initiative is a fundamental aspect that could determine the failure of circular practices. This paper responds to the call of recent literature to enhance understanding of circular economy practices in terms of consumers' effort, offering a measure of an effort index applied to twenty examples of Circular economy initiatives operating in the agro-food system. Findings presented hereafter, provide a rank of the 20 business initiatives in terms of the highest and the lowest level of effort; outcomes should represent a starting point to discuss about possible barriers consumers could experience in the CE, to promote these circular initiatives development, and suggest interventions to support their improvement and up-scaling.

The results of the evaluation process of the case studies through the selected effort parameters are reported in Table 3. Among all the case studies, the case study 20 - a German initiative of food sharing among community - and the case study 3 - an English company that redistributes surplus of food to consumers throughout mobile app - scored the highest index value (10 points). Followed, with a total score of 7, by Case study 17, a Dutch CSA with approximately 200 family members. At the base of the effort index ranking, we found two initiatives belonging to "Edibility of food" category, such as the Case study 12, an US start-up that offers a home stock management to avoid food waste, and case study 14, a new mobile application that helps consumers to better manage home food. These two cases scored just one point, appearing the less effort-requiring among the Circular economy initiatives in the food sector. None of the dimensions is present in all the case studies, indicating the variability in terms of the type of effort, among the different case studies.

Dwelling deeper in the results, and focusing on the top of the ranking, the CEI showed that initiatives ascribable to the category "Local and sustainable food" generally need higher level of effort (case studies 20 and 17). This finding is consistent with the engagement and the behaviour of consumers that participate to these initiatives. Consumers, called "members", shape a community-based group and are actively involved sharing interests, values and common actions such as co-production, distribution of food products, or marketing-oriented actions (Pascucci et al. 2016). Moreover, members invest money and share a certain level of risk with the organization (Pascucci et al. 2013).

In contrast, "Edibility of food" - with case studies 12 and 14 - seems to be the less effort-requiring category. This result is in line with the scope and the mode of operation of initiatives belonging to this class. Companies that want to operate in the light of "Edibility of food" principles have the scope to prevent and avoid food waste offering technological devises or Apps to manage home food stocks. Consumers who decide to use these Apps are advised on which foods or products are next to the expiration day or must be eaten before they go waste.

Table 3 – CEI scores among case studies.

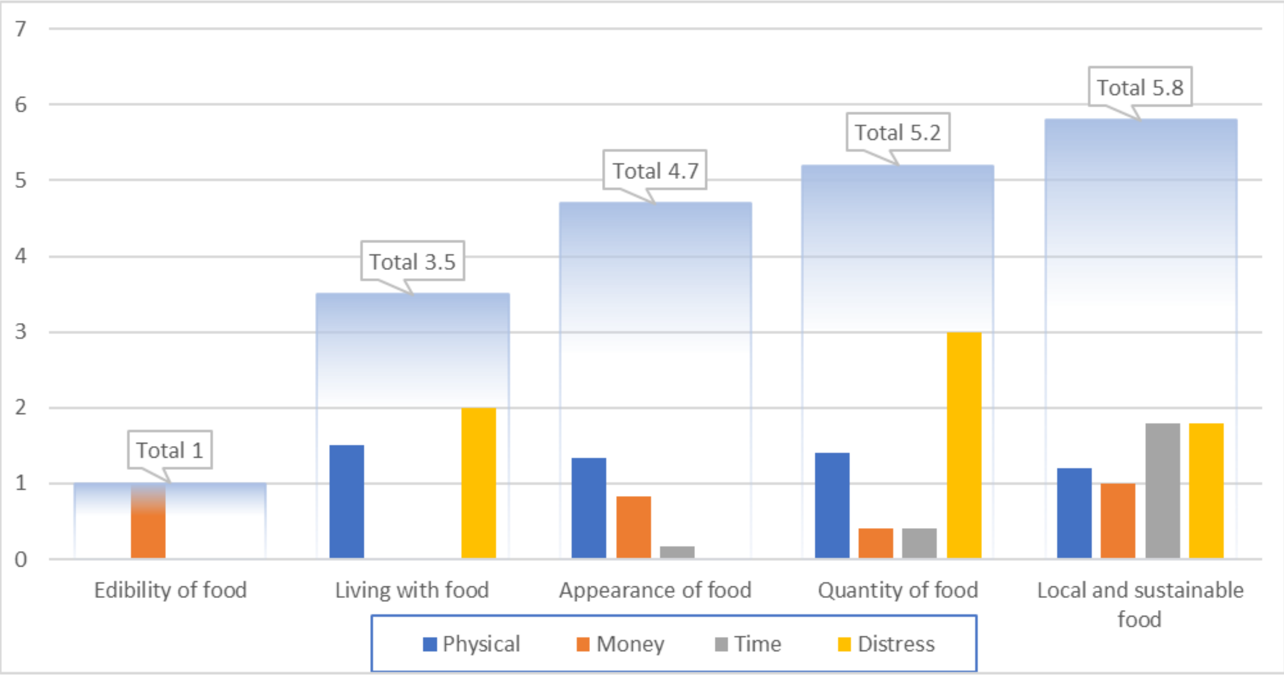
	Dimensions				
Case study N.	*Physical*	*Time*	*Money*	*Distress*	*Total CEI score*
3	2	2	1	5	10
20	2	2	1	5	10
17	2	2	2	1	7
16	2	1	1	2	6
1	2	0	0	4	6
10	1	0	1	4	6
6	1	0	1	4	6
7	2	1	1	1	5
8	2	0	0	3	5
2	2	0	0	3	5
18	0	2	1	1	4
13	2	0	0	2	4
11	1	0	1	1	3
5	1	0	1	1	3
15	1	0	0	2	3
9	1	0	1	1	3
4	0	0	0	2	2
19	0	2	0	0	2
12	0	0	1	0	1
14	0	0	1	0	1

The effort required in this case is mainly materialized with the storing of leftover food inside the containers. In this manner foods are being tracked in the app on mobile phones and it is easy to remember to eat them (the light ring on the SmartTag moves from green to yellow to red as food sits in the fridge).

Practices undertaken in the domestic sphere with the objective to avoid the production of large amount of waste are comprised in literature as a “circular food consumption practices” (Borrello & Cembalo 2021). More in detail, the practices of storing of food classifying them according to their expiry dates or using reusable packaging to store foods are considered fundamental elements in the shaping of circular food consumption, contributing to right material flows that is the main principle of circular economy (Borrello & Cembalo 2021).

Figure 3 presents the mean scores achieved by Case studies belonging to the five categories, *i.e.*: “Edibility of food”, “Living with food”, “Appearance of food”, “Quantity of food”, and “Local and sustainable food”.

Figure 4 - CEI average scores per category



The highest average score is reached by "Local and sustainable food" initiatives followed by "Quantity of food", "Appearance of food", "Living with food" and, at last, with the lower means score, by the category of "Edibility of food". Going in detail in the composition of the Effort Index (Physical, Money, Time and Distress component) for each category of companies, results showed that in the "Local and sustainable food", "Quantity of food" and "Appearance of food" each of the four components of effort are present with different levels of intensity. In the Local and Sustainable food category it is possible to underline a homogeneous distribution of each effort component with a slightly higher presence of "distress" and "time". The component "money" is present in each category of case studies except for the category "Living with food". The majority of start-ups working in the Circular economy principles are indeed based on a monetary risk sharing such as the presence of annual or periodical subscription at the beginning of the contract with the company. On the contrary the "money" component has a negative impact on the Effort index in the case of discounted prices for consumers that decide to buy circular products (*e.g.*, products next to the expiration date). The "physical" components of effort are observed in each category except for Edibility of food; this result suggests that physical actions and energy are required by the majority of CE initiatives: taking the products chosen, or inspecting it, washing and/or separating food components are, usually, fulfilled by consumers involved in the CE case studies. The "distress" dimension is present in three out of five categories; we can suppose that there are several points of uncertainty that can bring consumers in a status of personal stress as: not having complete information about the variety and the type of products obtained; not having exhaustive information about the quantity of products; not having enough variance among options, nor the possibility to buy whenever they want; the presence of a risk related to the shipments of the products and the "close expiration date" of most products that Circular economy initiatives sell. The influence of "distress aspects" have been already highlighted in previous literature: the lower level of consumers awareness and uncertainty about several aspects in CE model could translate into consumers' psychological and personal needs not satisfied, which could in turn lead to barriers in diffusion of the CE (Singh & Giacosa 2018). The "time" dimension of effort has emerged in three of the five groups of case studies ("Local and sustainable food", "Quantity of food" and "Appearance of food"). Interestingly only in Local and Sustainable food cases "time" scored very high compared to the other initiatives. This outcome reaffirms, as stated by Pascucci and colleagues (2016), that in "Local and sustainable food" cases consumers have the possibility to spend time in the organization and to be involved in lessons, workshops and practices such as co-production and firm labour. Finally, it is noteworthy that, coherently with the general result of the CE index score, for the group of case studies "edibility of food" the only component of effort emerged is the "money" one. The lowest score of this group depends on the central role of mobile App to manage household leftovers to avoid waste. There is no discounted price for products or periodical subscription for products such as vegetables and fruit as consumers just must follow the suggestion of their mobile app alerts.

Parameters apply to case studies with a different frequency. Figure 4 shows each parameter and the number of times these apply to each category of case study. The most frequent applied parameter is *Necessary moving in order to take the product / use the service*, while the less frequent is *Necessary moving in order to return part of the product*. Notably, two of the four most frequent parameters are included in the *physical* category reinforcing the necessity to make physical effort to be involved in CE initiatives at the minimum. Just one out of these four parameters applies to at least one case study for each category. This is due to the limited amount of efforts required for the case studies belonging to the Edibility of food category.

Figure 5 - Parameters frequency for CE category

	Local and sustainable food	Appearance of food	Edibility of food	Quantity of food	Living with food	Total
Physical						
A transfer is necessary moving in order to take the product / use the service	3	4	0	4	1	12
A transfer is necessary moving in order to return part of the product	1	0	0	0	0	1
Product cleaning, washing or inspection required	2	4	0	3	2	11
Time						
Time dedicated to the project, besides purchasing	4	0	0	1	0	5
Moments of sharing, lessons involved in the project	5	1	0	1	0	7
Money						
Money invested in the activity besides the purchase – Risk sharing	1	2	0	0	0	3
Incentives such as discounts or promotions and discounted prices	4	3	1	2	1	11
Distress						
Possibility of obtaining complete information about the purchased product	1	3	0	2	0	6
Possibility to decide the exact quantity of the product	2	3	0	2	0	7
Limited variety of choices	3	0	0	2	0	5
Purchase only on specific days	1	3	0	0	0	4
Long waiting time to obtain the product	0	0	0	1	1	2
The product may be close to deterioration	1	0	0	4	2	7
The product comes from waste, by-products or unsold	1	5	0	4	1	11

4.6 Conclusion

Circular Economy has the objective to transform the actual economic system in the light of sustainability principles. The negative response of consumers to the new pattern of circular offering could represent a strong barrier; consumer's approval is indeed crucial for the success of small and medium companies that have launched circular projects (Rizos et al. 2016). Certainly, the key to success of CE initiatives implies radical changes and depends on consumers' availability to modify their routine behaviour in different stages (Georgantzis Garcia et al. 2021; Parajuly et al. 2020), which entails, most of the time, an active engagement and a certain level of consumers' effort (Georgantzis Garcia et al. 2021). Nevertheless, in some cases consumers completely refuse the need of effort (Inzlicht et al. 2018) prompting the failure of initiatives or companies. Given the need to better understand the importance of consumers' effort in the real cases of CE initiatives, the scope of the present research is to offer a measure of consumer's effort in actual examples of Circular economy initiatives operating in the agro-food system. The study of consumers' effort in groups of companies operating in the market is relevant as the level of effort required to consumers could be completely refused, ratifying the failure of initiatives or firms. Stemming from the analysis of 20 circular initiatives' operation mode, the attempt was to build a novel Effort Index composed by 14 parameters (3 Physical, 2 Money, 2 Time and 7 Distress), with scores defining the level of consumers' required effort. Moreover, applying the identified parameters to the group of selected case studies, results have indicated which are the types of Circular initiatives that imply a higher level of effort. Findings revealed that the category of "Local and sustainable food" which was composed by examples of Community Supported Agriculture and the venture of sharing of unwanted and in excess food conducted by volunteers, had the highest level of effort due to the strong involvement of consumers who decide to participate. On the contrary initiatives that allow consumers to avoid food waste in the household by the use of a mobile App ("Edibility of food" category) have scored the lowest levels of effort required. The classification of cases studies in terms of total level of effort provides the first important portray on which are the initiatives that are more demanding for final consumers. Nevertheless, we acknowledge that this research is a first attempt to provide effort dimensions; and the parameters are obtained throughout an inductive process without consumers' participation into the research steps. However, consumers' positive or negative evaluation of product could be highly contingent on the judgement of required level of effort (Kivetz and Simonson, 2002; Franke et al. 2009; Franke et al., 2010; Troye and Supphellen 2012; Inzlicht et al., 2018). Therefore, drawing from the present study, future research should obtain consumers' insights to understand in detail individual opinions, evaluations and willingness to accept the required effort of circular initiatives. This information will provide practical suggestions for entrepreneurs that want to embark on circular projects, and at the same time could offer important feedbacks for policy makers interested in incentivizing and improving existing or new start-ups in the circular arena.

A further limitation of the current study is related to the parameters that explain the level of effort. We have extrapolated and listed 14 parameters and categorized them in the four types of effort previously validated in academic literature (Physical, Money, Time and Distress). However, it is important to underline that other categories of effort could be detected, and consequently other explanatory parameters should be taken into account. Finally, we have analysed only twenty firms operating in developed countries and in the agro-food sector. Future research should analyse a wider number of case studies and aim to broaden the geographical area and product domain.

Summary of findings

The thesis contributes to the literature on the Circular Economy (CE). The primary aim is to elucidate some facets concerning the transition process toward a CE model of the olive oil supply chain in Italy's Southern regions and to increase the theoretical basis for future CE-oriented policy options. The three main chapters, composed of journal articles, analyse different moments, or sub-systems, of the olive oil supply chain and try to fill gaps in knowledge from different perspectives. Acknowledging some of the main barriers to the diffusion of the CE, namely the farmers' hesitant culture and the lack of awareness by the consumers, we focus on deepening the link between these two actors of the olive oil supply chain and the CE. Moreover, the thesis also contributes to socio-environmental assessments of the supply chain.

The first article tackles the farmers' attitudes toward sustainable innovations. Specifically, it focuses on the analysis of the farmers' risk aversion. Risk aversion is one of the most critical behavioural aspects limiting sustainable innovations. For this reason, in conjunction with other universities, we conducted a direct measure of the European farmers' risk attitudes. The results show the presence of risk aversion for all the sub-samples analysed, including the Italian sub-sample represented by Apulian (South Italy region) olive growers. Additionally, we tested other theories regarding the farmers' behaviour in risky choices. (1) Farmers avoid losses more than they search for gains. (2) Farmers overweight small probabilities. Both assumptions are a progression of the well-known Expected Utility theory and come from the Cumulative Prospect theory, developed by Amos Tversky and Daniel Kahneman. Also here, the assumptions are confirmed. The Apulian olive growers, similarly to the other European farmers, show loss aversion and probability distortion. The importance of the results lies in different aspects. The most important is to provide robust data on farmers' behaviour in risky choices. In fact, knowing the farmers' risk aversion precisely helps provide more accurate ex-ante policy evaluations, primarily with farmers' voluntary enrolment policies and when an ideal number of farmers is targeted. In other words, policy-makers now have better instruments to promote farmers willing to innovate towards a Circular Economy model that may suffer the risk associated with the transition process.

The second part of the thesis addresses the socio-environmental assessment of the olive oil supply chain. Here the effort has been directed at the implementation of ALMaSS . ALMaSS is a collection of agent-based models created for environmental simulations. Its power is the capacity to recreate a digital-twin of agricultural landscapes and test hypothetical scenarios in terms of landscape agricultural management. Although the promising potential, the road to having reliable supply chain simulations is still long ahead. In this direction goes the article shown in the second chapter, where a more detailed model of interaction between farmers is presented. The application to the human agents of the simulation system of the bounded-rationality framework has already been described by other studies. Nonetheless, the innovation of our model is incorporating the uncertainty into the agents' interactions and the implementation of such interaction in a complex simulation system, i.e. the ALMaSS. Transitioning toward a Circular Economy model may produce unexpected benefits like virtuous flows of energy and materials. Thus, having an effective simulations model can incentive the transition process by making ex-ante evaluations of Circular scenarios and showing the possible emerging benefits, not only in terms of environments but also in terms of economic performances.

The thesis's last section tackles the consumers' contribution to the Circular Economy initiatives in the food sector. As already highlighted throughout the text, consumers must be involved in the transition toward a Circular Economy model to accomplish all the most important objectives of the Circular Economy, like reducing the amount of waste or returning material to virtuous loops of recycling and re-using. Consumer involvement, however, does not come for free. A toll, in terms of effort, is frequently asked to consumers participating in Circular Economy initiatives. Usually overlooked from the Circular Economy literature, our work elucidates the different kinds of effort required to the consumers with respect to twenty real case Circular Economy initiatives in the food sector. A "dimensionalization" of the concept is proposed by identifying four effort dimensions. These are the physical, money, time and distress dimension. Moreover, based on the analysis of different Circular Economy initiatives, we propose an Effort Index to evaluate the magnitude and type of effort related to the Circular Economy initiatives. The Effort index is then applied to the twenty Circular Economy examples, and a ranking is generated. The ranking is meant to outline possible improvements, stimulate the discussion about potential barriers consumers could experience in the Circular Economy, and suggest interventions to support their progress and up-scaling.

Final remark

The shift to sustainable olive oil production and consumption is necessary but still far from being accomplished. Transitioning toward a Circular Economy model gives encouraging perspectives, though. For this reason, deepening the circumstances to foster the transition and counterbalance its limitation is a remarkable research goal. The thesis accomplishes the objective: (1) by elaborating on the barriers to the spread of the Circular Economy, particularly among farmers and consumers, (2) by posing the basis for socio-environmental assessments of Circular Economy scenarios and, thus (3) by providing background and ideas for better-design policy interventions. Lastly, such a radical change in the food production processes should involve society as a whole, involving the academia and the institutions, not leaving scattered farmers, entrepreneurs and consumers to carry the burden all the way long.

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