Social Dynamics of True Price:

An Agent-Based Approach to Sustainable Transitions

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Declaration of Authorship

I, Isabel Klennert, declare that this thesis, entitled Social Dynamics of True Price: An Agent-Based Approach to Sustainable Transitions' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at the University of Amsterdam.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
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- I have acknowledged all main sources of help.
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Date: July 8, 2024

Abstract

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by Isabel Klennert

Include your abstract here Abstracts must include sufficient information for reviewers to judge the nature and significance of the topic, the adequacy of the investigative strategy, the nature of the results, and the conclusions. The abstract should summarize the substantive results of the work and not merely list topics to be discussed.

Length 200-400 words.

Acknowledgements

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1 | Introduction

1.1. Introduction

The future trajectory of life on Earth relies on the ability of humans to provide a high quality of life without irreversibly damaging Earth's natural ecosystem and depleting its resources (Tukker et al., 2008). This balance is central to the discussions on sustainable development and requires systemic changes to existing production and consumption patterns (Bidmon & Knab, 2018). This directly links to Goal 12 of the Sustainable Development Goals, advocating for responsible consumption and production, essential for sustaining the livelihoods of present and future generations. While consumption and production are vital for the global economy, most anthropogenic harm to human health and the environment results from it Chan et al., 2018. This highlights the need to decouple environmental degradation from economic growth, a challenge across many interconnected domains. This complexity necessitates a shift in perspective, promoting a complex systems approach, which recognises the interconnectedness and interdependence of various social, economic, and environmental factors (Levin et al., 2012).

Complex systems are characterised by their interconnected dynamics between various subsystems where non-linearity, heterogeneity, feedback loops and the presence of multiple time scales contribute to their complexity (Ambika & Kurths, 2021). Complex Adaptive Systems (CAS) are further characterised by their ability to adapt to internal or external changes (Lenton et al., 2023). Socio-ecological systems are a prime example of CAS, recognising that humans and nature are intricately connected(Fischer et al., 2015). These systems have the ability to resist change, staying in a stable state, as well as the ability to experience non-linear change, crossing into a new stable state. This tendency to undergo abrupt transformations is central to the concept of tipping points, which has drawn significant attention in complex systems research.

Tipping points are commonly defined as points where a minor change can lead to large, often irreversible shifts in a system's state (Ashwin et al., 2017). In a real non-autonomous system, tipping points are rarely caused by a single factor or mechanism and instead result from a combination of direct influences such as gradual parameter changes (bifurcation), random fluctuations (noise) and the rate of change in external conditions (rate-induced) (Ashwin et al., 2012). Positive tipping points, in particular, can be drivers for systemic transformations to accelerate change in a way that is beneficial for humans and the natural systems we rely on.

Human behaviour plays a crucial role in sustainability transitions, where behavioural changes at both individual and societal levels are necessary to achieve a safe operating space for Earth and humanity

(Linder et al., 2021). While the required re-configurations of cultures, institutions, policies and everyday systems may disrupt stability, they offer opportunities for large-scale beneficial changes (Köhler et al., 2019; Mintrom & Rogers, 2022). Positive tipping points are crucial here, as they represent the potential for small behavioural shifts to instigate broader sustainability transitions.

Within the integration of economic, social and environmental domains, the concept of True Price emerges as a potential catalyst for enabling positive tipping points towards sustainability. This approach introduces a shift in how goods and services are valued by addressing the externalities — unaccounted impacts of production and consumption — that are not reflected in traditional market prices (Hendriks et al., 2021). By incorporating environmental and social costs into the pricing of goods and services, True Price seeks to realign financial resources away from activities harmful to the environment and society. True Price has the potential to drive systemic change towards a more sustainable and equitable global economy by influencing consumption patterns and business strategies.

True Price has been implemented by businesses including Dutch supermarket Albert Heijn and German supermarket Penny. In 2023, over a week, the campaign by Penny featured nine products priced at their true cost. This resulted in a notable donation of 375, 000 euros to the "Zukunftsbauer" project. The effectiveness of this campaign was evaluated through a survey involving 2255 participants and an analysis of sales data. On the one hand, 53% of participants acknowledged increased awareness of the true costs of food products, and 38% felt the campaign sparked a debate on political reforms. However, only 19% believed it directly reduced environmental damages by influencing purchasing decisions, and 30% did not understand the campaign. Overall, this resulted in a significant drop in sales for eight out of the nine products. This experiment highlights the complex and sensitive dynamics between consumer behaviour, prices and environmental consciousness. While this gives an initial insight into the potential and the challenges inherent in implementing True Price, there is a need for exploring implementation strategies involving simulating the diverse effects of society, including the influence of social networks, preferences and norms.

1.2. Problem Formulation

Research at the intersection of business models, science and societal transition is crucial for understanding and influencing systemic societal change towards sustainable development. Sustainable business models focus on a variety of innovative and strategic activities and have the power to influence systemic transformations through the commercialisation or diffusion of such sustainable innovations (Hernández-Chea et al., 2021)). However, they often lack the macro-perspective analysis of broader system-wide impacts.

Non-technological innovations, such as the True Price movement, play a pivotal role in altering existing production and consumption patterns by moving away from conventional technological solutions. However, the challenge lies in integrating these innovations within the larger context of socio-economic and socio-ecological systems, ensuring their effectiveness and scalability. In addition, understanding the role of policymakers and other agents in influencing firm-level behaviours towards sustainability is essential.

This study recognises the need to incorporate behavioural dynamics into research that is often dominated by technological and economic perspectives. Consumption behaviour is influenced by a variety of factors, including rational choice, social norms, convenience, habits, and trust in brands or the quality of the information provided (Tukker et al., 2008). By ignoring these aspects in research, policy-making and business models, sustainable innovations may fail to achieve their expected results.

1.3. Research Questions and Objectives

Main question: Investigating the extent to which True Price can be implemented to enable positive tipping points towards a more sustainable society

1. What potential does True Price have in facilitating positive tipping points?
    - Objective: Determine the current state of True Price implementation and identification of social and economic components influencing its dynamics among consumers
    - Methodology: Literature Review and Case Study
2. How can the dynamics of True Price implementation be conceptualised in an Agent-Based Model?
    - Objective: Conceptualisation and formalisation of an ABM informed by theories, concepts, and data derived from the initial sub-question.
    - Methodology: Agent-Based Modelling techniques combined with network-based simulations
3. What are the key drivers to be leveraged for successful True Price implementation?
    - Objective: Conduct a series of experiments and sensitivity analyses within the ABM, using varying inputs and simulating different scenarios.
    - Method: Experiments and Global Sensitivity Analysis

1.4. Relevance

The significance of this research encompasses both the real-world impact of True Price implementation as well as the contribution in the field of Computational Social Science (CSS).

This study's exploration of True Price and its role in facilitating sustainable transitions aligns with global efforts to achieve sustainable development goals. A successful implementation of True Price could significantly contribute to reducing environmental degradation, promoting fair labor practices, and spurring innovation towards sustainable products.

This research underscores the relevance of computational science in addressing complex societal challenges. CSS leverages computational tools and data to test and develop social theories, offering new insights into human behaviour on a broader scale (Steinbacher et al., 2021). Agent-based modelling (ABM), as a computational tool, provides a refined understanding of systemic societal changes. It allows for the simulation of various scenarios and interventions, offering conditional predictions that can guide decision-making processes for firms and policymakers.

The use of ABM in exploring the dynamics of True Price and its potential to facilitate a positive tipping point towards sustainability demonstrates the efficacy of computational methods in social science research. By integrating Computational Social Science (CSS) principles, this research adopts an interdisciplinary approach to addressing sustainability transition challenges. This thesis aims to provide a comprehensive understanding of social phenomena and contribute to the development of effective interventions and policies.

1.5. Outline

This report is divided into eight chapters. Chapter 1 introduces the objective of the research. Chapter 2 explains the various concepts, theories, and main ideas used in the study. Chapter 3 reviews current research to highlight gaps and establish the relevance of this study. Chapter 4 details the methodology used to answer the second research question, focusing on the conceptualisation and formalisation of an Agent-Based Model (ABM) to explore the dynamics of True Price implementation. Chapter 5 presents the results, including the outcomes of the global sensitivity analysis conducted to identify key drivers and their impact on True Price adoption. Chapter 6 gives the results of the experiments conducted to test different interventions for True Price implementation. Chapter 7 analyses the findings, addresses limitations and suggests directions for future research. Finally, Chapter 8 summarises the key insights and contributions of the research and offers concluding thoughts on the role of True Price in sustainability transitions.

2 | Theoretical Background

This chapter outlines the concepts and theories essential for this thesis.

2.1. Sustainability Transitions in Complex Adaptive Systems

The concept of "transition" in science typically refers to a nonlinear shift from one equilibrium state to another. (Loorbach et al., 2017). Sustainability transitions, specifically, represent pivotal changes from unsustainable to sustainable modes, including technology, business practices, policies, as well as norms, values and behaviours. These transitions are a response to global interconnected challenges, in line with the Sustainable Development Goals of the 2030 Agenda for Sustainable Development (Stefani et al., 2022).

The study of Complex Adaptive Systems (CAS) offers valuable insights into sustainability transitions, providing a framework for understanding how emergent properties arise from simple interactions at a micro level (Levin et al., 2012). In CAS, various individual components interact dynamically, leading to organised and adaptive behaviours that cannot be simply inferred from the individual interactions Lenton et al., 2023. CAS is characterised by properties like emergence, irreducability, resilience, self-organisation, adaptation, learning and uncertainty (Cilliers, 2002; Gallopín et al., 2001). These systems are further characterised by heterogeneous agents with unique preferences, behaviour and decisionmaking processes Lenton et al., 2023.

Understanding sustainability transitions within Complex Adaptive Systems (CAS) extends to various social contexts, such as the subdomains of socio-technological, socio-political, and socio-economic systems. These systems exist within a broader socio-ecological framework and are continuously influenced by various external factors, such as environmental changes, technological innovations, and socio-political fluctuations (Vasconcelos et al., 2023). Conceptualising these systems as complex adaptive systems (CAS) highlights their dynamic nature, characterised by resilience and adaptability, which is crucial for addressing sustainability challenges. With this perspective, it is possible to better understand how sustainability transitions occur in various societal domains and how they represent the ongoing process of adaptation and reorganisation in response to global sustainability issues.

Building on this foundation, the characteristics of sustainability transitions, as identified by Köhler et al., 2019, highlight the complexity and interconnectivity of these processes. Sustainability transitions are multi-dimensional and co-evolutionary as they involve not only a variety of elements like supply chains and policies but also changes across environmental, social, and economic dimensions in a nonlinear and interdependent manner. Similar to complex adaptive systems (CAS), simple interactions at a micro level, like individual behaviours and decisions, can lead to complex and emergent macro-level outcomes. This means transitions are not reducible to individual components, reflecting the irreducibility of CAS. Sustainability transitions have a long-term nature, where the development from niche innovations to widespread adoption requires time to de-stabilise and create new lock-ins. This aligns with the resilience and adaptability of CAS, emphasising the ability to endure disturbances and evolve. The open-endedness and unpredictability of sustainability transitions reflect the uncertainty inherent in CAS. In addition, transitions involve agency due to the presence of multiple actors, each having their own beliefs, strategies, interests and resources. This necessitates the application of multiple theories and disciplines for a comprehensive understanding. Here, each actor or element within the system contributes to the emergence of new patterns and behaviours.

The interplay between stability and path dependence with change and innovation is crucial to sustainability transitions. These transitions represent significant changes in how societies operate beyond just technological shifts. This transformation is driven by continuous learning and adaptation, where systems evolve in response to new information and changing conditions. Values, contestation and disagreement are central to this, as existing economic positions and business models are challenged. Finally, the concept of normative directionality is important in sustainability transitions. Since sustainability is a public good, public policy is essential in guiding these transitions. This emphasises the role of public policy in shaping the direction of these transitions. It involves guiding actions towards a sustainable future through regulations, standards, incentives and taxes.

S-curves are used to describe how innovations and behaviours spread over time. In sustainability transitions, the S-curve shows how a system moves from being unsustainable to sustainable. This curve has three phases: emergence, where new practices or technologies start to appear; acceleration, where they grow and spread quickly; and stabilisation, where they become standard and their growth levels off.

As shown in Figure 2.1, the blue S-curve represents the growth and acceptance of sustainable technologies and practices, starting small and eventually becoming widespread. The yellow S-curve, which declines, shows the phase-out of unsustainable practices. Together, these curves create an 'X-curve', illustrating the rise of sustainability and the fall of outdated methods. However, real-world transitions are not always smooth. The inset box in the figure highlights the complexity of these transitions, with feedback loops and external shocks causing fluctuations. This model not only illustrates the process of change, but from it, we are able to identify critical junctures and tipping points at which the system's behaviour shifts significantly.

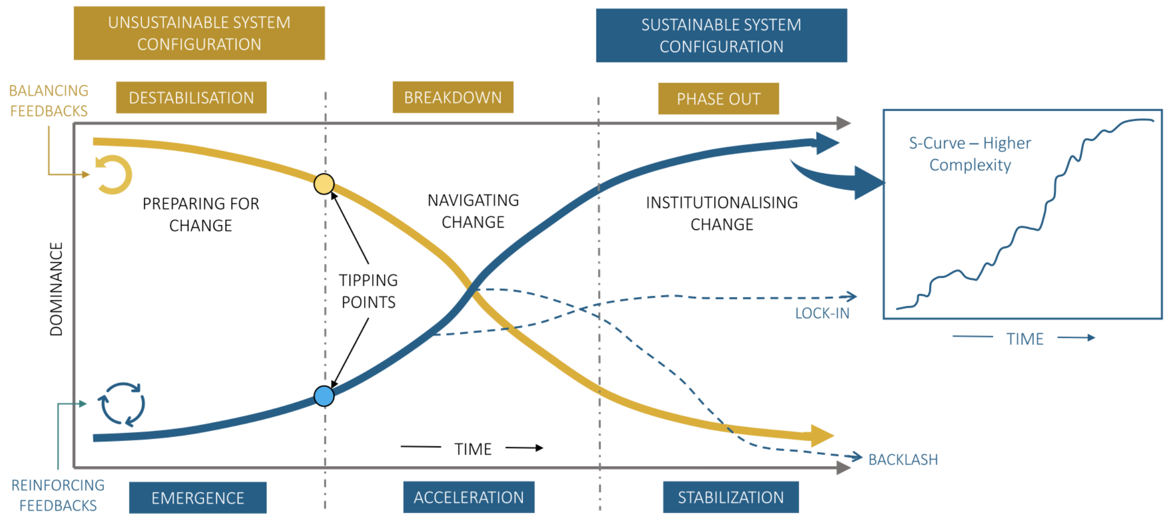


Fig. 1 An ideal-type sustainable development transition. Rising and declining S-curves across three phases of transformation. Inertia and non-linear dynamics are shaped by balancing (negative) and reinforcing (positive) feedbacks. Tipping points demarcate the inflection point between emergence and acceleration. Dotted lines depict alternative pathways (lock-in, backlash). In the right panel, an ideal transition pathway is rarely smooth and faces many impediments

Figure 2.1: Caption

2.2. Tipping Points

The concept of tipping points is critical in understanding the dynamics of sustainability transitions. Tipping points represent moments or thresholds where small changes can lead to significant, often irreversible shifts in system states (Lenton, 2020). They are characterised by their nonlinear dynamics, driven by feedback mechanisms within the system, and typically exhibit multiple stable states, abrupt changes, feedbacks as system-internal drivers of change, and limited reversibility (hysteresis) (Milkoreit et al., 2018).

The origins of tipping points are traced to mathematics and chemistry (Hoadley 1884 and Poincare 1885). Within mathematics, tipping points are often described as bifurcations (Lohmann et al., 2021). In physics, tipping points are often likened to phase transitions. However, the concept of tipping points has been more broadly studied by both natural and social sciences. In Earth and climate sciences, negative tipping points have been identified and are important for setting planetary boundaries (Rockström et al., 2009). In recent years, approaching these points has led to more efforts to tackle climate change (Lenton et al., 2022). The concept of tipping points has evolved significantly with the introduction of insights from non-autonomous and random dynamical systems. This evolution broadens the traditional understanding of bifurcations, typically associated with time-independent systems, to encompass systems that are influenced by time-varying changes and randomness (Ghil & Lucarini, 2020). Following the work of Ashwin et al., 2012 and the Global Tipping Points Report (Lenton et al., 2023), three types of tipping points are identified, each representing a different way complex systems can undergo significant transformations.

Bifurcation-induced tipping occurs when a gradual change in an external control parameter leads to an abrupt shift from one stable state to another. The tipping point where this shift occurs arises from the self-reinforcing feedback mechanisms that become self-propelling, driving the system to a new stable state (attractor), regardless of how slowly this tipping point is approached. This type of tipping is often irreversible, marked by hysteresis, indicating that simply reversing the external conditions does not necessarily revert the system to its initial state. This path-dependent nature makes it challenging to predict and manage complex systems. However, if the new "locked-in" state is beneficial, reinforcing feedback to stabilise these practices can help achieve sustainability goals.

Noise-induced tipping occurs when a random perturbation in the system causes a transition. While small disturbances might be absorbed, large ones can push the system into a new regime, extending beyond the basin of attraction of the current stable state. This is due to the fact that the current stable state may have lost some stability and is, therefore, sensitive to stochastic variability. In practice, it is often noise prior to reaching the bifurcation point that causes the system to tip (Lenton et al., 2023).

Rate-induced transitions occur in non-autonomous systems when the rate of environmental change, not the magnitude itself, surpasses the system's adaptive capacity. This leads to a sudden and significant change in the system's behaviour (Vasconcelos et al., 2023). This is due to the rapid forcing of the system where the system's damping feedbacks are not fast enough to counter (Lenton et al., 2023). This is unlike the previously discussed tipping points, as the relationship between the timescales is considered decisive as well, and this mechanism does not necessarily require the existence of alternative stable states

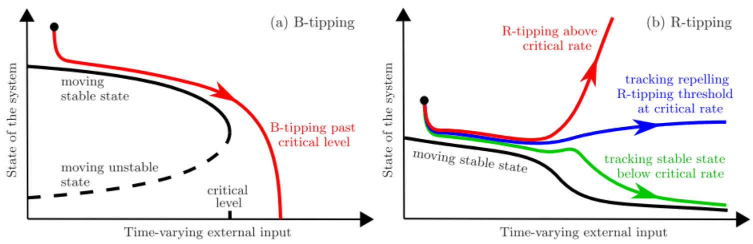


Figure 1. The conceptual difference between (a) B-tipping and (b) R-tipping for monotonically changing external inputs. The (solid black) moving stable state is a stable state of the frozen system for different values of a fixed-in-time external input. The (colour) trajectories show the system behaviour for a time-varying external input. (a) In B-tipping, there is a *critical level* of the external input, and tipping occurs for any rate of passage through the critical level. (b) In R-tipping, there is no critical level, but there is a *critical rate* of change of the external input above which the system fails to track the moving stable state and tips. The (blue) special critical-rate trajectory tracks what we define as a repelling R-tipping threshold.

Figure 2.2: (Wieczorek et al., 2023)

With regards to sustainability, tipping points shed light on how modifications in policies, technologies or behaviours can cumulatively build up to trigger widespread changes in social, economic and environmental systems. Understanding tipping points not only underscores the delicate balance within complex systems but also highlights the potential for targeted interventions to foster sustainable outcomes. To this end, 'intentionality' is a key characteristic of social tipping points, referring to the purposeful actions and strategies to deliberately create changes (Graham et al., 2023; Milkoreit, 2023).

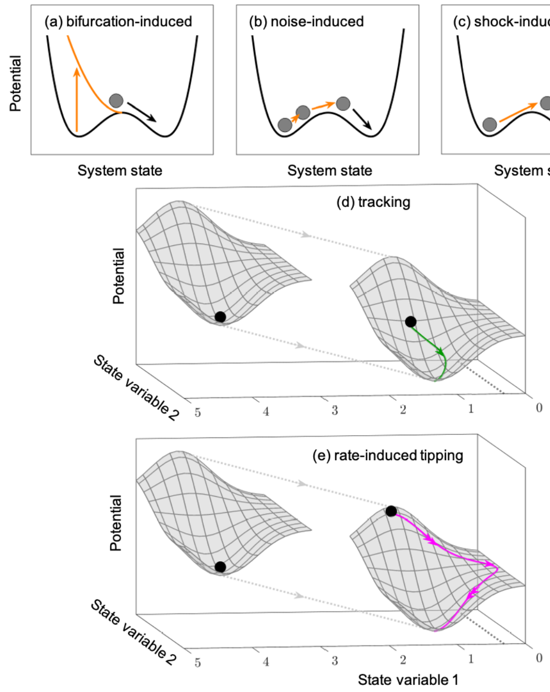


Figure 2.3: (Feudel, 2023)

When the system is detected to be vulnerable, a small perturbation can be deliberately introduced to take it down an alternative path (Lenton, 2020). Bifurcation-induced tipping highlights how gradual policy adjustments or technological innovations can lead to significant systemic shifts once a critical threshold is crossed. Noise-induced tipping underscores the importance of resilience in the face of unpredictable events or disturbances, suggesting that strategic planning and robust system design can mitigate against unintended transitions. Rate-induced tipping emphasises the challenges and opportunities of the speed of environmental or societal changes, as well as the timing of interventions.

2.3. Socio-economic Systems

The intricate interplay of human activities and their environmental impacts are at the core of sustainability. Socio-ecological systems integrate environmental and human subsystems, forming a complex adaptive system (Fischer et al., 2015; Ostrom, 2009). Within this, socio-economic systems are crucial, as human economic activities significantly impact ecological components and vice versa (Tachiiri et al., 2021). Economic processes such as resource extraction and consumption patterns directly and indirectly affect ecological systems. In turn, the state and availability of ecological resources shape and constrain human economic activities, influencing industries, markets, and livelihoods (Stefani et al., 2022).

This thesis, therefore, shifts the focus towards social innovations, rather than solely technological innovations, to achieve sustainability goals. This socio-economic perspective emphasises the influence of market capitalism on human identity, values, norms, and behaviour. Social systems comprise diverse and adaptive agents whose interactions create complex structures and patterns, making it challenging to identify tipping points and conduct analyses (Juhola et al., 2022). Although these systems are characterised by their ability to innovate, learn and reorganise in response to external pressures like climate change, technological advancements and socio-economic shifts, they are susceptible to rate-induced transitions where changes occur more rapidly than the system's ability to adapt (Vasconcelos et al., 2023). Studying these socio-economic systems within the broader socio-ecological context requires a multi-faceted approach to understanding their complexity.

Theories from various disciplines influence research on socio-economic systems. These theories, ranging from psychology to economics, offer different perspectives on human behaviour. For example, social psychology examines decisionmaking, social influence, and information processing, while behavioural economics looks at heuristics, biases, and prospect theory (Schlüter et al., 2017). Using established behavioural theories instead of ad hoc decision rules in models has several advantages (Schwarz et al., 2020). It makes models more reusable and comparable and focuses on relevant processes, providing deeper insights into societal responses in different scenarios.

The socio-economic perspective recognises humans as social and moral beings whose behaviours, identities, beliefs, and interests are shaped within their socio-economic environments (European Environment Agency (EEA), 2017). Many behavioural theories, such as social comparison theory and the theory of planned behaviour, explain parts of the processes that determine consumer behaviour. Dual cognition theories are another critical consideration. Almost all authors agree on a distinction between unconscious, rapid, automatic, and high-capacity processes and those that are conscious, slow, and deliberative. We can rapidly formulate answers to questions but sometimes engage in deliberate reasoning processes before responding (Evans, 2008; Pennycook, 2017)

Understanding the economic components of decision making is crucial, especially in contexts involving risk and uncertainty. Economics is essential when assessing the trade-offs between the benefits of actions that drive change and their potential adverse environmental impacts. Tipping points pose a significant challenge to traditional economic models, which often focus on steady growth and may not account for sudden, drastic changes (de Zeeuw & Li, 2016). As a result, research in this area frequently emphasises linear processes and struggles to capture rapid socio-economic changes (Lemoine & Traeger, 2012).

The rationale behind developing an integrated approach is the understanding that many environmental challenges are rooted in human behaviour. The interaction between social and economic factors is crucial in sustainability transitions, affecting how consumers and firms behave under various influences. These factors include pricing strategies, information disclosure, and a mix of economic incentives and social norms, all of which significantly affect the acceptance and success of innovative approaches like True Price strategies. While previous behavioural theories have addressed specific aspects of consumer behaviour, the Consumat framework seeks to integrate these into a comprehensive model (Jager et al., 2000).

2.3.1. Consumat Framework

The Consumat approach, as developed by Jager, 2000, represents a pioneering effort in modelling consumer behaviour. This meta-theoretic framework is based on the premise of agent-based simulation of human decisionmaking in the context of the consumption of goods or opportunities. The approach is based on three primary ideas (Balke & Gilbert, 2014). Firstly, humans are multi-faceted and heterogeneous; secondly, making decisions requires both time and cognitive resources; and lastly, uncertainty is a common factor in decisionmaking.

The Consumat model operates through a two-step decisionmaking process. Initially, it assesses each agent's level of need satisfaction and their uncertainty. This is based on the inclusion of three core needs- existence, social and personality (Jager & Janssen, 2012). Existence refers to having means of survival such as income, social relates to the interactions with others, and personality refers to individual preferences. Using threshold functions, agents employ one of four decisionmaking strategies: repetition, imitation, deliberation, or social comparison. If an agent is satisfied and faces low uncertainty, they tend to repeat past behaviour. If an agent is satisfied but faces high uncertainty, they might imitate the behaviour of others. Agents who are not satisfied but face low uncertainty will deliberate, analysing different options before making a decision. Lastly, if agents are not satisfied and face high uncertainty, they engage in social comparison, looking at the behaviour of similar others before deciding. The dynamic framework allows agents to switch between their decision strategies as their circumstances change.

The Consumat model synthesises individual actions to predict broader societal trends when implemented across a heterogeneous population. This includes impacts on human aspects, like cultural consumption patterns and social norms, and environmental factors, such as emissions (Antosz et al., 2018). Additionally, the model reintegrates these collective outcomes back into each agent's decisionmaking process for the next moment in time. This feature is critical for realistically simulating both personal developments (like the formation of habits) and larger societal shifts (for instance, how new norms emerge and evolve over time)(Antosz et al., 2018). The Consumat approach is applied to important general frameworks, including the commons dilemma, where multiple individuals manage a shared resource, and market dynamics, which involve lock-in, social networks and diffusion processes.

One of Consumat's key strengths is its integration of elements from psychological and economic theories, making it particularly effective in modelling the influence of social networks on individual behaviour. However, the framework is not without its limitations. A notable challenge is the lack of clear guidelines on which needs should be included in the model and how they should be measured, which can lead to variability in the application and interpretation of the model across different studies and contexts.

The Consumat approach can aid in identifying tipping points within social systems by simulating how individual decisions, influenced by social context, aggregate to effect substantial systemic changes. It captures how individuals' choices are shaped by their social environment by integrating factors like social

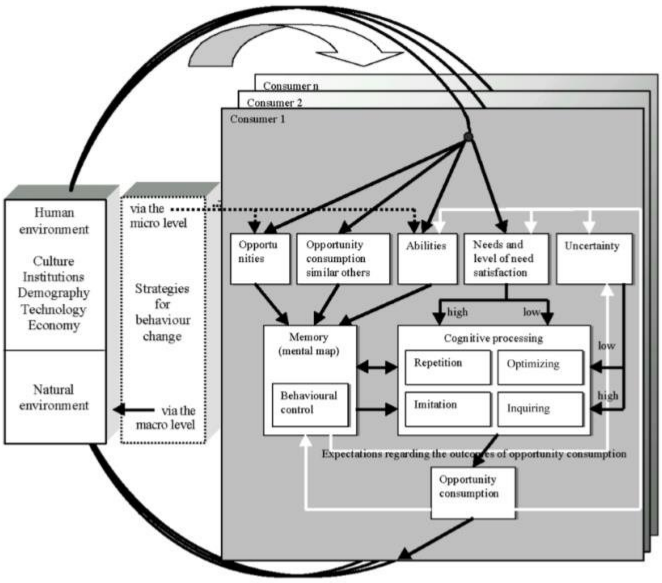


Figure 2.4: Original Consumat Framework

norms, peer influence, and cultural dynamics into its simulation of consumer behaviour. By observing how small changes in behaviour or attitudes can lead to large shifts in overall population behaviour, the Consumat model identifies critical tipping points. Such insights are helpful for understanding and potentially guiding large-scale societal transitions, especially in domains where social context plays an important role.

2.4. Simulation and Modelling

Modelling socio-economic transitions encompasses various methodologies, each with strengths and limitations. A comprehensive understanding of these approaches is important for accurately representing the complexity of societal transitions.

Including social complexities into models is non-trivial (Taberna et al., 2020). Integrated Assessment Models (IAMs) combine climate, economic, and policy analyses to understand the interactions between climate and socio-economic systems on a macro scale. However, they often lack the inclusion of micro-scale human behaviour, which makes them unsuitable to realistically and sufficiently understand social tipping points (Juhola et al., 2022). In contrast, the Multi-Level Perspective (MLP) framework divides the analysis into three interconnected levels: Regimes, Landscapes, and Niches. This approach acknowledges the complexity of societal transitions by considering the influence of various factors, from social networks to geographical positions (Westley et al., 2011). However, MLP mainly offers broad models that map the entire transition process and give less attention to individual actors. It uses narrative explanations and process theory to describe patterns emerging from interactions instead of traditional dependent and independent variables (F. W. Geels & Schot, 2007). Critics have noted its niche-centric view, which sometimes overlooks the broader picture (Markard & Truffer, 2008).

While these methodologies offer valuable insights, there is a growing need for models that can effectively capture the micro-level behaviours and interactions that drive macro-level phenomena. This is particularly relevant in sustainability transition studies, where the behaviours and decisions of individual agents play a critical role. This is especially important in sustainability transition studies, where individual actions are crucial. Evolutionary game theory helps explore how individual strategies evolve over time within a population, influenced by cooperation, competition, and adaptation. This approach simplifies the analysis of strategic interactions in a homogeneous setting. Agent-based modelling (ABM) is a powerful tool for incorporating heterogeneity within the population, connecting macro and micro perspectives. By using this sequential modelling approach, we can better capture and analyse complex behaviours and patterns.

2.4.1. Evolutionary Game Theory

Game theory, developed by John van Neumann and Oskar Morgenstern, is a fundamental mathematical framework for understanding strategic interactions within societies (Nowak, 2006). Its principles, rooted in mathematics, provide insights into the complexities of human decisionmaking processes where the outcomes for individuals depend on the actions of others.

Evolutionary game theory builds on classical game theory by including the idea of strategies changing over time. This approach suggests that the effectiveness of a strategy is not fixed but varies with its frequency within a population, providing a way to study adaptive behaviours (Nowak, 2006). At the core is the replicator dynamic, representing the idea that strategies that perform better tend to become more common over time (Gintis, 2009). This does not imply that individuals consciously choose the best strategies; instead, successful strategies naturally increase in frequency by "replicating" their success. Agents in a replicator system have "bounded rationality", meaning they only have limited information about the overall system. This reflects real-world decisionmaking, where agents lack perfect information and cannot foresee all possible outcomes, leading to decisions that might not always be optimal. By considering the expected value, or the weighted average of all possible outcomes, the community's overall strategy tends to evolve towards more successful outcomes on average. This dynamic reflects the adaptive nature of strategic interactions in biological and social contexts, a key aspect of evolutionary game theory.

The replicator equation is given by:

$$\dot{x_i} = x_i(f_i - \phi), i = 1, \ldots, n \tag{2.1}$$

where x_i denotes the frequency of strategy i, f_i is the expected payoff for strategy i and ϕ represents the average payoff in the population - $\phi = \sum_{i=1}^{n} x_i f_i$. This dynamic can be analysed by examining the fixed points and their stability using the Jacobian matrix, which shows how strategies stabilise, spread, or disappear over time.

2.4.2. Agent-Based Models (ABMs)

Agent-Based Models (ABMs) are increasingly recognised as dynamic tools for understanding and representing the behaviour of complex systems, particularly in social sciences. ABMs centre around agents, autonomous entities that simulate actions of system components and their interactions within a specific environment (Sánchez-Maroño et al., 2022). These models provide a unique perspective by simulating individual behaviours and observing how they collectively generate larger systemic outcomes. In societal settings, they bridge the gap between micro-level agent behaviours and macro-level systemic outcomes by explicitly linking individual motivations and decisions to large-scale patterns of social organisation and change (Bruch & Atwell, 2015).

The flexibility of ABMs is a significant advantage. They allow for the representation of heterogeneous agents, each with unique attributes, strategies, and decisionmaking processes, capturing the diversity of actors and strategies in real-world systems. This capability helps in understanding complex social dynamics. ABMs can model and analyse dynamic interactions between different agents, revealing emergent behaviours not apparent at the individual level (Bruch & Atwell, 2015). This is valuable for exploring unexpected social patterns, such as residential segregation or the spread of diseases. ABMs also enable scenario exploration and 'what-if' analysis, allowing researchers and policymakers to simulate various conditions and interventions to gain insights into their potential impacts on system dynamics (Bruch & Atwell, 2015).

However, the development and application of ABMs are not without challenges. A key issue is the balance between agent behaviour specification and parameterisation. Some ABMs are highly stylised and grounded in predominant theories, while others focus on replicating empirically observed behaviour (Filatova et al., 2013). Ensuring that ABMs accurately replicate realistic scenarios requires careful calibration and validation, which can be both complex and resource-intensive. Additionally, the replication and understanding of ABMs can be complex due to incomplete or inconsistent model descriptions. Despite these challenges, ABMs have become essential tools in social sciences, providing a way to represent societies and observe collective phenomena based on the characteristics and behaviours of individuals and their environments (Jager, 2021).

2.4.3. Networks

Network science has a wide range of applications, including both natural and social systems. Social systems, however, include an additional level of transmission, such as shared norms, identities, cultures and ideas, as well as economic and political relationships, such as citizenship and employment (Winkelmann et al., 2022). These relationships need not be dependent on physical distance due to these abstract and often technological connections. Therefore, network theory is important in studying socio-economic systems and their tipping points. In fact, Winkelmann et al., 2022 defines a social tipping element as small changes in the system that, under certain critical conditions, lead to qualitative changes, often through cascading network effects such as positive feedback mechanisms and complex contagion.

Multiple network models offer different perspectives on social systems. The random regular network represents a structure where each node has the same number of connections, making it useful for studying uniform social interactions. In contrast, the Barabási-Albert model suggests a scale-free network with low clustering, where some nodes, known as 'hubs,' are highly connected compared to others (Barabási & Albert, 1999). The Watts-Strogatz model represents a small-world network characterised by high clustering but lacking scale-free properties (Watts & Strogatz, 1998). Meanwhile, the Holme-Kim model combines elements of both scale-free and small-world networks, providing high clustering and maintaining some hub characteristics.

Networks in ABMs can help model complex social interactions and dynamics, as they allow for the representation of diverse agent interactions beyond spatial relationships. In this way, researchers can capture nonlinear and unpredictable behaviour inherent in social systems (Will et al., 2020). There are three important considerations to this end (Sánchez-Maroño et al., 2014): the creation of the initial social network, the evolution and the influence of the social network. The initial configuration of the social network involves establishing the network topology by creating links between different agents. Real-life social networks are dynamic, with the strength of ties among individuals changing over time. Some connections may dissolve, while new ones often emerge through existing relationships. Similarity between agents is a key factor in forming connections. Therefore, ABMs should include mechanisms that allow networks to evolve, with links forming and breaking. The aspect of social influence is important as agents use their network connections to engage in social interactions, exchange opinions, and influence one another's behaviour in ABMs.

3 | Literature Study

3.1. Sustainability Transitions

Sustainability transitions in markets and societies are complex processes characterised by the interplay of various actors and power dynamics within systemic frameworks. These transitions, often driven by sustainable entrepreneurship and technological and social innovations, require a reorientation of market structures and organisations (Schaltegger et al., 2022).

A key element in these transitions is the role of agency in overcoming established practices and driving change. The case of Melbourne's stormwater management, explored by Brown et al. (2013), illustrates this. Their research shows the impact of a core group of frontrunners from diverse sectors in driving long-term institutional transformations. It highlights the effectiveness of innovative strategies and collaboration among different actors in shaping sustainable transitions.

Exploring the dynamics of actor roles, Wittmayer et al., 2017 provides insights from sociological perspectives. They distinguish between individual roles and how these roles reflect shifts in social norms, values, and beliefs. Their study reveals the transformative potential of roles in governance, showing that creating, altering, or negotiating roles can lead to significant changes in collective processes and dominant institutional patterns. This analysis emphasises the complexity of actor interactions and the strategic use of roles in enabling sustainability transitions.

Further, F. Geels et al. (2023) discuss how actors in consumption-production systems change during transitions. They highlight how new entrants, established players, and other participants adapt their capabilities, strategies, and identities to navigate the uncertainties and complexities of these processes. Innovation extends beyond research and development, including market introduction, diffusion, and system reconfiguration. Additionally, the study emphasises the importance of deliberate interventions in shaping and guiding sustainability transitions.

Finally, the concept of "systems thinking," as discussed by Loorbach (2009), is essential for understanding the complexity of societal transitions. This approach provides a comprehensive view of the interactions within complex adaptive systems characterised by uncertainties and nonlinear changes. It focuses on emergent behaviours and mechanisms that drive societal evolution, offering a framework to understand and influence the dynamics of sustainability transitions. According to Loorbach (2009), the complexity of society is evident in three key areas: the societal structure, the nature of its challenges, and the governance mechanisms used to address these issues.

The literature on sustainability transitions highlights several key takeaways relevant to modelling the social dynamics of True Price implementation. First, diverse actors and their agencies are critical in overcoming established practices and driving change. Second, their dynamic interactions show how shifts in social norms, values, and beliefs can lead to significant changes in governance and institutional patterns. Third, continuous learning, adaptation, market introduction, diffusion, and system reconfiguration processes are important in consumption-production systems. Finally, systems thinking provides a practical framework to analyse the complex, nonlinear interactions within socio-ecological systems.

(Positive) Social Tipping Points

Schelling's segregation model (Schelling, 1971) is a pioneering model in understanding social phenomena. It demonstrates how individual preferences can unintentionally lead to significant collective outcomes like racial segregation. Granovetter later generalised this to various social phenomena, including riots. Granovetter's threshold model provides a foundational understanding of social tipping dynamics by modelling collective behaviour(Granovetter, 1978b). This model assumes that the behaviour of individuals depends on the number of others already engaging in that behaviour. The model also suggests that various factors shape individual thresholds, including norms, preferences, goals, and beliefs. This is also known as the process of complex contagion, which has been experimentally shown to enable social tipping points (Centola et al., 2018) and has drawn attention recently due to its potential to bring about rapid change within entire socio-ecological systems (Bentley et al., 2014; Milkoreit et al., 2018). Together, these models contribute to understanding how micro-level decisions can lead to substantial macro-level societal changes, a concept critical in exploring social tipping points.

However, many analyses of social tipping ignore such existing social theories, specifically the notion of thresholds. Milkoreit, 2023 argues that while thresholds are necessary for tipping dynamics, not all threshold occurrences lead to tipping points. This distinction is vital for accurate modelling and understanding of social transitions.

While these theories provide a foundation for understanding tipping points, they often miss key elements like network theory and feedback mechanisms as drivers of change (Winkelmann et al., 2022). Moving from one stable state to another through social tipping points involves changes in power relations, resource flows, agency, norms, strategies, and decision-making (Milkoreit et al., 2018; Moore et al., 2014). Therefore, studying these transitions requires diverse methodological approaches. The complexity of social tipping points underscores the need for advanced empirical techniques to simulate these dynamics effectively.

A significant contribution in this area is the work of Wiedermann et al., 2020, which builds on Granovetter's threshold model for social tipping using a network-based approach. Wiedermann addresses the limitations of Granovetter's model by refining it to tackle modern global challenges. He employs a network cascade model to show how broad threshold distributions arise when individuals are activated through social interactions. With its intuitive parameters and simplicity, this refined model is useful for analysing the likelihood of collective behaviour. It presents social tipping processes as saddle-node bifurcations and hysteresis, providing a clearer understanding of how social tipping can occur.

Andreoni et al., 2021 conducted large-scale laboratory experiments to test a threshold model for social tipping and norm change. This study revealed that societal preferences change gradually, and interventions that facilitate a common understanding of the benefits of change can help societies abandon detrimental norms.

Eker et al., 2023 identifies several key challenges in the current social tipping literature. There is a tendency to focus on single systems or scales, such as studies on electric vehicle technology within the transportation system. This often ignores the broader interconnectedness and interactions across different systems. Additionally, there is an overemphasis on positive feedback mechanisms, while negative feedback loops, crucial for understanding resistance and unintended consequences in social interventions, are often neglected. Moreover, there is a significant lack of empirical evidence or quantitative analysis to demonstrate social tipping dynamics in real-world scenarios. To address these challenges, a comprehensive approach that includes multiple empirical methods, a broad systems outlook involving various systems and scales, and dynamic simulation modelling is needed to provide a more precise and more practical understanding of social tipping points.

It is important to, therefore, consider the broader context in which these tipping points occur: complex adaptive systems.

Lenton et al., 2022 explores how technological improvements and changes in actor behaviour can speed up the spread of sustainable practices and technologies. Recent research has focused on how social-technological systems and policymakers can drive change, while earlier work looked at how social-ecological feedback triggered by different actors can lead to tipping points. Lenton combines these perspectives to examine tipping points across social-technological-ecological systems. The study highlights several conditions that can encourage positive tipping, such as focusing on smaller populations, changing social network structures, and providing useful information.

Engaging with debates on climate change mitigation, F. W. Geels and Ayoub, 2023 adopts a socio-technical transition perspective to analyse feedback loops in the acceleration of offshore wind and electric vehicles. It underscores the importance of co-evolutionary interactions between technological developments and actor reorientations in tipping point dynamics.

True Price

The approach of True Pricing, although novel, is starting to gain attention in the study of consumer behaviour and market dynamics.

(Michalke et al., 2023) is one of the few empirical studies on True Price, focusing on its practical application in current food systems. The study examines an informational campaign by a German supermarket that used a dual pricing strategy to show the difference between market prices and 'true' prices, which include environmental costs calculated using True Cost Accounting (TCA). Through consumer surveys and expert interviews, the research found that consumers generally support the idea of true food pricing and are somewhat willing to pay these 'true prices.' However, significant concerns were raised about transparency and equitable wealth distribution in TCA's implementation. This highlights the need for careful social measures and a supportive legal framework to ensure the fair and transparent application of True Price.

(Taufik et al., 2023) emphasises the need for more empirical research on consumer perceptions and reactions to True Pricing. Their studies, focusing on Dutch supermarket patrons and a representative sample of the Dutch population, provide insights into how consumer acceptance of True Price food products can be improved. (Taufik et al., 2023) identifies three types of potential value that True Pricing can offer to consumers: environmental impact ("green value"), social status, and the remediation of external costs. These factors significantly influence consumer purchase intentions, demonstrating the multifaceted impact of True Pricing on consumer behaviour and market trends.

The perceived 'green value' is a consumer's overall assessment of the net benefit of a product or service, factoring in the trade-offs between what is received and what is given, based on their desires, expectations for sustainability, and green needs (Chen & Chang, 2012). Buying sustainable products is a way for consumers to differentiate themselves from others (Noppers et al., 2014). The perception of gaining social status can reduce consumers' sensitivity to price (Goldsmith et al., 2010), making them more willing to pay higher prices. Incorporating external environmental and social costs into product pricing offers opportunities for addressing these issues. However, consumers may struggle to verify the effectiveness and legitimacy of these efforts, which can affect their trust and acceptance. (Taufik et al., 2023) hypothesises that the more consumers perceive true-price products as providing green value, enhancing social status, and effectively addressing externalities, the more they will trust and be likely to purchase these products.

Wilken et al., 2024 investigate the impact of True Cost Communication (TCC) on consumer preferences for sustainable products by highlighting the lower hidden costs of sustainable options. Two empirical studies found that TCC increases consumer preference for sustainable products when these products have lower hidden costs than conventional alternatives. This effect is mediated by perceived price fairness, as consumers view the higher prices of sustainable products as more justified when the hidden costs are disclosed. However, the price difference between sustainable and conventional products remains a significant factor, suggesting that making sustainable products more affordable is crucial.

The studies reveal that True Pricing has the potential to significantly influence consumer behaviour. Consumers generally support the idea of true pricing and are willing to pay these prices to some extent, but concerns about transparency and fairness must be addressed. The perceived benefits of true pricing, such as environmental impact, social status, and effective cost remediation, play crucial roles in consumer acceptance. Additionally, true cost communication (TCC) effectively increases preference for sustainable products when their hidden costs are lower than those of conventional alternatives, with price fairness being a key factor. These findings highlight the importance of ensuring transparency, affordability, and fair implementation to foster consumer trust and acceptance of True Pricing in market dynamics.

3.2. Modelling Socio-economic Systems

3.2.1. Evolutionary Game Theory

Evolutionary game theory emerges as a powerful tool for addressing modern challenges, particularly in environmental economics and sustainable development.

Encarnação et al., 2018 investigate the transition to electric vehicles (EVs) using evolutionary game theory, focusing on the interactions between public policy, private companies, and consumer choices. The study identifies a "behavioural gap" in environmental consumerism, where consumers with pro-environmental attitudes are still hesitant to adopt sustainable behaviours. By applying evolutionary game theory, the research emphasises the role of strategic behaviour adoption and societal influence in reducing reliance on internal combustion engine vehicles. These findings highlight the need for coordinated efforts across sectors and the significant impact of government regulations, subsidies, and taxes on the transition to EV adoption.

Zhu et al., 2023 applies evolutionary game theory to examine interactions between enterprises and consumers, focusing on the role of green supply chains in reducing carbon emissions. By incorporating green sensitivity into the model, the study analyses replicator dynamics, revealing the potential for periodic oscillations in the frequency of green enterprises and consumers. The research also identifies conditions under which a stable, environmentally friendly equilibrium can be achieved.

Roca et al., 2009 review the application of evolutionary game dynamics across various fields, including biology and economics, focusing on the replicator equation. They discuss how this equation parallels the mean-field approximation in physics, which assumes an ideally mixed population interacting with an average strategy. While this simplification makes analysis easier, Roca et al., 2009 point out the limitations of the replicator equation, particularly its failure to account for non-mean-field effects like spatial correlations. They suggest incorporating network structures can provide a deeper understanding of evolutionary dynamics.

These studies show how evolutionary game theory can address environmental sustainability challenges. They illustrate the role of strategic behaviour and societal influence in promoting sustainable practices. Additionally, incorporating network structures into game theory models can deepen our understanding of complex socio-economic interactions, making sustainability interventions more effective. These insights highlight the importance of advanced modelling techniques for developing effective sustainability strategies.

3.2.2. Modelling the intersection of social and economic components

Agent-Based Models (ABM) have been extensively employed to analyse and predict the outcomes of various policy interventions and systemic changes across multiple domains (Moglia et al., 2017). These models have been used to explore a wide range of objectives, including the adoption of sustainable technologies, the management of natural resources, and the effects of economic policies. However, like all modelling approaches, ABMs provide predictions that are conditional upon the assumptions and parameters defined within the model (Boschetti, 2012)

The study by Bourceret et al., 2022 provides valuable insights into the modelling of social and economic systems using agent-based models. The research focuses on nonpoint source pollution from agriculture, a significant cause of water quality degradation, and examines how farmers' behavioural dynamics affect the success of policy measures. By employing the social-ecological systems framework and the theory of planned behaviour, the model explores how farming practices evolve in response to different policy interventions. Key findings highlight that farmers' behavioural characteristics greatly influence policy outcomes, underscoring the need to incorporate these traits into policy design to improve efficiency. Additionally, the study suggests that a combination of financial incentives and training, although more expensive, might be more effective when behavioural characteristics are unknown. These insights underscore the critical role of behavioural dynamics in modelling social and economic systems and inform the development of more effective sustainability policies.

Kaaronen and Strelkovskii, 2020 explores how agent-based models can help achieve social tipping points in sustainability transitions. The study looks at promoting pro-environmental behaviours and cultural traits through feedback loops. By introducing pro-environmental options in a social system, the research shows that even small increases can lead to significant positive changes in collective behaviour. Validated with data from Copenhagen's cycling and driving behaviours, the model emphasises making pro-environmental behaviour easy and the default choice. It highlights the role of urban design in supporting these behaviours and suggests that changes in physical environments can create feedback loops that strengthen pro-environmental habits through social learning. This suggests that urban planning and policy should focus on designing environments that naturally encourage sustainable behaviours, even if the effects are not immediately visible. The findings also highlight the importance of allowing communities to self-organise to foster sustainable practices.

These studies collectively underscore the critical role of ABMs in understanding and shaping the dynamics of social and economic systems. They illustrate the importance of integrating behavioural characteristics, historical context, and environmental design into policy modelling to achieve more effective and sustainable outcomes.

3.2.3. Consumat

The Consumat approach has emerged as a significant framework for ABM, particularly in the context of technology adoption. Initially developed to align ABMs with advanced behavioural science, Consumat models have been applied to various scenarios, such as the uptake of electric vehicles. Despite its theoretical robustness, the Consumat model faces challenges, such as the need for extensive empirical parameterisation and adaptation to specific contexts. The model's flexibility allows it to be tailored to different problems, but this also involves managing a large number of parameters (Jager & Janssen, 2012).

Research using the Consumat approach has successfully addressed various environmentally-related issues (Antosz et al., 2018). For instance, in the adoption and diffusion of heating systems in Norway, the Consumat theory was instrumental in modelling varied decision strategies among agents, reflecting the significance of human behaviour in adopting new technologies (Sopha et al., 2013). This empirically grounded model successfully replicated Norway's general patterns of heating system diffusion by incorporating decision-making variables identified from the literature and validated through surveys.

In another application Kangur et al., 2017, the Consumat framework was employed to develop a model for the diffusion of electric vehicles. This model, named STECCAR, expands upon the traditional Consumat by including financial, functional, social, and environmental needs. STECCAR shows how cross-sectional survey data can be used to explore long-term behavioural dynamics in the electric vehicle market. Kangur et al., 2017 illustrates that the Consumat-based STECCAR model, by integrating complex behavioural rules and factors like technology development and economic policy, offers a more comprehensive and intuitive understanding of electric vehicle adoption dynamics than traditional psychological models. In addition, agent-based models can more intuitively determine how and when challenges should be addressed.

Zhang et al., 2023 also uses Consumat to simulate the diffusion of new energy vehicles. This study highlights the role of opinion leaders in the spread of information and product adoption, providing insights for marketing strategies and policy assessments promoting sustainable behaviours. By integrating the Consumat framework into a scale-free network, this study adapted the model to capture different cognitive processes among agents based on their need satisfaction thresholds.

The Consumat approach was utilised in the agricultural sector to analyse social-ecological interactions in potato late blight control in the Netherlands (Pacilly et al., 2019). This study integrated a behavioural theory framework with empirical data, showcasing the Consumat approach's capacity to develop behaviorally rich agents for simulating farmers' decision-making. Pacilly et al., 2019 suggests that the Consumat model's formalised structure allowed for easy implementation in an agent-based model with minimal assumptions.

Schoenmacker et al., 2022 applied the Consumat model to assess the adoption of sustainable lighting under the European Ecodesign Directive. This research implemented an agent-based simulation to model consumer behaviour in the EU lighting market, aiming to understand and explore alternative policies. These scenarios included soft bans consisting of a gradual price increase, hard bans making certain products unavailable to consumers, and information-only policies. Findings show that a soft ban led some to continue using cheaper incandescent bulbs, while others, seeking alternatives, moved towards more affordable LEDs. Furthermore, scenarios involving stricter bans or information-only policies resulted in initial deliberation and a shift to alternative strategies driven predominantly by financial considerations. The research shows the strengths of agent-based models in policy generation and evaluation and in generating specific hypotheses about consumer behaviour grounded in psychological theory.

Moglia et al., 2018 reports on an Agent-Based Model of Residential Energy Efficiency Adoption. This model was developed to describe households' uptake of low-carbon and energy-efficient technologies and practices under different interventions. It focused on modelling non-financial incentives, the influence of social networks, and the decision-making by multiple types of agents. The decision-making model for household agents was inspired by the Consumat approach, emphasising the need to embed behavioural science insights into fine-tuning key parameters in the delivery of interventions.

Janssen and Jager, 2003 explores how different structures of social networks influence agent decisions within the Consumat framework. It employs mathematical models such as the Watts-Strogatz model and the Barabasi-Albert model. These models reveal that network shape significantly impacts market dynamics, especially regarding product dominance. Hubs are crucial in spreading new products in scale-free networks, leading to market dominance by fewer products. This is consistent with the idea that early adopters with many connections significantly influence others' consumption decisions. The study highlights the importance of understanding network structures to predict consumer behaviour accurately and refine simulation models.

Integrating the Consumat framework with network theory enhances our understanding of consumer behaviour and market dynamics. Studies utilising the Consumat approach have shown its effectiveness and highlight the importance of behavioural factors, such as decision strategies and social influence, in shaping outcomes. These insights emphasise the necessity of considering network structures in modelling social dynamics, which will be further explored in the next section on networks.

3.2.4. Networks

Krönke et al., 2020 notes that networks with large clustering coefficients and spatial structuring tend to be more vulnerable to tipping cascades, suggesting that densely interconnected groups can rapidly amplify changes throughout the network. This is particularly relevant in understanding how small changes in one part of a social network can lead to significant shifts in the overall system.

Granovetter's notion of "the strength of weak ties" underlines the importance of weak relational ties (e.g., acquaintances) in spreading new information and ideas (Granovetter, 1978a). Although weak in a relational sense, such ties can be structurally strong in bridging distant parts of a network.

Incorporating network theory into agent-based modelling, studies like Caillault et al., 2013 and Lee et al., 2013 show how different network structures impact individual and collective behaviours. For instance, Lee et al., 2013 utilises the small-world network model to explore the dual impact of global information diffusion and local social reinforcement on consumer behaviour. This model, characterised by high clustering and short information transfer times, mirrors many real-world social networks.

Applying complex network theory in socio-economic studies involves quantifiers like modularity, degree distribution, centrality, or clustering to capture network tipping processes (Winkelmann et al., 2022). Such analyses help in understanding the dynamics of socio-economic systems, especially in scenarios where the behaviour of agents is influenced by both global policies and local social interactions, as demonstrated in the works of Caillault et al., 2013 and Lee et al., 2013

Lee et al., 2013 delves into the structural features of social networks and their impact on consumer behaviour, especially in product information diffusion. The study emphasises the role of rewiring probability in creating network shortcuts and facilitating the rapid and broad dissemination of information among consumers. This structural aspect of the network aids in the global spread of product knowledge. In contrast, the degree of connectivity within the network, which dictates the number of clustered ties or immediate neighbours, plays a critical role in local information diffusion, as it reinforces social influences in consumer decisions. Employing the small-world network model characterised by high clustering and short information transfer times, the study aligns with empirical evidence suggesting that such network structures are prevalent in various real-world social contexts. This approach effectively captures the dual dynamics of global and local influences on consumer behaviour within social networks.

This literature study highlights the complex nature of sustainability transitions, emphasising the importance of understanding the roles of various actors, the dynamics of social tipping points, and the use of advanced modelling techniques. The studies reviewed show the significance of agency, social norms, and environmental design in driving sustainable change. Evolutionary Game Theory and Agent-Based Models (ABM) provide valuable tools for analysing these interactions, offering insights into policy effectiveness and behavioural dynamics. Integrating the Consumat framework with network theory further enhances our understanding of consumer behaviour and market dynamics. These insights collectively inform the development of more effective sustainability strategies and demonstrate the crucial role of advanced modelling techniques in achieving positive socio-economic outcomes.

4 | Methodology

4.1. Overview

This chapter details the iterative methodology used to model the social dynamics of True Price implementation, integrating evolutionary game theory, agent-based modelling (ABM), and network theory. The approach is structured to build progressively from foundational models to more complex simulations, justifying each methodological decision based on its relevance and contribution to understanding the problem.

Initially, evolutionary game theory is applied to capture the strategic interactions between homogeneous producers and consumers concerning True Pricing. This theoretical framework allows for analyzing how different strategies evolve over time and under varying conditions of green sensitivity and environmental awareness.

The next step involves developing a heterogeneous agent-based model using the Consumat framework. This model simulates consumer behaviour, considering financial, social, and personal factors. The Consumat framework is chosen for its ability to represent complex decision-making processes, capturing how consumers adapt their strategies based on satisfaction and uncertainty.

Network theory is incorporated to make the model more representative of real-life societies, examining how social network structures influence the diffusion of True Price products. This involves exploring different types of network configurations, such as small-world and scale-free networks, to understand how connections between consumers affect their purchasing decisions. Including homophily, or the tendency for individuals to associate with similar others, further refines the model by highlighting how network structures and social similarity impact consumer behaviour.

The iterative nature of this methodology ensures that each stage builds upon the insights gained from previous models, progressively increasing the complexity and realism of the simulations. This comprehensive approach aims to provide a detailed understanding of the mechanisms driving the adoption of True Pricing to inform more effective sustainability strategies.

4.2. Evolutionary Game Theory

In this paper, we utilise evolutionary game theory to define and analyse the green sensitivity of both consumers and enterprises, establishing a model that reflects their interactions within the True Price framework. In the context of True Price, green sensitivity reflects an understanding of the environmental and social impact of production and consumption decisions. It is a measure of the willingness of both producers and consumers to engage with and respond to the true cost of products. The green sensitivity of consumers defines the degree to which they are willing to pay a premium for products. Consumers with a high green sensitivity value the ethical consideration of their purchases and are motivated by the desire to support sustainable practices, even if it means paying more. The green sensitivity of producers reflects a commitment to environmental responsibility, recognising that True Pricing plays a crucial role in driving the industry towards more sustainable practices. Green sensitivity quantifies the strategic advantage producers may have by engaging in True Pricing, which is more than revenue and costs. It can compensate for short-term losses because of the long-term benefits of True Price. This helps to rationalise why a company would choose to use True Pricing over normal pricing by acknowledging the broader benefits of such a choice. This mutual recognition of environmental costs and benefits facilitates a market dynamic where True Pricing is a mechanism for promoting sustainability. By prioritising green sensitivity, producers and consumers contribute to a more sustainable economy, recognising that the long-term benefits of environmental stewardship outweigh the short-term financial costs.

We consider two players interacting in a market environment: producers and consumers. Consumers have two distinct pricing strategies: normal pricing (N) and True Pricing (T). Note that the actual product and method of production do not change.

We consider different strategy combinations between producers and consumers in the context of true pricing and normal pricing strategies. The payoffs for each party under various combinations are summarized in Table 4.1 below:

Strategy Combinations	**Producer Payoff**	**Consumer Payoff**
(T, P)	$+I_p + G_p$	$-C_N - C_T + G_c$
(N, P)	$-I_p$	$-C_N - D_c$
(T, NP)	$-L_T + I_p$	0
(N, NP)	$-L_N$	$-D_c$

Table 4.1: Payoffs for different strategy combinations between producers and consumers in the context of True Pricing and normal pricing strategies. Producers can choose between True Pricing (T) and normal pricing (N), while consumers can choose to purchase (P) or not purchase (NP) the product.

where:

- I_p: Green image
- G_p: Green sensitivity of Producer
- L_i: Loss from product unsold, for $i = N, T$
- C_N: Cost of product (normal price)
- C_T: Extra cost for True Price
- G_c: Green sensitivity of Consumer
- D_c: Environmental damage

The strategies for different combinations of producer pricing and consumer purchasing decisions are described as follows:

(T, P) If the producer decides to use the True Pricing method (T) and the consumer purchases (P), the company gains a green image and leverages green sensitivity, attracting consumers who value sustainability. The consumer pays the normal price plus an additional price but gains in terms of green sensitivity, as they are contributing towards a more sustainable future.

(N, P) If the producer uses normal pricing (N) and the consumer purchases, the company loses its green image. The consumer pays the normal price but also faces the intangible costs of environmental damage not reflected in the market price.

(T, NP) If the producer uses True Pricing (T) and the consumer does not purchase (NP), the company faces a loss from unsold products, highlighting the risk. However, efforts towards sustainability and transparency are still recognised as they can positively affect a company's image, regardless of immediate financial transactions. There is no payoff for the consumer.

(N, NP) If the producer uses normal pricing (N) and the consumer does not purchase (NP), the company faces a loss from unsold products. The consumer indirectly supports practices that may cause environmental harm and faces environmental damage.

We can assume that L_N and L_T are equal because the loss from unsold products would be the same for both true pricing and normal pricing strategies given that the actual revenue remains unchanged and any extra from True Pricing is not retained by the company. This loss will be denote as L_p from now on.

We use the replicator equation to describe the evolutionary process of strategy selection by producers and consumers. The following proportions are considered:

- x: The proportion of producers that adopt the "true pricing" strategy.
- $1 - x$: The proportion of producers that adopt the "normal pricing" strategy.
- y: The proportion of consumers choosing to purchase (any product).
- $1 - y$: The proportion of consumers choosing not to purchase.

The replicator equation can then be written as follows:

$$\begin{cases} \frac{dx}{dt} = x\left(V_x - \overline{V_x}\right), \\ \frac{dy}{dt} = y\left(V_y - \overline{V_y}\right), \end{cases} \tag{4.1}$$

where

- $\overline{V_x}$:the average payoff of producers,
- $\overline{V_y}$:the average payoff of consumers

More formally,

$$\begin{cases} \overline{V_x} = xV_x + (1-x)V_{1-x}, \\ \overline{V_y} = yV_y + (1-y)V_{1-y}, \end{cases} \tag{4.2}$$

where,

- V_x : the expected payoff of producers choosing true pricing,
- V_{1-x} : the expected payoff of producers choosing normal pricing,
- V_y : the expected payoff of consumers choosing purchase strategy,
- V_{1-y} :the expected payoff of consumers choosing non-purchase strategy:

These are defined by the payoffs in Table 4.1

$$\begin{cases} V_x = y\left(I_p + G_p\right) + (1-y)(-L_p + I_p), \\ V_{1-x} = y\left(-I_p\right) + (1-y)(-L_p), \\ V_y = x\left(-C_N - C_T + G_c\right) + (1-x)\left(-C_N - D_c\right), \\ V_{1-y} = (1-x)(-D_c) \end{cases} \tag{4.3}$$

Combining equations 4.1 and 4.2 we find:

$$\begin{cases} \frac{dx}{dt} = x(1-x)(V_x - V_{1-x}) \\ \frac{dy}{dt} = y(1-y)(V_y - V_{1-y}) \end{cases} \tag{4.4}$$

Substituting in equations 4.3 into 4.4 we find:

$$\begin{cases} \frac{dx}{dt} = x(1-x)\left(y(2I_p + G_p) + (1-y)(I_p)\right) \\ \frac{dy}{dt} = y(1-y)\left(x(-C_N - C_T + G_c) + (1-x)(-C_N)\right) \end{cases} \tag{4.5}$$

Otherwise written as

$$\begin{cases} F(x) = \frac{dx}{dt} = x(1-x)\left(my + I_p\right) \\ G(y) = \frac{dy}{dt} = y(1-y)\left(nx - C_N\right) \end{cases} \tag{4.6}$$

where

$$\begin{cases} m = I_p + G_p \\ n = -C_T + G_c \end{cases} \tag{4.7}$$

By setting this system equal to zero, we find 5 fixed points, the trivial ones

$$(0,0), (1,0), (0,1), (1,1)$$

and the internal fixed point

$$(x^*, y^*) \text{ where } x^* = \frac{C_N}{n}, y^* = \frac{-I_p}{m}$$

Next, we analyze the stability of each equilibrium point. The Jacobian matrix provides information about the local behaviour of a system near its equilibrium points. By computing the eigenvalues of the Jacobian at each equilibrium point, we can determine whether the equilibrium point is unstable, a saddle or ESS. Evolutionary stable strategy (ESS) refers to a strategy that, if adopted by a population, cannot be easily replaced by any alternative strategy due to its higher fitness or payoff (Maynard Smith, 1972). The stability theorem of differential equations tells us that $F'(z) < 0$ at the point of evolutionarily stable strategy.

$$\begin{cases} F'(x) = (1-2x)\left(my + I_p\right) \\ G'(y) = (1-2y)\left(nx - C_N\right) \end{cases} \tag{4.8}$$

When the determinant of the Jacobian is positive, and the trace of the Jacobian is negative, the equilibrium point is the evolutionary stable point of the system. The Jacobian is given by:

$$J(x,y) = \begin{bmatrix} (1-2x)(I_p + my) & mx(1-x) \\ ny(1-y) & (1-2y)(-C_N + nx) \end{bmatrix} \tag{4.9}$$

Table 4.2 gives the equilibrium points and their corresponding eigenvalues, determinant and trace. These values provide insights into the stability characteristics of each equilibrium point, which is essential for understanding the dynamics of the system.

Equilibrium point	Eigenvalues	Determinant	Trace
$(0,0)$	$I_p, -C_N$	-$I_p C_N$	$I_p - C_N$
$(0,1)$	$I_p + m, C_N$	$(I_p + m)C_N$	$I_p + m + C_N$
$(1,0)$	$-I_p, -C_N + n$	$-I_p(-C_N + n)$	$-I_p - C_N + n$
$(1,1)$	$-I_p - m, C_N - n$	$(-I_p - m)(C_N - n)$	$-I_p - m + C_N - n$
(x^*, y^*)	$\pm\sqrt{mx^*(1-x^*)ny^*(1-y^*)}$	$-x^*(1-x^*)my^*(1-y^*)n$	0

Table 4.2: Equilibrium points and their corresponding eigenvalues, determinant and trace

Next, we analyse the stability of each equilibrium point. For $(x,y) = (0,0)$ we find

$$J(0,0) = \begin{bmatrix} I_p & 0 \\ 0 & -C_N \end{bmatrix} \tag{4.10}$$

This equilibrium point is ESS when $I_p < 0$ and $C_N > 0$. Note that this would mean that the green image for the producer is negative when choosing the True Price strategy and positive when choosing the normal price strategy. This would reflect a market environment where being green is not valued, possibly due to scepticism or lack of consumer interest.

For $(x, y) = (0, 1)$ we find

$$J(0,1) = \begin{bmatrix} I_p + m & 0 \\ 0 & C_N \end{bmatrix} \tag{4.11}$$

This equilibrium point is ESS when $I_p + m < 0$ and $C_N < 0$. This would mean that the cost of a product is negative, which is not representative of real life. Hence, we don't consider the stability of this point further.

For $(x, y) = (1, 0)$ we find

$$J(1,0) = \begin{bmatrix} -I_p & 0 \\ 0 & -C_N + n \end{bmatrix} \tag{4.12}$$

This equilibrium point is ESS when $I_p > 0$ and $-C_N + n < 0$. This represents a scenario where a green image is seen as desirable and where the green sensitivity for a consumer is smaller than the cost of the product plus the extra true price cost. This suggests that while there is a willingness to pay for green products, it does not extend beyond a certain cost threshold.

For $(x, y) = (1, 1)$ we find

$$J(1,1) = \begin{bmatrix} -I_p - m & 0 \\ 0 & C_N - n \end{bmatrix} \tag{4.13}$$

This equilibrium point is ESS when $-I_p - m < 0$ and $C_N - n < 0$. This represents a scenario where $-2I_p < G_p$ and $C_N + C_T < G_c$. So, the green sensitivity for a consumer is greater than the cost of the product plus the extra true price cost, suggesting a market where consumers are willing to pay a premium for green products driven by a high valuation of sustainability.

For $(x, y) = (x^*, y^*)$ we find

$$J(x^*, y^*) = \begin{bmatrix} 0 & mx^*(1 - x^*) \\ ny^*(1 - y^*) & 0 \end{bmatrix} \tag{4.14}$$

When $mn < 0$, the determinant of the Jacobian matrix is greater than 0, while its trace is always equal to 0. At this point, there are no real eigenvalues, and the point is neutrally stable.

We establish that the system is a conservative Hamiltonian system, meaning there's a constant of motion. This property can reveal the system's inherent stability and predictability over time, showing that despite changes, there's an underlying conservation principle at play.

$$\frac{dy}{dx} = \frac{y(1 - y)\,(nx - C_N)}{x(1 - x)\left(my + I_p\right)}$$

such that

$$\int \frac{nx - C_N}{x(1 - x)} dx = \int \frac{my + I_p}{y(1 - y)} dy.$$

Given $0 < x < 1$ and $0 < y < 1$, the equation can be integrated on both sides. Accordingly, we have

$$\int \frac{nx - C_N}{x(1-x)} dx = (-n + C_N)\ln(1-x) + (-C_N)\ln(x) + C_1,$$
$$\int \frac{my + I_p}{y(1-y)} dy = \left(-m - I_p\right)\ln(1-y) + \left(I_p\right)\ln(y) + C_2.$$

In this way, we are able to identify the constant of motion

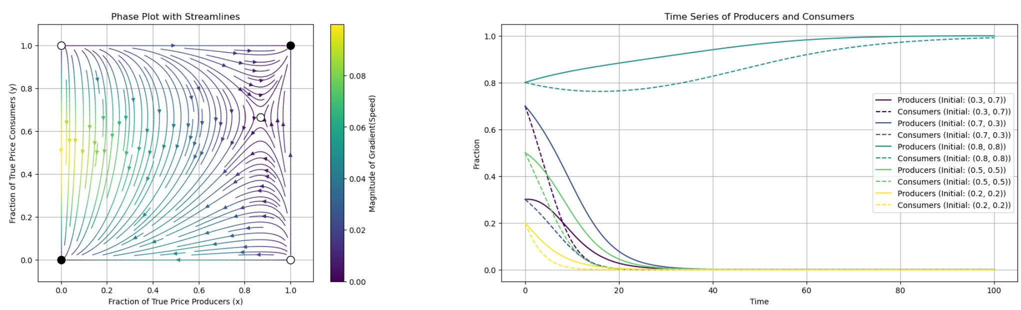
$$\begin{aligned} H(x,y) = &(-n + C_N)\ln(1-x) + (-C_N)\ln(x) \\ &- \left(-m - I_p\right)\ln(1-y) - \left(I_p\right)\ln(y) + C. \end{aligned}$$

H is a constant of motion since

$$\dot{H} = \frac{\partial H}{\partial x}\frac{dx}{dt} + \frac{\partial H}{\partial y}\frac{dy}{dt} = 0$$

This means that as the system evolves over time, the value of $H(x,y)$ remains unchanged, indicating a conservation property within the dynamics of the model. This also has implications for the dynamics in terms of the orbits. If we have a Hamiltonian system, under certain conditions, we have closed, periodic orbits: a system initialised with (x^*, y^*) in the interior of the square $0 < x, y < 1$ and not a fixed point will display closed, periodic orbits.

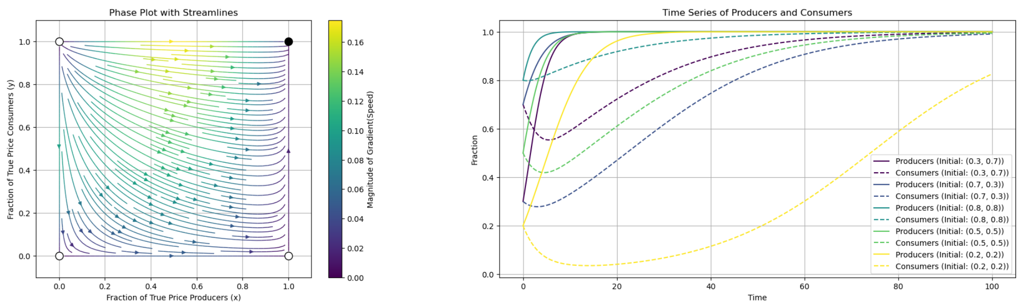
To illustrate various properties of the theoretical analysis, we look at numerical examples to simulate various outcomes True Pricing could have.



(a) **(b)**

Figure 4.1: The replicator system shows bistable dynamics. Figure 4.1a provides the phase portrait, showing two stable points (0,0) and (1,1). Figure 4.1b shows the temporal evolution of the frequency of strategies under various initial conditions. Parameter values are $I_p = -0.2, G_p = 0.5, C_N = 0.4, C_T = 0.04, G_c = 0.5$

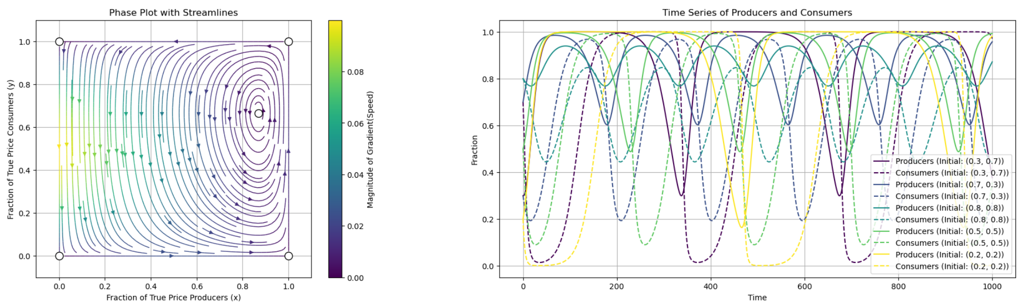
Figure 4.1 represents a scenario with bistable dynamics. Here, the points (0,0) and (1,1) are both stable and the interior (x^*, y^*) is a saddle. By looking at the trajectories over time, we can see that it depends on the initial conditions for which the frequency of consumers and producers either reaches 1 or 0 over time. We can see that for an initial proportion of 0.8 of True Price producers and 0.8 or True Price consumers, the frequencies both tend to 1. In contrast, for other initial proportions such as (0.7, 0.3), we see that the frequencies both tend to be zero. In these scenarios, the green image is negative, and the condition $-2I_p < G_p$ implies that even though the producer has a negative green image, the producer's green sensitivity is greater than the negative image.



(a) **(b)**

Figure 4.2: The replicator system shows that an ideal state is achievable. Figure 4.2a provides the phase portrait, showing all trajectories converge to the stable point (1,1), indicating that all producers engage in True Pricing and all consumers buy True Priced products. Figure 4.2b shows the temporal evolution of the frequency of strategies under various initial conditions. Parameter values are $I_p = 0.2, G_p = 0.3, C_N = 0.4, C_T = 0.04, G_c = 0.5$

Figure 4.2 illustrates an ideal scenario where all trajectories converge to (1,1), indicating that all producers engage in True Pricing and all consumers purchase True Price products. Here, (0,0) is no longer stable as the green image is positive.

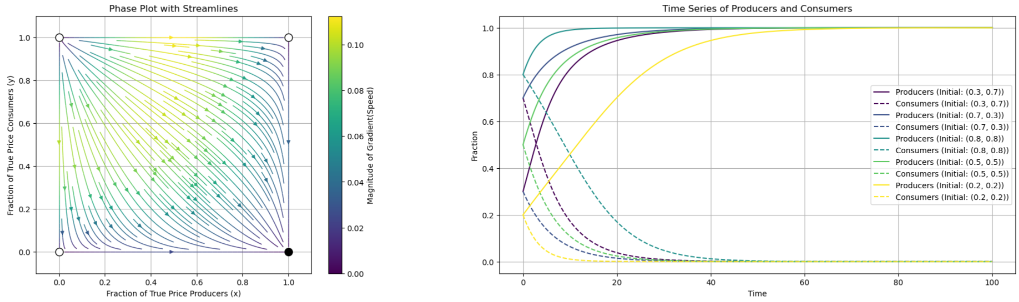


(a) **(b)**

Figure 4.3: The replicator system shows unstable dynamics. Figure 4.3a provides the phase portrait, where the interior equilibrium at (x^*, y^*) represents a centre. Figure 4.3b shows the temporal evolution of the frequency of strategies under various initial conditions, showing persistent oscillations. Parameter values are $I_p = 0.1, G_p = -0.25, C_N = 0.4, C_T = 0.04, G_c = 0.5$

Figure 4.3 shows unstable dynamics in all equilibrium points. The behaviour near the centre suggests that the strategies oscillate without stabilizing, indicating that neither strategy becomes dominant or extinct. A negative green sensitivity for producers suggests that producers are less inclined to adopt green practices as they do not have a strategic advantage, even though we have a positive green sensitivity for consumers. Overall, this model could represent a market where environmental consciousness is important to consumers but where producers are somewhat resistant to fully committing to green practices. This tension creates a cyclic pattern where green practices by producers and the purchasing behaviours of consumers ebb and flow.

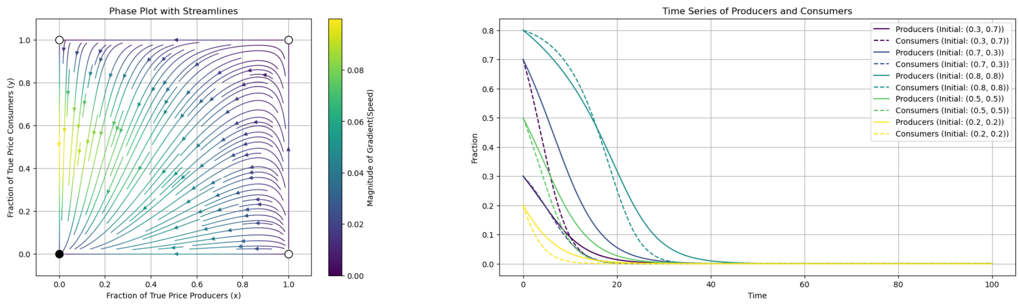
Figure 4.4 shows the equilibrium point (1,0) being stable. Regardless of the initial proportions, all producers will use true pricing, and all consumers will purchase normal-priced products. This is due to the fact that the willingness to purchase a product because of its green value is bounded by the costs of the product. While the producers have made a shift towards environmental responsibility, the consumers prioritize cost over environmental impact within the given parameter range. This



(a) **(b)**

Figure 4.4: The replicator system shows stable dynamics in the point (1,0) as seen in Figure 4.4a. Figure 4.4b shows the temporal evolution of the frequency of strategies under various initial conditions. All producers, over time, adopt the True Pricing strategy, but all consumers, over time, buy normal-priced products. Parameter values are $I_p = 0.1, G_p = 0.25, C_N = 0.4, C_T = 0.04, G_c = 0.3$

scenario could be indicative of a transitional phase in consumer behaviour, where despite the market offering more environmentally accountable products, consumer habits have not yet fully adapted to this new norm. This could suggest the need for more consumer education, stronger incentives, or policy interventions to close the gap between environmentally responsible production and consumption.



(a) **(b)**

Figure 4.5: The replicator system shows stable dynamics in the point (0,0) as seen in Figure 4.5a. Figure 4.5b shows the temporal evolution of the frequency of strategies under various initial conditions. All producers, over time, adopt a normal pricing strategy, and all consumers, over time, buy normal-priced products. Parameter values are $I_p = -0.2, G_p = 0.35, C_N = 0.4, C_T = 0.04, G_c = 0.5$

Figure 4.5 shows a scenario where there is no possibility for the success of True Pricing as all producers end up using normal pricing, and all consumers purchase normal-priced products, regardless of the initial conditions. This represents a scenario where having a green image is not valued for producers and where the green sensitivity of a producer does not outweigh this.

As applied in this analysis, the evolutionary game theory framework offers valuable insights into the dynamics of True Pricing adoption among producers and consumers. The results demonstrate how green sensitivity and pricing strategies influence market behaviour, revealing scenarios where True Pricing can achieve widespread adoption, face resistance, or result in cyclical adoption patterns. Key findings highlight the conditions under which True Pricing is sustainable and emphasize the importance of balancing short-term costs with long-term environmental benefits. These insights form a foundation for the subsequent development of a heterogeneous agent-based model (ABM), which will incorporate more detailed individual decision-making processes and social network influences to explore the complexities of True Pricing implementation further.

4.3. Agent-Based Model

This section outlines the agent-based modelling (ABM) approach used to explore consumer behaviour and the adoption of True Price products. The methodology is structured into two main parts: model conceptualisation and model implementation. Model conceptualisation involves defining the core entities, attributes, and decision-making processes using the Consumat framework. Model implementation focuses on the technical aspects of building and executing the simulation, including coding the model and integrating various submodels.

4.3.1. Model Conceptualisation

Overview

The model is designed to simulate consumer behaviour in the context of product choices, mainly focusing on the adoption of True Price (TP) products. Built upon the Consumat framework, this model explores whether True Pricing can be widely accepted by consumers and act as a catalyst for sustainable behaviour. The Consumat framework integrates various cognitive and social processes to model how consumers make decisions under different conditions, allowing for a comprehensive analysis of the factors influencing consumer choices.

The model's primary purpose is to understand the dynamics and potential of TP implementation to drive positive tipping points towards sustainability. It examines how factors such as financial considerations, social influences, and personal satisfaction impact consumer decision-making processes. Additionally, the model investigates the role of social networks in shaping consumer choices, highlighting the impact of peer behaviour and social norms on the adoption of TP products. Agents form social networks that influence their behaviour, with network structures imposed by the model. These social networks play a critical role in shaping consumer decisions, ensuring that consumer behaviour is influenced not only by individual preferences and constraints but also by the social dynamics within their network.

Entities and Attributes

The primary entities in the model are Consumer Agents and Products.

Consumer agents represent heterogeneous individuals within the model, each characterized by attributes influencing their decision-making processes. These include a budget to represent the agent's financial means, job stability as a measure of economic security and preferences that indicate the agent's leanings towards sustainability and conformity. Consumer agents are assigned weights representing the relative importance they place on financial, social, and personal (sustainability) values when making decisions. These weights, distinct from preferences, play a crucial role in shaping consumer behaviour. Preferences indicate an agent's inclination towards specific attributes or behaviours, such as sustainability or conformity. In contrast, weights determine how much influence financial, social, and personal factors have on the decision-making process. Thus, an agent's final choice is not solely driven by their preferences but also by the relative importance they assign to different values. The choice of an initial product marks the beginning of the agent's interaction with the marketplace. The combination of these attributes plays a critical role in how the agent responds to product offerings and social cues throughout the simulation.

Products available for purchase are characterized by their normal price, which is the standard price of the product. The True Price increase percentage indicates the percentage increase in price when the product is considered a True Price product to account for the integration of social and environmental costs. Each product also has a green score, measuring its environmental sustainability and a remediation level, indicating the extent to which the product contributes to addressing environmental or social issues. This also relates to the transparency of how the additional costs might be allocated, whether for off-setting environmental impacts or reinvested into the supply chain, for example.

Products are also heterogeneous in their prices and sustainability characteristics. The normal price is calculated using a log-normal distribution, ensuring that the price falls within the specified range. The green score and remediation level are assigned using uniform random distributions. When a product is classified as a True Price product, the price increase percentage is determined by the product's green score, with the increase being higher for products with lower green scores.

Decision-Making and Adaptation

At the core of the agent's decision-making lies the assessment of satisfaction and uncertainty across three key areas: financial, social, and personal (sustainability). To distinguish between these terms, satisfaction is conceptualized as the degree to which an agent feels content with their product choice, while uncertainty refers to the agent's confidence in the correctness of their decision.

Financial considerations involve evaluating the cost of products in relation to the agent's budget and the influence of economic conditions like inflation and job stability on their financial well-being. Financial satisfaction means that the agent feels content with the purchase because the cost fits comfortably within their budget and does not cause financial strain. This satisfaction reflects a state of financial comfort and ease in the decision.

$$F_{\text{satisfaction}} = \begin{cases} 1 - \frac{(p_c/c_b)^2}{1+(p_c/c_b)^2} & \text{if } p_c \leq c_b \\ \frac{1}{(p_c/c_b)^2} & \text{if } p_c > c_b \end{cases} \tag{4.15}$$

where p_c is the product cost and c_b is the consumer's budget.

In contrast, financial uncertainty pertains to the agent's confidence in their overall economic stability and resilience. This uncertainty is influenced by factors such as how much of the budget is spent, job security, and inflation rates. High financial uncertainty indicates that the agent feels less secure and more doubtful about their financial future, potentially fearing unforeseen expenses or economic downturns

$$F_{\text{uncertainty}} = \frac{(p_c/c_b)(1 + (1 - c_j)) + \left(\frac{p_i}{100}\right)(1 + (1 - c_j))}{2} \tag{4.16}$$

where c_j is the job stability factor and p_i is the inflation percentage.

Social influences capture the agent's desire for conformity and acceptance within their peer group. Social satisfaction measures how content the agent is with their product choice based on the similarity to the choices of their neighbours. Higher social satisfaction indicates greater alignment with peer choices, leading to a sense of belonging and acceptance. This is derived from the proportion of neighbours who have made similar product choices, with diminishing returns as conformity increases.

$$S_{\text{satisfaction}} = \sqrt{c_{pc} \cdot \frac{n_s}{n}} \tag{4.17}$$

where c_{pc} is the preference for conformity, n_s is the number of neighbours with similar product choices, and n is the total number of neighbours.

Social uncertainty is affected by the consistency with which neighbours adopt True Price products. High social uncertainty indicates that the agent is unsure about their decision because of inconsistent adoption of True Price products among neighbours, making it difficult to predict social acceptance.

$$S_{\text{uncertainty}} = 1 - \frac{n_p}{n_t} \tag{4.18}$$

where n_p is the number of neighbours who used True Price products in the previous step, and n_t is the total number of neighbours who have ever used True Price products.

Personal values are centred around the agent's sustainability goals. Personal satisfaction and uncertainty in this context are influenced by the environmental attributes and perceived sustainability of the products.s. Personal satisfaction measures how content the agent is with their product choice based on its environmental attributes. This satisfaction increases when the product aligns with the agent's sustainability preferences, indicating that the product has desirable environmental benefits. The satisfaction is modelled by the equation:

$$P_{\text{satisfaction}} = c_{ps} \cdot p_g \tag{4.19}$$

where c_{ps} represents the agent's preference for sustainability, and p_g is the green score of the product. A higher p_g (green score) indicates better environmental attributes, thus increasing the overall satisfaction for agents who prioritize sustainability.

On the other hand, personal uncertainty evaluates the agent's confidence in their decision based on the product's ability to meet environmental standards. This uncertainty reflects the agent's doubts about whether the product truly adheres to the claimed sustainability attributes. High uncertainty indicates a lack of confidence in the product's environmental claims, which can be influenced by factors such as the perceived reliability of the product's green credentials. This is represented by the equation:

$$P_{\text{uncertainty}} = 1 - (p_r \cdot c_{ps}) \tag{4.20}$$

where p_r is the remediation level of the product, indicating the extent to which negative environmental and social impacts are mitigated.

The consumer's overall satisfaction and uncertainty are determined by integrating their financial, social, and personal assessments using a weighted average. Total satisfaction is calculated by combining financial, social and personal satisfaction with their respective weights:

$$\text{Total Satisfaction} = \frac{w_{\text{financial}} \cdot F_{\text{satisfaction}} + w_{\text{social}} \cdot S_{\text{satisfaction}} + w_{\text{personal}} \cdot P_{\text{satisfaction}}}{w_{\text{financial}} + w_{\text{social}} + w_{\text{personal}}} \tag{4.21}$$

Similarly, total uncertainty is computed by combining financial, social and personal uncertainty using the same weights:

$$\text{Total Uncertainty} = \frac{w_{\text{financial}} \cdot F_{\text{uncertainty}} + w_{\text{social}} \cdot S_{\text{uncertainty}} + w_{\text{personal}} \cdot P_{\text{uncertainty}}}{w_{\text{financial}} + w_{\text{social}} + w_{\text{personal}}} \tag{4.22}$$

The resulting scores provide a comprehensive representation of the consumer's overall satisfaction and uncertainty, which guides their decision-making processes.

Based on these satisfaction and uncertainty levels, the Consumer Agent employs one of four strategies for making decisions: repetition, imitation, deliberation, or social comparison.

Repetition is the strategy of choice when the agent is content with their current product and feels certain about their decision, showing a preference for maintaining their current choice. This strategy emphasizes stability in consumer behaviour, reflecting a reluctance to change when current needs are met satisfactorily. The process is straightforward: if the agent has a previously chosen product that still aligns with their preferences and values, they will continue to choose this product. If the agent does not have a previous product, they will select a new product at random from the available options, ensuring that the agent always has a product to use.

Imitation is adopted when the agent is generally satisfied with their product choice but faces notable uncertainty regarding their decision. This situation arises when the agent feels positive about the product itself but lacks confidence in the decision-making process. In such cases, the agent turns to their social network, replicating the choices observed in their peers to navigate this uncertainty. In the imitation strategy, a consumer agent looks to its social network to see which products are being chosen by its neighbours. This approach is particularly used when the agent is uncertain about which product to choose, leading it to mimic the product choices observed within its social circle. The process counts each neighbour's last purchased product, distinguishing between True Price and non-True Price items. If one product or a category of products is more frequently chosen, the agent will follow this popular choice. If no single option stands out because of equal preferences or a balanced split between True Price and non-True Price products, the agent will randomly select from the most commonly chosen products. Alternatively, if there is a clear majority of one product type, the agent will lean towards that product type. This method enables the agent to navigate uncertainty by adopting the prevailing choices within its social network.

Deliberation is exercised by agents who are not satisfied with their current product but have a clear understanding of their needs, prompting a detailed analysis of available products. This strategy involves a thorough evaluation of products based on financial and personal criteria, excluding social considerations due to the agent's certainty in their decision-making process. Agents systematically compare product attributes, such as price and environmental impact, to identify the option that best meets their individual requirements. The exclusion of social influence underscores the agent's reliance on objective assessments over collective preferences, ensuring decisions are based on personal values and practical considerations. Through deliberation, agents actively seek to optimize their satisfaction by choosing products that best align with their financial capabilities and environmental or ethical standards. This approach ensures that the agent selects a product that better aligns with their needs and expectations, driven by a desire to improve their satisfaction levels while maintaining confidence in their decision-making process.

Social Comparison is used when agents find themselves both dissatisfied and uncertain, prompting them to look at the choices of similar others for guidance. In this strategy, consumer agents examine the choices of neighbours with similar financial situations and sustainability preferences. This involves identifying peers who closely match the agent's characteristics and observing the most frequently chosen products among this group. If a clear preference emerges, the agent adopts this product. If there is no single dominant choice, the agent may choose among the equally popular options or, if no clear preference is evident, consider all available products. This method allows agents to make informed decisions by leveraging insights from peers with comparable priorities.

With these strategies, the Consumer Agent updates its product selections based on changes in personal circumstances and the broader social and economic environment. This adaptive decision-making approach reflects the complexity of consumer behaviour, particularly in the context of choosing True Price products. The simulation, through these detailed behavioural models, provides insights into how individual preferences, financial constraints, and social network influences interact to shape sustainable purchasing decisions.

Observation and Emergent Properties

Key emergent properties of the model include the adoption rate of True Price products, changes in decision modes, and the average satisfaction and uncertainty levels of the population of agents. These outcomes arise from the individual interactions and adaptation mechanisms embedded within the model.

The adoption rate of True Price products is a crucial indicator of the True Price campaign's effectiveness in consumer acceptance. This rate is calculated by tracking the proportion of agents who choose True Price products over time, reflecting the success of True Price implementation.

Average satisfaction and uncertainty levels provide insights into the overall well-being and confidence of the agents. Financial, social, and personal satisfaction levels are monitored, along with their corresponding uncertainties. These metrics help in understanding how different factors influence consumer contentment and decision-making stability. By analyzing these emergent properties, the model offers a comprehensive view of the interplay between individual preferences, social influences, and economic conditions in shaping sustainable consumer behaviours.

4.3.2. Model Implementation

Implementation details?

The model is implemented using the Mesa framework, which facilitates agent-based modelling in Python. The core components include the `ConsumatModel` class, representing the simulation environment, and the `ConsumerAgent` class, defining the behaviour of individual agents, as well as the `Product` characterizing the products available for consumers to buy. Key libraries used include `NetworkX` for network operations, `NumPy` for numerical computations, and `pandas` for data handling.

Input Data

Using publicly available survey data is a widely adopted method for initializing or validating models, particularly in studies of economic and social behaviour (Steinbacher et al., 2021).

The first dataset utilized in this study is from the European Social Survey (ESS). Specifically, the ESS8 integrated file, edition 2.3, with data collected from September 1, 2016, to January 31, 2017, was used (European Social Survey European Research Infrastructure (ESS ERIC), 2023). The ESS is a large-scale survey conducted across multiple European countries aimed at understanding changes in public attitudes and values over time (European Social Survey European Research Infrastructure (ESS ERIC), 2016). Funded by the participating countries, the survey involves random sampling and face-to-face interviews with a minimum response rate requirement. In its eighth round, the survey covers 23 countries and includes questions on various topics, such as attitudes towards climate change and welfare, providing valuable insights into societal views and trends.

For the purposes of this study, data pertaining to the Netherlands (NL) was extracted from the dataset. This choice was made to focus the analysis on a specific geographical area, allowing for more targeted insights into societal attitudes and trends within this region.

To understand consumer behaviour towards sustainability, variables relevant to the adapted Consumat framework were selected. These variables include preferences towards sustainability, preferences towards conformity, and the weight agents place on social, personal, and financial values. Several variables fitting into the categories of social, financial, and personal (sustainability) values were identified, necessitating further methodology to select specific variables. In preparation for this, the data was filtered and pre-processed to include observations within specified valid ranges and converted to a suitable numeric format. Next, data normalization was performed to scale the selected variables to a range between 0 and 1, ensuring uniformity and comparability across variables, which is crucial for avoiding biases introduced by differences in the scales of the variables.

Principal Component Analysis (PCA) was employed to reduce dimensionality and identify the most significant variables. PCA transforms the original variables into a new set of orthogonal components, which are linear combinations of the original variables. The variables with the highest loadings on these components indicate their significant influence on the underlying structure of the data. To ensure the selection of diverse and non-redundant variables, one variable per principal component was chosen. This method helps maintain a comprehensive representation of the data without overemphasizing similar information. Following Kaiser's criterion, components with eigenvalues greater than 1 were retained, ensuring that each selected component explains a meaningful amount of variance in the data.

Table 4.3 below summarises the variables selected through PCA, providing their descriptions and corresponding agent attributes used in the agent-based model.

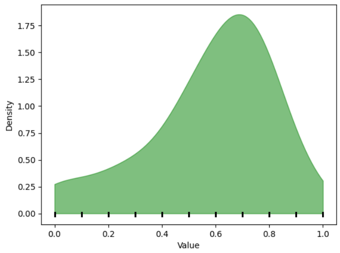
Variable	Description	Agent Attribute	Range
ccrdprs	Degree of personal responsibility to reduce climate change	Weight of sustainability	(0, 1): Low degree, High degree
impenv	Importance of caring for nature and the environment	Preference for sustainability	(0, 1): Not important, Very important
ppltrust	Most people can be trusted or you can't be too careful	Weight of social value	(0, 1): Mistrusting, Trusting
ipfrule	Importance of doing what is told and following rules	Preference for conformity	(0, 1): Anti-conformist, Conformist
imprich	Importance of being rich, having money, and expensive things	Weight of financial value	(0, 1): Not important, Important
lknemny	Likelihood of not having enough money over the next 12 months for household necessities	Job stability	(0, 1): Likely, Not likely

Table 4.3: Selected Variables for Agent-Based Model

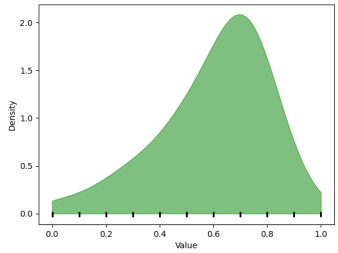
To visualise the attributes of the agents, Kernel Density Estimation (KDE) is employed as a statistical method to estimate the probability density function of the selected variables. KDE is chosen for its non-parametric nature, which does not make assumptions about the underlying distribution of the data, making it suitable for capturing complex and potentially unknown patterns.

Utilizing the grid search method with Leave-One-Out cross-validation, the optimal bandwidth for KDE is determined. This bandwidth parameter influences the smoothness of the estimated probability density function and is selected to balance bias and variance in the estimation process. KDE is then applied using a Gaussian kernel, chosen for its simplicity and effectiveness in capturing the underlying distribution of the data. The optimal bandwidth determined previously is used to control the smoothness of the KDE estimate. The probability density function (PDF) obtained from KDE is visualized, providing insights into the distribution of the variables of interest and facilitating further analysis and interpretation of the data.

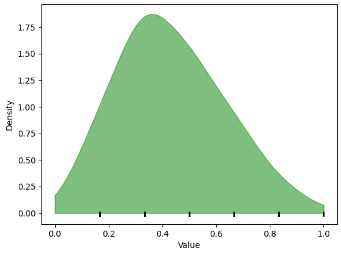
The KDE plots for the six selected variables in Figure 4.6 provide insights into the characteristics of consumer agents within the model, reflecting the diverse considerations that shape consumer behaviour in the Dutch population. The distribution of sustainability weight is unimodal and right-skewed, indicating that many agents place a high weight on sustainability, meaning a significant portion of the population feels a strong personal responsibility to reduce climate change. The distribution of the social weight is unimodal with a slight right skew, showing that a large portion of the population tends to trust others. The financial weight is unimodal with a left skew, suggesting that fewer agents place high importance on being rich and having money. The preference for sustainability is strongly right-skewed, demonstrating that the majority of the population considers caring for nature and the environment very important. The preference for conformity is unimodal with a slight right skew, indicating a tendency towards conformity, although there is also a notable presence of agents with lower values who lean towards anti-conformism. The distribution for job stability is bimodal, with one significant peak near the higher values, indicating that a large number of agents are not worried about having enough money to cover necessities, reflecting high job stability. There is another peak suggesting that a notable portion of agents feel fairly secure about their job stability, while the tail extending from 0 towards 0.5 indicates that a smaller number of agents are more concerned about their financial means to cover costs.



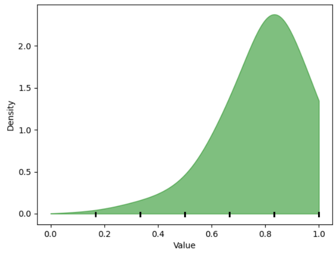
(a) Weight Sustainability



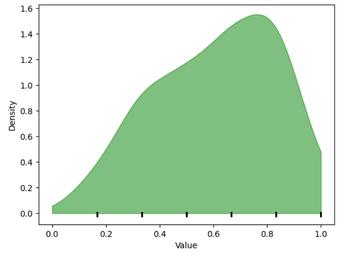
(b) Weight Social



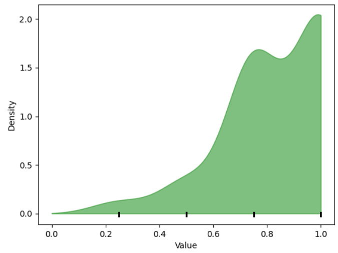
(c) Weight Financial



(d) Preference Sustainability



(e) Preference Conformity



(f) Job Stability

Figure 4.6: KDE distributions of agent attributes

Another critical aspect of consumers in ABM is their financial means of purchasing products. To this end, data from the Centraal Bureau voor de Statistiek (CBS) on the spendable income of Dutch households in 2022 was used. Figure 4.7 displays the spendable income of households, illustrating the purchasing power of the agents.

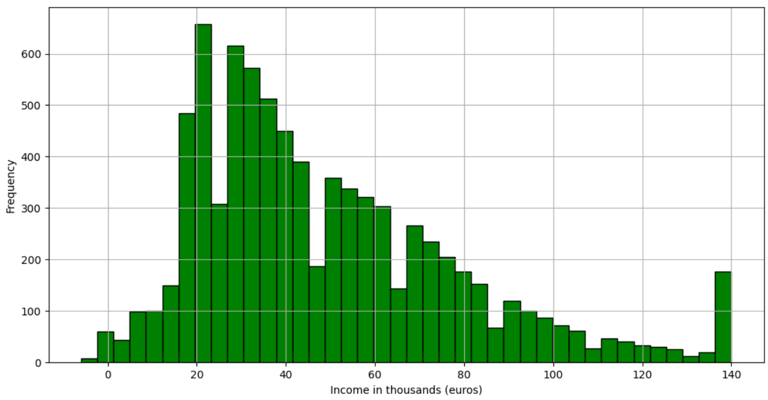


Figure 4.7: Spendable income distribution of the population of the Netherlands in 2022

Process Overview and Scheduling

The model operates through a structured sequence of steps designed to simulate consumer behaviour over time. At the start of the simulation, agents and products are initialized with specific attributes, as outlined previously.

At each time step, agents are activated to update their state and make decisions. They assess their flowchart.png

Figure 4.8: Flow chart of the model will be included here

satisfaction and uncertainty levels based on their current product choices. Depending on their satisfaction and uncertainty, agents determine their decision mode based on the previously outlined 4 decision modes.

During each time step, agents interact with their neighbors in the social network, influencing and being influenced by the choices of others. This social interaction plays a crucial role in the imitation and social comparison strategies, affecting how product choices spread through the network. After all agents have made their decisions, the model updates the state of the system, calculating new satisfaction and uncertainty levels, adjusting product adoption rates, and potentially introducing new products such as True Price items.

Throughout the simulation, data on key metrics such as the adoption rate of True Price products, decision mode changes, and average satisfaction and uncertainty levels are collected for analysis. The process repeats for the specified number of time steps, allowing the model to capture the evolution of consumer behaviour and the dynamics of product adoption over time. This structured scheduling of interactions and decision-making processes ensures a comprehensive simulation of consumer behaviour and the factors influencing the adoption of sustainable products.

Algorithm 1 Agent-based model for True Price product adoption

```
Require: parameter set {budget, preference_sustainability, preference_conformity, stability_job
initial_product, weight_financial, weight_social, weight_personal, TP_percentage,
satisfaction_threshold, uncertainty_threshold, inflation_rate}
Initialize all agents with a unique ID and model reference.
for each agent do
    Assign initial budget, preferences, stability, and product.
    Determine initial satisfaction and uncertainty.
    Initialize True Price usage status.
end for
for each simulation step do
    for each agent do
        Update True Price usage status.
        Calculate satisfaction and uncertainty for the current product.
        Determine if the agent is satisfied and/or uncertain.
        if satisfied and not uncertain then
            Perform repeat action.
        else if satisfied and uncertain then
            Perform imitation action.
        else if not satisfied and not uncertain then
            Perform deliberation action.
        else
            Perform social comparison action.
        end if
        Update the chosen product for the next step.
    end for
    Collect data for the current step.
    if True Price not introduced and conditions met then
        Introduce True Price products.
    end if
    Calculate True Price adoption rate.
end for=0
```

Sub-models

In the proposed model, several sub-models are implemented to capture the diverse dynamics influencing consumer behaviour and product adoption. These sub-models build upon each other, progressively increasing the complexity and realism of the simulations. The key sub-models are as follows:

Sub-model 1: Heterogeneous Model The heterogeneous agent model serves as the baseline ABM that introduces heterogeneity among agents, distinguishing itself from the initial homogeneity assumed in the evolutionary game theory model. This sub-model is the second step in our approach, building upon the more simplistic homogeneous model to reflect the diversity found in real-world consumer populations. In this heterogeneous agent model, agents are assigned distinct attributes, including financial budget, preferences for sustainability, conformity, and job stability.

The decision-making process is an intermediate step towards a more complex network-based model. At this stage, agents do not yet have social networks; hence, social comparison is not a strategy used. Instead, the agent's decision-making process is structured around repetition, imitation, and deliberation. Specifically, agents repeat their previous actions if they are satisfied and not uncertain, imitate others if they are satisfied but uncertain, deliberate if they are not satisfied but certain, and fall back to imitation if they are neither satisfied nor certain.

Imitation is chosen as a replacement for social comparison in this sub-model because it allows agents to incorporate social influence without the need for complex network structures. Imitation considers the aggregate behaviour of all agents, providing a straightforward way to model social influence in the absence of networks. This choice is methodologically significant as it facilitates the gradual introduction of complexity in the model. Deliberation and repetition are more individualistic strategies that do not account for social influence, making them unsuitable substitutes for social comparison.

The use of imitation instead of social comparison at this stage provides a foundational understanding of how agents adapt to the choices of others in a non-networked environment. This approach simplifies the social influence mechanism, making it easier to isolate and study the impacts of agent heterogeneity on decision-making. This iterative approach ensures a systematic and controlled exploration of consumer behaviour dynamics, progressing from homogeneity in evolutionary game theory to heterogeneity in the ABM and eventually incorporating network effects.

Sub-model 2: Dynamic Network Models In the proposed sub-model, dynamic network models are introduced to capture the complexity of social interactions among agents. This builds upon the heterogeneous agent model by incorporating network structures, allowing for more realistic simulations of consumer behaviour. Two sub-models are implemented under this category: one without homophily and one with homophily, influencing the presence and absence of social comparison.

Agents are placed on a network grid, and their decision-making processes are influenced by the behaviours of their neighbours. The network structures used can include various types, each representing different patterns of social connections:

- Watts-Strogatz Network: This model generates small-world networks characterized by high clustering and short path lengths, mimicking real-world social networks where individuals form tightly-knit groups with occasional long-distance connections. It allows the study of how local and global social influences impact consumer behaviour.
- Barabási-Albert Network: This model produces scale-free networks with a few highly connected nodes (hubs) and many nodes with fewer connections. It reflects the presence of influential individuals or entities in social networks and their role in spreading behaviours such as the adoption of True Price products.
- Random Regular Network: In this model, each agent has the same number of connections, creating a uniform structure. Although not realistic for social networks, it serves as a controlled baseline environment to analyze the effects of equal peer influence and to compare with more complex network structures.
- Holme-Kim Network: This network model extends the Barabási-Albert model by adding a clustering mechanism, creating networks with both scale-free properties and high clustering. It provides a more nuanced view of how tightly-knit communities with influential hubs affect consumer choices.

Sub-model 2.1: Standard Network Model Without Homophily In the network model without homophily, agents do not preferentially connect with similar agents, meaning there is no preference for agents to form connections based on shared attributes. This lack of preferential attachment ensures that social connections are formed randomly or uniformly. Consequently, social comparison is also excluded because it can be considered a type of homophily where agents compare their choices with similar peers. Instead, the agent's decision-making process includes repetition, imitation, and deliberation, without any bias towards connecting with or imitating similar agents.

Imitation is based on the choices of an agent's neighbours rather than the entire population. This shift introduces localized social influence, where agents are more likely to imitate the product choices of their immediate neighbours. The decision-making process is structured as follows: if agents are satisfied and not uncertain, they repeat their previous action; if they are satisfied but uncertain, they imitate their neighbours; if they are not satisfied but certain, they deliberate; and if they are neither satisfied nor certain, they imitate their neighbours again.

This setup allows for a gradual increase in model complexity. By focusing on localized interactions without homophily, the model can analyze how agents adapt to the behaviours of their direct neighbours, providing a baseline understanding of social dynamics in a networked environment.

Sub-model 2.2: Standard Network Model with Homophily-Based Social Comparison The next level of complexity introduces homophily through social comparison, where agents compare their choices with those of their peers but without preferential attachment in the network formation. In this model, agents still form connections randomly or uniformly, but they now use social comparison as a decision-making strategy. This means that agents look at the choices of their neighbours and adjust their behaviour based on the similarity of their neighbours' choices to their own preferences and attributes.

In this model, the decision-making process is structured as follows: agents repeat their previous action if they are satisfied and not uncertain, imitate their neighbours if they are satisfied but uncertain, deliberate if they are not satisfied but certain, and perform social comparison if they are neither satisfied nor certain.

To implement social comparison, agents assess their neighbours to identify those with similar attributes, using a comparison factor to determine similarity. The model allows for flexibility in defining which attributes to consider for similarity, specified in the configuration. These attributes could include budget, sustainability preferences, conformity preferences, job stability, or any other relevant factors. The degree of similarity is controlled by a parameter, often referred to as epsilon, which defines the acceptable range of difference between the agent and their neighbours for each attribute. For instance, if two agents have budgets within a specified percentage range of each other, they are considered similar in terms of budget. This flexible approach enables a detailed exploration of how different attributes influence social comparison.

By introducing social comparison without preferential attachment, the model adds a layer of complexity that allows for the study of how peer influence affects decision-making. This step is essential before further increasing complexity by incorporating preferential attachment, ensuring that each element of social behaviour can be isolated and analyzed. By varying parameters such as the comparison factor (epsilon) and the attributes considered for similarity, we can explore different degrees of social comparison and their impacts on agent behaviour.

Sub-model 3: Preferential attachment network model The preferential attachment network model incorporates a sophisticated mechanism for simulating social network formation. This model builds upon the previous submodels by integrating preferential attachment and attribute-based rewiring, reflecting the complex nature of real-world social connections.

Initially, the network structure is generated using one of several algorithms, including Watts-Strogatz, Barabási-Albert, Random Regular, and Holme-Kim networks. These algorithms provide a robust foundation by capturing essential properties such as clustering, short path lengths, and scale-free distributions.

To introduce homophily, an adaptive rewiring process is applied, where agents are more likely to form connections with similar others based on a specified attribute, such as preferences for sustainability, preferences for conformity, and budget. This approach aligns with well-documented principles in social network theory, which emphasize the tendency of individuals to associate with similar others.

In this model, each agent's position is dynamically updated through a similarity-driven rewiring process involving disconnection from first-order neighbours and the potential connection with second-order neighbours.

Initially, each agent evaluates its immediate neighbours and, based on a probability P from Talaga and Nowak, 2020, may sever an existing edge, given by the formula:

$$P = \frac{1}{1 + \left(\frac{\text{attribute\_difference}}{\beta}\right)^{\alpha}} \tag{4.23}$$

This formula is a sigmoidal function, which smoothly varies the probability based on attribute differences. Here, α and β are parameters influencing the shape and scale of the function. α serves as an exponent, amplifying or diminishing the impact of attribute differences. When α is high, the probability changes very quickly, meaning even small attribute differences can lead to a high probability of disconnection, making the network more sensitive to attribute differences. When α is low, the probability changes more gradually, meaning attribute differences have a less pronounced effect on the probability of disconnection. β acts as a scaling factor; a higher β normalizes the attribute differences, making them less impactful, whereas a lower β increases the sensitivity to attribute differences.

If a random number is greater than P, the edge between the node and the neighbour is removed. This ensures that edges are more likely to be removed when the attribute difference is large.

After potential disconnection, the agent considers its second-order neighbours for potential new connections based on the same probability formula. If second-order neighbours are identified, the connection probabilities are calculated for each and are then normalized to ensure they sum to 1. The new neighbour is selected based on these probabilities to ensure that while more similar neighbours (higher probabilities) are more likely to be chosen, there remains a chance for less similar neighbours to be selected. This reflects the stochastic nature of real-life social interactions and avoids overly deterministic network structures, allowing for more realistic and diverse network evolution. The edge is then added between the node and the new neighbour.

This rewiring process is inherently stochastic, with the actual addition or removal of edges determined by random events governed by the computed probabilities. The model maintains a constant expected mean degree by either randomly adding an edge if one is removed without replacement or establishing a new connection between two randomly selected nodes if an edge is added without a corresponding removal.

By integrating preferential attachment with similarity-based rewiring, the model captures the dual aspects of social influence and preferential attachment observed in real-world social networks. This setup provides a robust framework to study complex consumer behaviour dynamics, offering flexibility to explore various scenarios and their impacts on agent behaviour within networked environments.

In the Barabasi-Albert network, while hubs might lose some direct connections, they can regain new ones with similar second-order neighbours, preserving the scale-free nature but potentially shifting the composition of hubs to reflect attribute similarity. In the Holme-Kim network, the clustering nature is expected to be maintained, with clusters reorganizing around attribute similarity, thereby enhancing the homophily effect within clusters. For the Random Regular network, the uniform degree distribution is expected to be disrupted, leading to a more heterogeneous structure with new clusters forming based on attribute similarity. In the Watts-Strogatz network, high clustering is anticipated to be preserved but with an increase in path lengths, reducing the small-world properties while forming more homophilous groups.

4.4. Experimental Set-Up

4.4.1. Global Sensitivity Analysis (GSA)

Global Sensitivity Analysis (GSA) is a crucial statistical method utilized to understand the behaviour of complex computational models, particularly agent-based models (ABMs). In our research, GSA is essential for systematically examining how variations in network and model parameters affect model outcomes. This analysis helps identify the key parameters that drive model behaviours. By isolating and understanding the impact of each factor within our complex model, GSA addresses potential sources of uncertainty and provides a comprehensive view of the model's behaviour under various conditions.

Key Parameters and Measures

The key model parameters varied in our sensitivity analysis include the percentage of True Price products introduced to the market, satisfaction threshold, uncertainty threshold, minimum and maximumum price increase percentages of True Price products. As the complexity of the submodels increase, other key parameters are included in the analysis such as various network parameters and homophily parameters.

The key output measures analyzed are the adoption rate of TP products as well as the average satisfaction and uncertainty in each of the 3 areas of social, financial and personal (sustainability) needs.

Initialization of Global Sensitivity Analysis

The GSA was initialized with predefined parameters, each assigned a specific range as shown in Table 4.4. We employed the Saltelli sampling method to generate parameter sets for the analysis. To ensure a thorough exploration of the parameter space, the number of samples was set at a predetermined count of 256 per parameter. This sample size was chosen to balance the computational load and the accuracy of the results for the scope of this thesis.

Parameter	Description	Range	Sub-models
TP_percentage	Percentage of True Price products introduced	[0, 1]	All
satisfaction_threshold	Satisfaction Threshold	[0, 1]	All
uncertainty_threshold	Uncertainty Threshold	[0, 1]	All
min_increase_percentage	Minimum Price Increase Percentage for TP products	[1, 10]	All
max_increase_percentage	Maximum Price Increase Percentage for TP products	[11, 20]	All
k	Number of Neighbors in Watts-Strogatz Network	[2, 10]	2.1, 2.2, 3
p	Rewiring Probability for Watts-Strogatz and Holme-Kim Networks	[0, 1]	2.1, 2.2, 3
m	Number of edges to add for each new node in Barabasi-Albert and Holme-Kim Networks	[2, 10]	2.1, 2.2, 3
d	Degree of Each Node in Random Regular Network	[2, 10]	2.1, 2.2 & 3
epsilon	Threshold for Comparability in Social Comparison	[0, 1]	2.2, 3
alpha	Exponent parameter for homophily rewiring probability	[0, 10]	3
beta	Scale parameter for homophily rewiring probability	[0, 1]	3

Table 4.4: Input Parameters for Global Sensitivity Analysis

Analysis

The Sobol method, a widely recognized technique for conducting Global Sensitivity Analysis, was employed to analyze the collected data. This method calculates first-order and total-order sensitivity indices, providing insights into the influence of each parameter independently as well as in combination with others. Confidence intervals were included to assess the reliability of our findings.

For each output variable, first-order and total-order sensitivity indices are calculated and visualized. The visual representations included error bars for each index, which correspond to the confidence intervals, allowing us to assess the reliability of our findings. These sensitivity indices help in understanding the contribution of each parameter to the variance in the model outputs, offering a detailed picture of parameter impacts and interactions.

This comprehensive approach to sensitivity analysis ensures that we can robustly assess and interpret the effects of various parameters on our model, leading to more reliable and insightful conclusions.

4.4.2. True Price experiments

Conducting experiments is essential for simulating real-life intervention options to understand how different strategies can influence consumer behaviour and market dynamics. These experiments help identify effective methods for promoting sustainable practices, such as the adoption of True Price products. Two critical aspects emerge in this context: the percentage of True Price products introduced and the impact of network structures, mainly through the use of influencers. The introduction percentage is vital as it determines the initial market penetration of True Price products, which can significantly affect the tipping points and overall adoption rates. Network structures and influencers play a crucial role in social dynamics, as they can amplify the spread of behaviours and preferences through social comparison and imitation. By experimenting with these parameters, we can gain insights into the mechanisms that drive sustainable consumer behaviour and identify the conditions under which True Price products can achieve widespread adoption.

In the following experiments, sub-model 2.2 is utilised, with the social comparison attributes being budget, preference conformity, and preference sustainability. This model is chosen over sub-model three due to its balanced complexity and fewer assumptions. Sub-model 2.2 incorporates homophily, allowing for social comparison based on specific attributes without the added complexity of homophily-based network rewiring. This more straightforward approach provides a clear understanding of the direct effects of homophily and social comparison on consumer behaviour, making it easier to isolate and study the impacts of gradually introducing TP products.

Gradual introduction of True Price products

In this experiment, True Price products are integrated into the market incrementally over time, in contrast with the standard model, in which a pre-defined percentage of True Price products are introduced simultaneously at a specific step. The process begins by calculating the total number of TP products to be introduced based on a specified percentage of the overall product count. A certain rate of new TP products is introduced at each time step. These products are selected randomly from the existing non-TP products. This gradual introduction allows for observing how the market and consumer behaviours adapt over time as the availability of TP products increases.

Impact of Influencers in a network

In this experiment, the impact of influencers on the adoption of True Price products is examined. Influencers are identified based on their degree of connectivity within the network, and those with the highest number of connections are selected. These influencers are then designated to adopt True Price products. This intervention simulates influential agents consistently promoting True Price products. This setup aims to investigate how the presence and behaviour of influential agents affect the overall adoption rate of sustainable products within different network structures.

The experiment explicitly examines the Barabasi-Albert and Watts-Strogatz networks to focus on the impact of influencers. The Barabasi-Albert network, characterised by its scale-free structure with highly connected hubs, enables influencers to affect a large portion of the network due to their extensive connections, potentially accelerating the adoption rate of True Price products. In contrast, the Watts-Strogatz network is known for its small-world properties, featuring high clustering and short average path lengths. This network structure mimics real-world social networks where individuals form tightly-knit groups but also have a few long-distance connections that bridge different clusters. Influencers in the Watts-Strogatz network can effectively spread new behaviours within their local clusters while also having the potential to reach distant parts of the network through these bridging connections.

Examining these networks helps us understand how influential agents can impact consumer behaviour, offering insights into promoting sustainable behaviours in various social contexts. The Barabasi-Albert network highlights the importance of key influencers or hubs that can rapidly disseminate new practices through their extensive reach. Meanwhile, the Watts-Strogatz network underscores the role of local community leaders and the critical bridging ties that can facilitate widespread adoption through clustered yet globally connected groups. Together, these insights can inform strategies for effectively leveraging social networks to encourage the adoption of True Price products and other sustainable practices.

5 | Results

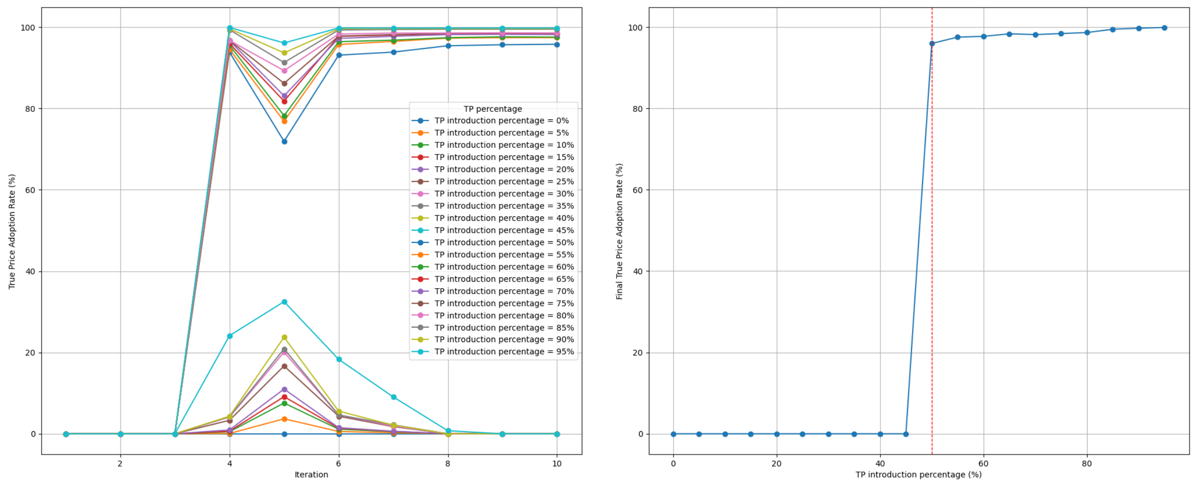
5.1. Evolutionary Game Theory

**Possibly move numerical examples here instead of in methodology **

5.2. Agent-Based Model

5.2.1. Submodel 1: Heterogeneous, no network

Figure 5.1 illustrates the True Price adoption rate for varying introduction percentages of True Price products. This example is initiated with satisfaction and uncertainty thresholds of 0.5, a product price range of 5 - 10 euros, where the minimum increase is 4% and the maximum increase is 10% when products are True Priced. The model considers 20 products, with an inflation rate of 3% and 1600 agents. A predefined percentage of True Price products is introduced in step 3.



(a) TP adoption over time

(b) TP adoption for varying TP introduction percentages

Figure 5.1: True price adoption amongst consumers for varying introduction percentages of True Price products in Submodel 1

In Figure 5.1a, initially, there is a significant spike in the adoption rate across all introduction percentages, indicating a strong initial impact when True Price products are first introduced. For introduction percentages above 50%, the adoption rates peak sharply and then experience a decline around time step 5. This decline is followed by a stabilization near 100%, suggesting a high and sustained adoption rate.

This stabilization reflects the tendency of agents to continue using True Price products once they are widely available, driven by their initial positive reception and possibly reinforced by imitation behaviour among satisfied agents.

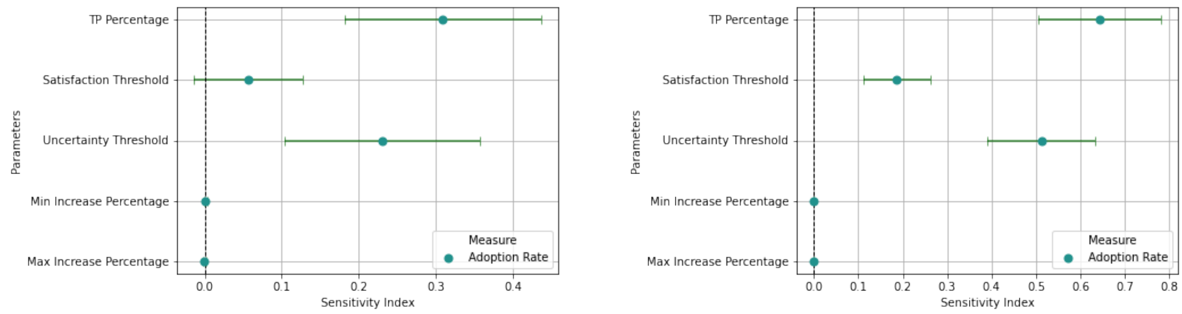
Conversely, for introduction percentages below 50%, the adoption rate initially spikes less dramatically. These lower percentages experience a gradual increase in adoption until iteration 5, coinciding with the period when higher introduction percentages show a decline. This inverse relationship can be attributed to the dynamics of agent decision-making in the absence of a critical mass. The lower initial adoption rates at lower introduction percentages might be due to a smaller influence base, where fewer agents adopting True Price products lead to less overall visibility and influence. However, as the system adjusts, agents may begin to adopt True Price products based on the slow but accumulating influence of early adopters. Eventually, the adoption rate for lower introduction percentages declines and stabilizes near 0%, indicating that a lower initial presence of True Price products struggles to maintain sustained adoption. This pattern underscores the importance of a critical mass of True Price products to achieve long-term adoption, as lower percentages do not create sufficient influence or visibility to sustain consumer interest over time.

Figure 5.1b reveals a sharp transition or tipping point in the adoption of True Price (TP) products. For TP introduction percentages below approximately 50%, the final adoption rate remains near zero, indicating minimal uptake due to insufficient influence or visibility. This suggests that when less than half of the products are TP, there is not enough critical mass to drive widespread adoption among agents. However, once the TP introduction percentage crosses the 50% threshold, there is a sudden and dramatic increase in the final adoption rate, quickly rising to nearly 100%. This signifies a positive tipping point where the market dynamics shift decisively in favour of TP product adoption. Beyond this threshold, the presence of TP products becomes sufficiently pervasive, making it more likely for agents to encounter and adopt these products, either through direct preference or imitation of other adopters. This finding highlights the importance of achieving substantial initial market penetration to ensure long-term sustainable behaviour change, as network effects and social influence mechanisms become strong enough to drive near-universal adoption when more than half of the available products are TP.

Global Sensitivity Analysis

In this section, we present the results of the Global Sensitivity Analysis (GSA) for the heterogeneous submodel without homophily. In this model, agents do not preferentially connect with similar agents, ensuring that social connections are formed randomly or uniformly. The agents' decision-making process includes repetition, imitation, and deliberation, without any bias towards connecting with or imitating similar agents. This setup allows for a gradual increase in model complexity and provides a baseline understanding of social dynamics in a networked environment.

The sensitivity analysis for the adoption rate, depicted in Figure 5.2, shows that the percentage of True Price products introduced is the most influential parameter, with positive first-order and total-order



(a) First Order Analysis of Adoption Rate

(b) Total Order Analysis of Adoption Rate

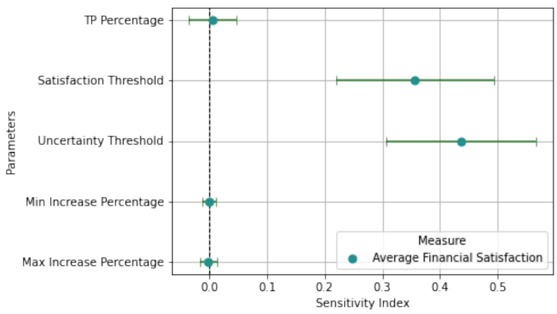
Figure 5.2: First and Total Order Sensitivity Analysis for Adoption Rate (Submodel 1: Heterogeneous, No Network)

sensitivity indices (Figures 5.2a and 5.2b). This suggests that an increase in the percentage of True Price products directly enhances the adoption rate and also interacts significantly with other parameters to amplify this effect. The uncertainty threshold also has a substantial positive impact, indicated by its significant first-order and total-order indices, highlighting its importance in both direct and interactive effects on the adoption rate. The satisfaction threshold, although positive, has a moderate impact, whereas the minimum and maximum increase percentages exhibit negligible influence, suggesting their effects are minimal and largely non-interactive.

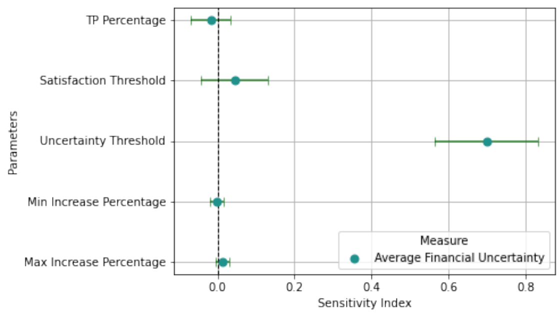
Financial satisfaction and uncertainty are most influenced by the uncertainty threshold parameter, with significant positive first-order and total-order sensitivity indices (Figures 5.3a, 5.4a, 5.3b, and 5.4b). The satisfaction threshold plays a moderate role in financial satisfaction and uncertainty, whereas the True Price product introduction percentage, minimum increase percentage, and maximum increase percentage have negligible influences on both financial satisfaction and uncertainty.

Social satisfaction and uncertainty are also most influenced by the uncertainty threshold parameter with strong first-order and total-order sensitivity indices (Figures 5.3c, 5.4c, 5.3d, and 5.4d). The True Price product introduction percentage exhibits a moderate influence on social satisfaction and uncertainty, with sensitivity indices suggesting both direct and interactive effects. The satisfaction threshold plays a moderate role, more so in social satisfaction than uncertainty. The minimum increase percentage and maximum increase percentage again have negligible effects, with their sensitivity indices indicating minimal and largely non-interactive influences.

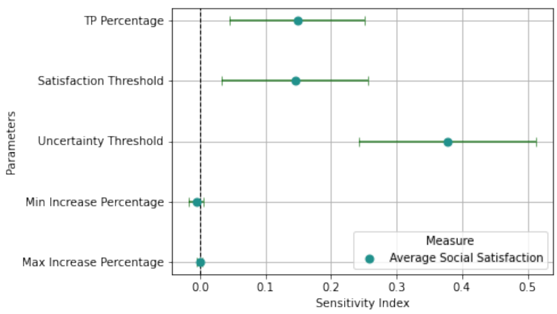
When it comes to personal uncertainty, the uncertainty threshold is once again the most influential parameter (Figures 5.3f and 5.4f). However, for personal satisfaction, the satisfaction threshold has the most influence, but the uncertainty threshold still also has a strong influence (Figures 5.3e and 5.4e). The True Price product introduction percentage shows a very minor influence on both personal satisfaction and uncertainty, with some interaction effects but minimal direct impact, while the minimum and maximum increase percentages have negligible effects on both measures, with sensitivity indices indicating no significant influences.



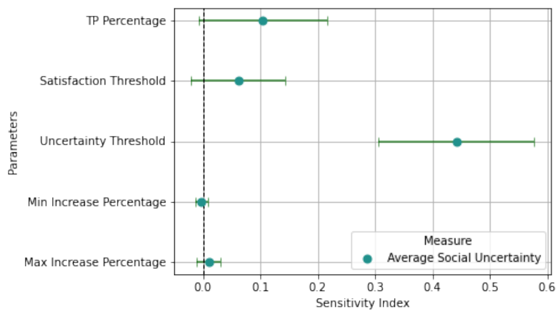
(a) First Order Analysis of Average Financial Satisfaction



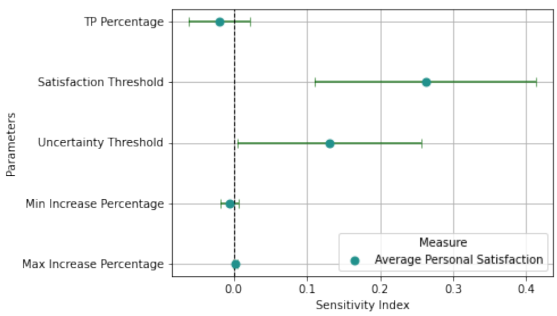
(b) First Order Analysis of Average Financial Uncertainty



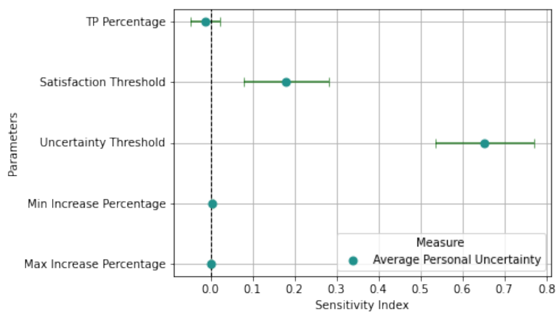
(c) First Order Analysis of Average Social Satisfaction



(d) First Order Analysis of Average Social Uncertainty

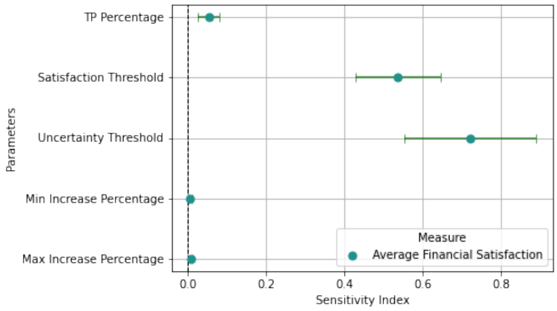


(e) First Order Analysis of Average Personal Satisfaction

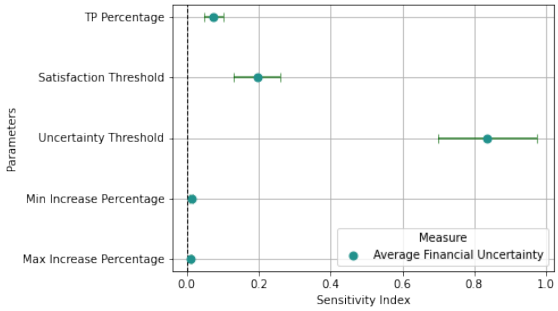


(f) First Order Analysis of Average Personal Uncertainty

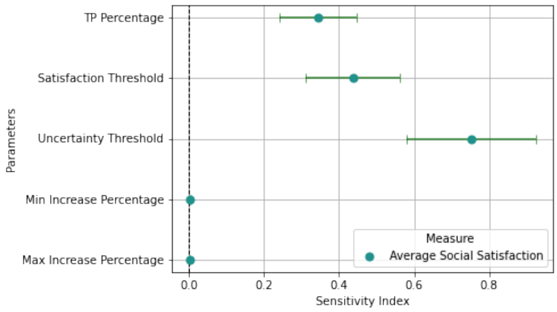
Figure 5.3: First Order Sensitivity Analysis for Satisfaction and Uncertainty Measures for Submodel 1



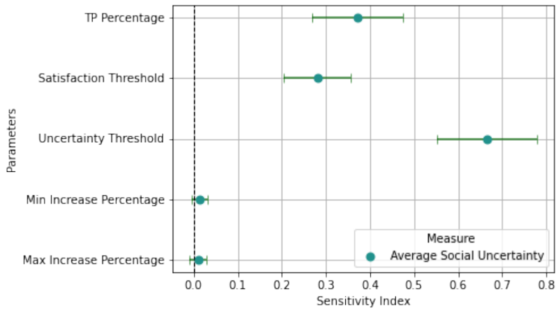
(a) Total Order Analysis of Average Financial Satisfaction



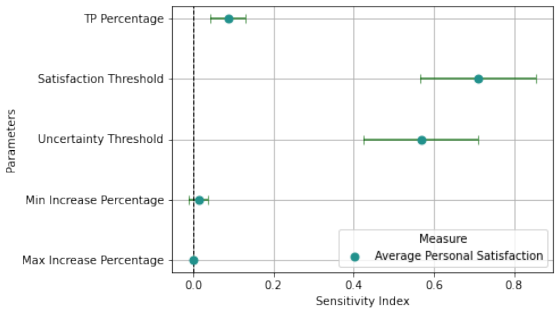
(b) Total Order Analysis of Average Financial Uncertainty



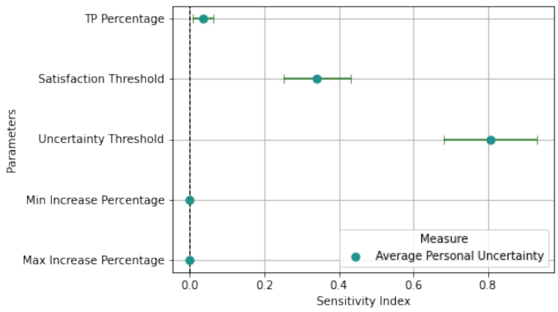
(c) Total Order Analysis of Average Social Satisfaction



(d) Total Order Analysis of Average Social Uncertainty



(e) Total Order Analysis of Average Personal Satisfaction



(f) Total Order Analysis of Average Personal Uncertainty

Figure 5.4: Total Order Sensitivity Analysis for Satisfaction and Uncertainty Measures for Submodel 1

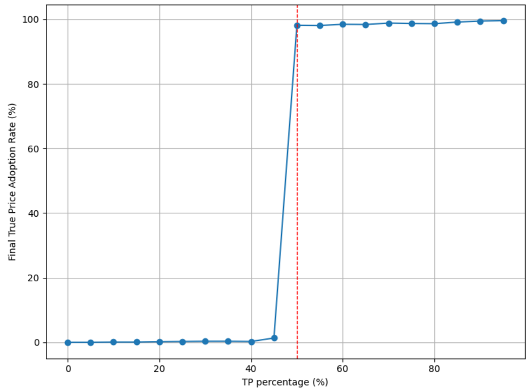
Discussion

The Global Sensitivity Analysis reveals that the introduction percentage of True Price products is the most influential parameter in driving the adoption rate. This suggests that increasing the market share of True Price products can have substantial positive impacts on overall adoption rates and satisfaction levels. Additionally, managing uncertainty is generally more influential than enhancing satisfaction across various measures, indicating that agents prioritize reducing uncertainty in their decision-making processes. Consequently, strategies aimed at managing and reducing uncertainty are likely to be more effective in boosting adoption rates and overall satisfaction levels. While the minimum and maximum increase percentages of True Price products have negligible influence, the satisfaction threshold still plays a moderate but significant role in financial and personal satisfaction.

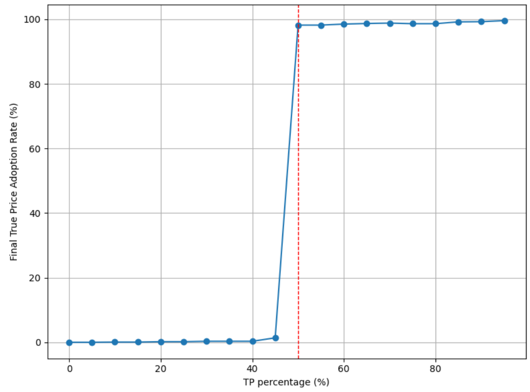
This sub-model's results align most closely with the bistable dynamics scenario of the evolutionary game theory model. In the game theory model, the points (0,0) and (1,1) are both stable, with the interior point acting as a saddle. Depending on initial conditions, the system either converges to full adoption or none at all, similar to how this sub-model shows a sharp tipping point at approximately 50% introduction of True Price products, leading to either high or minimal final adoption rates. The observed behaviour in the ABM mirrors the game theory's dependence on initial conditions for reaching a stable equilibrium. This reflects the importance of achieving a critical mass, emphasizing how initial proportions significantly impact the long-term adoption of True Price products, validating the theoretical predictions of evolutionary game theory within a more complex, heterogeneous agent-based framework.

5.2.2. Submodel 2.1 - Dynamic Network no homophily

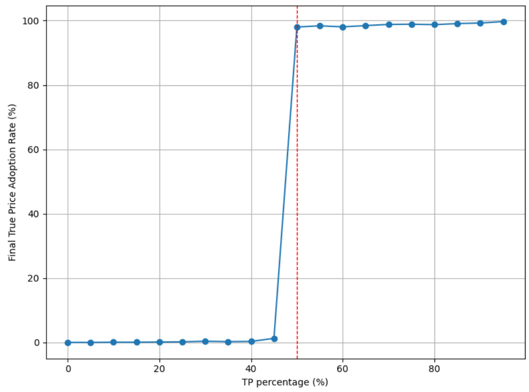
In this sub-model dynamic network models are introduced, building upon the heterogeneous agent model. Figure 5.5 shows a similar pattern to the previous sub-model, where a critical mass is reached at around 50% introduction of True Price products. At first glance, the differences between the networks are very minor, necessitating a deeper analysis of the impacts of the network structure,



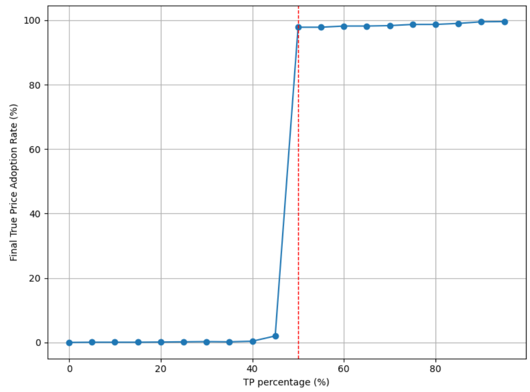
(a) Barabasi-Albert network with $n = 1600$ and $m = 8$



(b) Holme-Kim network with $n = 1600$, $m = 8$, and $p = 0.3$.



(c) Random Regular network with $n = 1600$ and $d = 8$.

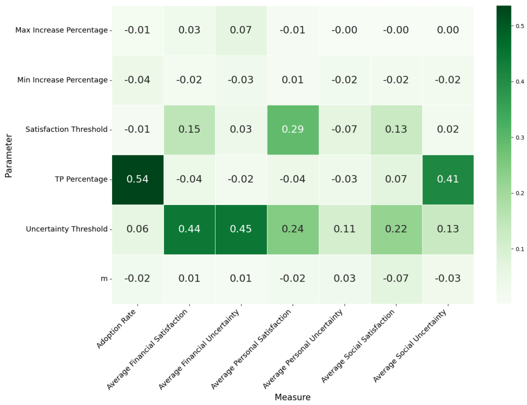


(d) Watts-Strogatz network with $n = 1600$, $k = 8$, and $p = 0.3$.

Figure 5.5: Final True Price Adoption Rate by TP percentage for different network configurations. Base configuration: satisfaction threshold = 0.5, uncertainty threshold = 0.5, product price range = (5, 10), minimum increase percentage = 4, maximum increase percentage = 10, number of products = 20, inflation rate = 3, seed = 42. The red dashed line represents a TP percentage of 50%.

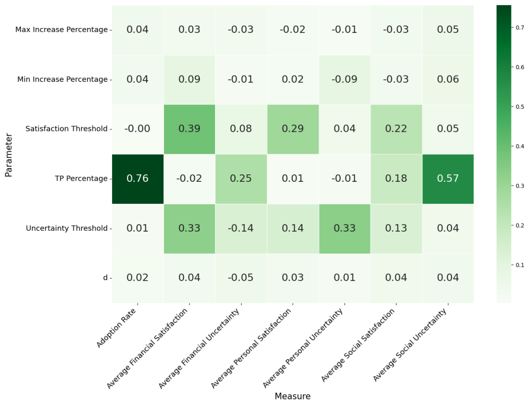
Global Sensitivity Analysis

In the Barabasi-Alberts network, the TP percentage is the most influential parameter for the adoption rate with high first-order and total-order indices, indicating significant direct and interactive effects. The uncertainty threshold shows moderate impact, while other parameters, including satisfaction threshold, minimum and maximum increase percentages, and m, exhibit minimal direct effects but some interaction effects. For Average Financial Satisfaction and Uncertainty, the uncertainty threshold has a strong influence with high first-order and total-order indices, while the satisfaction threshold also plays a significant role. The TP percentage shows negligible direct influence but moderate interaction effects, and m has a moderate total-order effect for uncertainty. In average Personal Satisfaction, both the satisfaction threshold and uncertainty threshold show strong influences, with the TP percentage having minimal direct influence but some interaction effects. Average Personal Uncertainty is strongly influenced by all parameters through interaction effects but minimally through direct influence. In Average Social Satisfaction and Uncertainty, the uncertainty and satisfaction thresholds are influential, with the TP percentage showing significant total-order effects for social satisfaction, while other parameters have minimal effects.



(a) Barabasi-Albert

(b) Holme-Kim



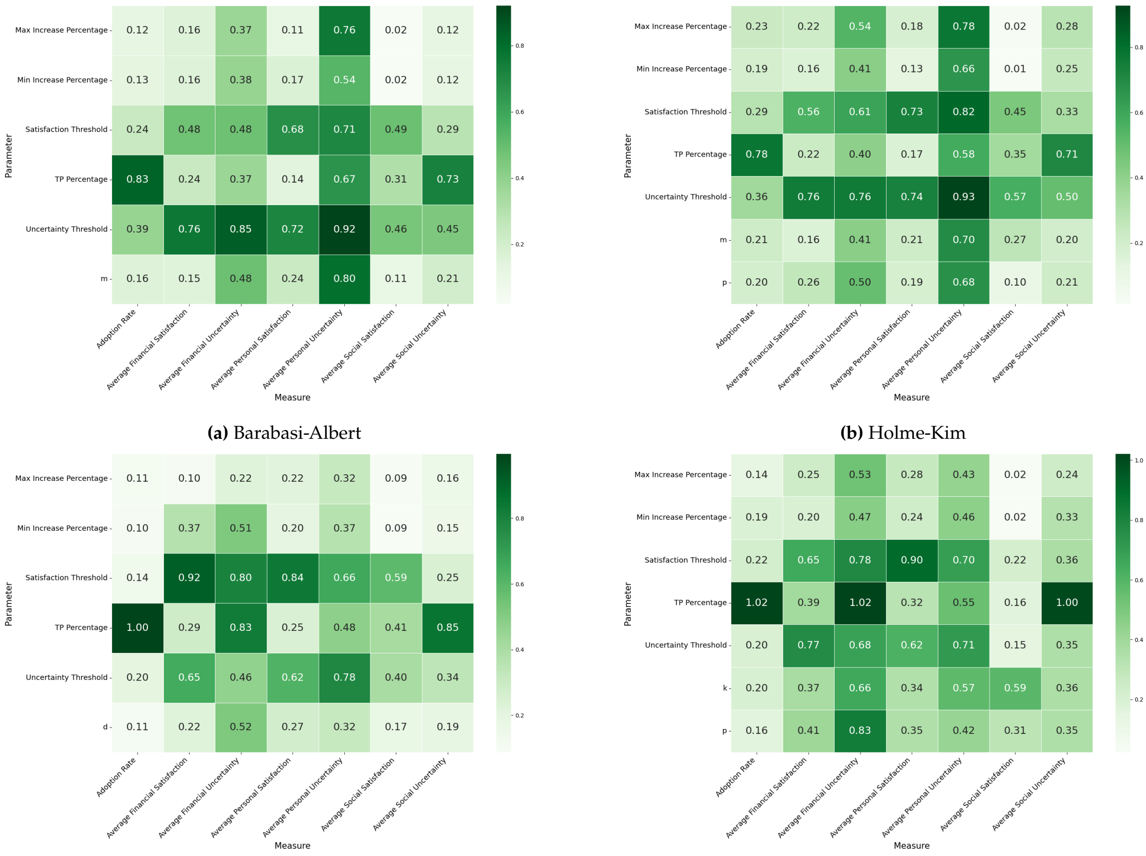
(c) Random Regular

(d) Watts-Strogatz

Figure 5.6: Heatmaps for each network displaying the first-order Sobol indices of each parameter for the corresponding measures for Submodel 2.1

In the Holme-Kim network, the TP percentage is the most influential parameter for the adoption rate, with high first-order and total-order indices indicating significant direct and interactive effects. The uncertainty threshold shows a moderate impact, while other parameters, including satisfaction threshold, minimum and maximum increase percentages, m, and p, exhibit minimal direct effects but some interaction effects. For Average Financial Satisfaction and Uncertainty, the uncertainty threshold has a strong influence with high first-order and total-order indices, while the satisfaction threshold also plays a significant role. The TP percentage shows negligible direct influence but moderate interaction effects, and p has a notable total-order effect for uncertainty. In Average Personal Satisfaction, both the satisfaction threshold and uncertainty threshold show strong influences, with the TP percentage having minimal direct influence but some interaction effects. Average Personal Uncertainty is strongly influenced by all parameters through interaction effects but minimally through direct influence. In Average Social Satisfaction and Uncertainty, the uncertainty and satisfaction thresholds are influential, with the TP percentage showing significant total-order effects for social satisfaction, while other parameters have minimal effects.

In the Random Regular network, the TP percentage is the most influential parameter for the adoption rate, with high first-order and total-order indices, indicating significant direct and interactive effects.



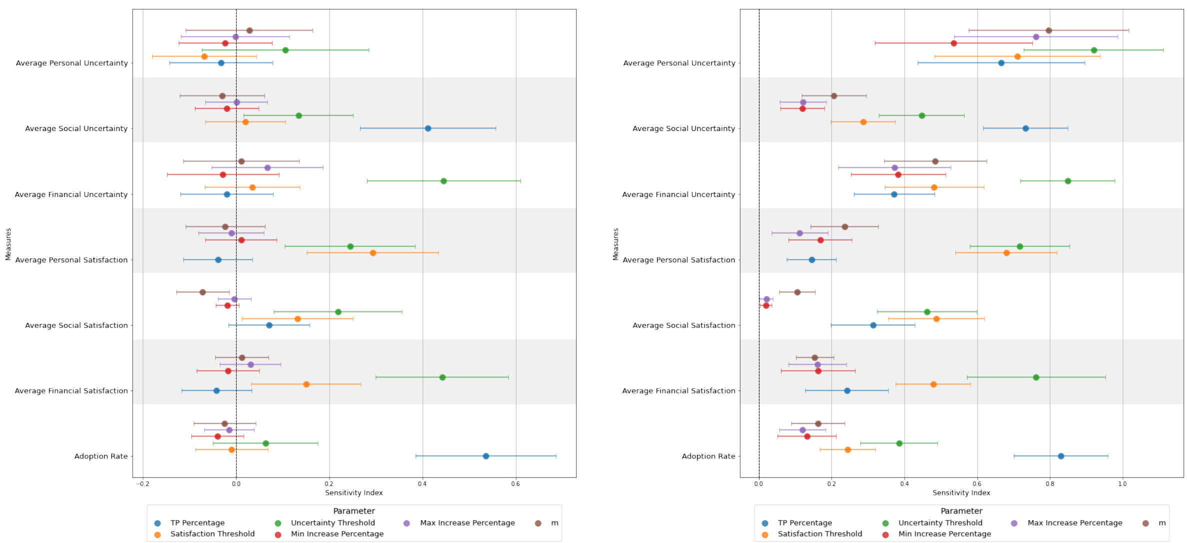
(a) Barabasi-Albert

(b) Holme-Kim

(c) Random Regular

(d) Watts-Strogatz

Figure 5.7: Heatmaps for each network displaying the total-order Sobol indices of each parameter for the corresponding measures for Submodel 2.1

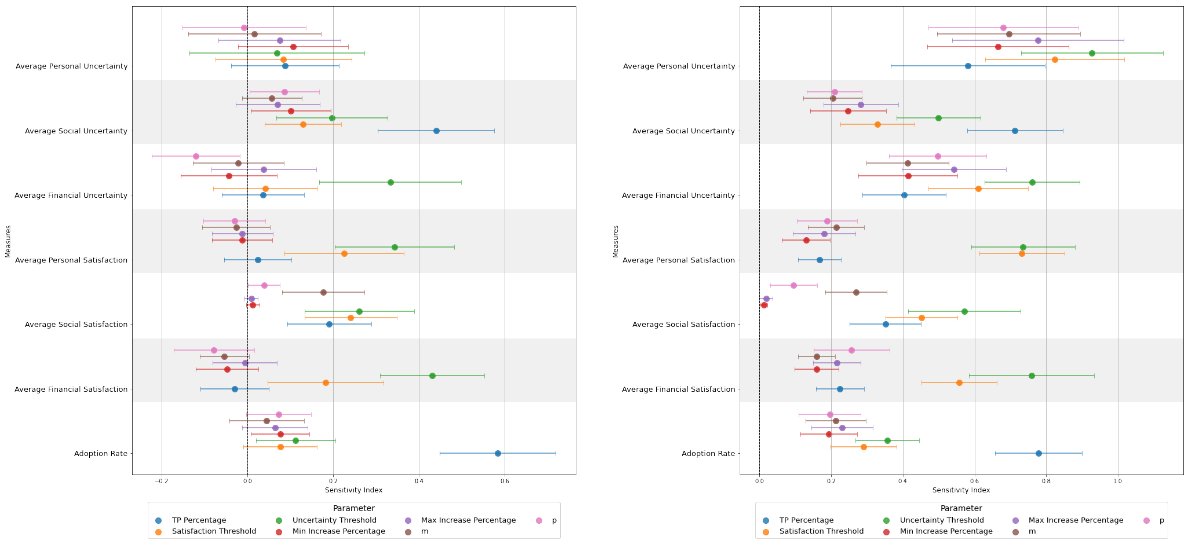


(a) First Order Sobol Indices

(b) Total Order Sobol Indices

Figure 5.8: GSA Sobol indices for Barabasi-Albert network without homophily.

The uncertainty threshold shows a moderate impact, while other parameters, including satisfaction threshold, minimum and maximum increase percentages, and d, exhibit minimal direct effects but some

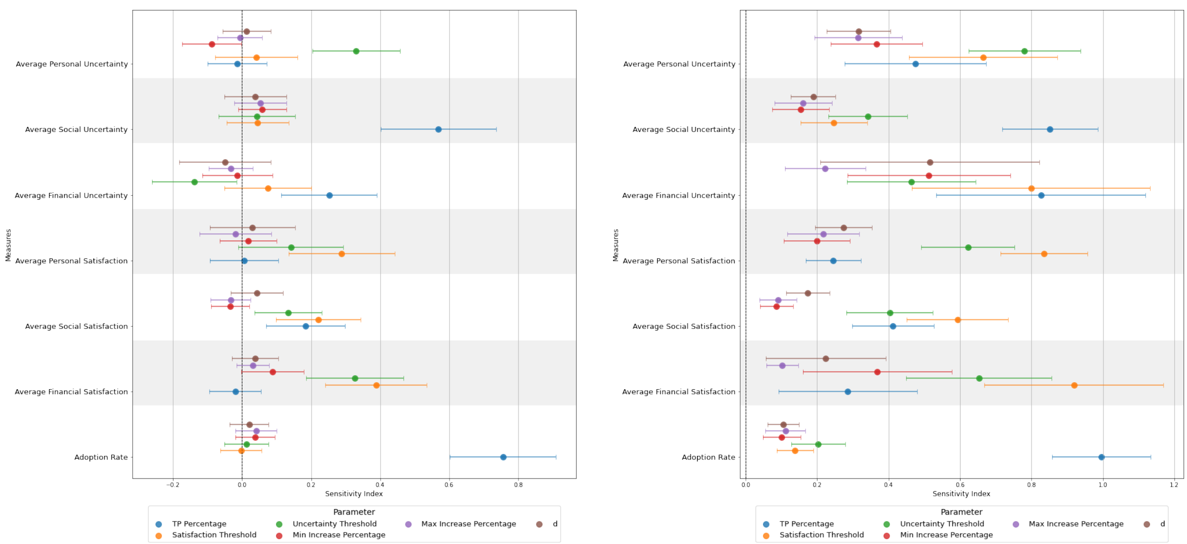


(a) Holme-Kim - S1

(b) Holme-Kim - ST

Figure 5.9: Sensitivity analysis plots for Holme-Kim network without homophily.

interaction effects. For Average Financial Satisfaction and Uncertainty, the satisfaction threshold has a strong influence with high first-order and total-order indices, while the uncertainty threshold also plays a significant role. The TP percentage shows negligible direct influence but moderate interaction effects, and d has a notable total-order effect for financial uncertainty. In Average Personal Satisfaction, both the satisfaction threshold and uncertainty threshold show strong influences, with the TP percentage having minimal direct influence but some interaction effects. Average Personal Uncertainty is strongly influenced by all parameters through interaction effects but minimally through direct influence. In Average Social Satisfaction and Uncertainty, the TP percentage shows significant total-order effects for social uncertainty, while the uncertainty and satisfaction thresholds are influential. Other parameters have minimal effects. In the Watts-Strogatz network, the TP percentage is the most influential parameter

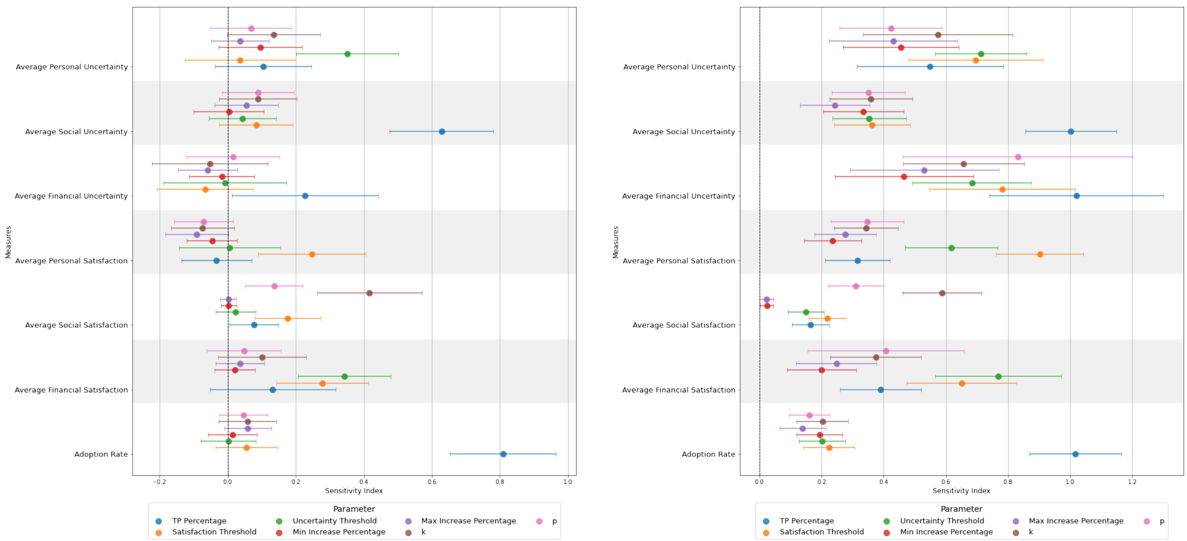


(a) Random Regular - S1

(b) Random Regular - ST

Figure 5.10: Sensitivity analysis plots for Random Regular network without homophily.

for the adoption rate with high first-order and total-order indices, indicating significant direct and interactive effects. The uncertainty threshold and network-specific parameters k and p show moderate impact, while other parameters, including satisfaction threshold and minimum and maximum increase percentages, exhibit minimal direct effects but some interaction effects. For Average Financial Satisfaction and Uncertainty, the uncertainty threshold has a strong influence with high first-order and total-order indices, while the satisfaction threshold also plays a significant role. The TP percentage shows negligible direct influence but moderate interaction effects, and k and p have notable total-order effects. In Average Personal Satisfaction, both satisfaction threshold and uncertainty threshold show strong influences, with the TP percentage having minimal direct influence but some interaction effects. Average Personal Uncertainty is strongly influenced by interaction effects of all parameters but minimally through direct influence. In Average Social Satisfaction and Uncertainty, the uncertainty and satisfaction thresholds are influential, with the TP percentage showing significant total-order effects for social uncertainty, while k and p have notable interaction effects. Other parameters have minimal effects.



(a) Watts-Strogatz - S1

(b) Watts-Strogatz - ST

Figure 5.11: Sensitivity analysis plots for Watts-Strogatz network without homophily.

Discussion

Across all networks, the TP percentage consistently emerges as the most influential parameter for the adoption rate, with high first-order and total-order indices indicating significant direct and interactive effects. This highlights the critical role of the TP percentage in driving adoption across different network structures. The uncertainty threshold also shows a moderate to strong influence across various measures in all networks, underscoring its importance in both direct and interaction effects. The satisfaction threshold generally has a moderate impact on financial and personal satisfaction while showing less influence on other measures.

Key differences between the networks include the varying impact of network-specific parameters such as m, p, d, and k. In the Barabasi-Alberts network, m shows some interaction effects but minimal direct influence. In the Holme-Kim network, p has a notable total-order effect on uncertainty, while m remains largely negligible. The Random Regular network sees d having a notable total-order effect on financial uncertainty, while other parameters remain minimally impactful. In the Watts-Strogatz network, k and p exhibit moderate total-order effects, particularly influencing financial and personal uncertainty, highlighting the unique network-specific dynamics.

Despite these differences, a common theme is that Average Personal Uncertainty is strongly influenced by interaction effects of all parameters, though minimally through direct influence, across all networks. This indicates a complex interplay of factors affecting personal uncertainty levels. Overall, while the TP percentage and uncertainty threshold are consistently influential, the network-specific parameters introduce unique dynamics that differentiate the networks' sensitivities.

Table 5.1: Summary of GSA results comparing the networks in terms of the parameter's first-order and total-order Sobol Indices for each measure

Measure	Parameter	Barabasi-Albert		Holme-Kim		Random Regular		Watts-Strogatz	
		S1	ST	S1	ST	S1	ST	S1	ST
Adoption Rate	Max Increase Percentage	-0,015	0,120	0,064	0,230	0,041	0,111	0,059	0,139
	Min Increase Percentage	-0,039	0,132	0,076	0,194	0,038	0,101	0,015	0,194
	Satisfaction Threshold	-0,009	0,244	0,076	0,291	-0,003	0,139	0,055	0,224
	TP Percentage	0,536	0,830	0,584	0,778	0,756	0,996	0,809	1,017
	Uncertainty Threshold	0,063	0,385	0,112	0,356	0,013	0,203	0,001	0,201
	d					0,021	0,105		
	k							0,059	0,203
	m	-0,025	0,164	0,045	0,213				
	p			0,072	0,196			0,046	0,161
Average Financial Satisfaction	Max Increase Percentage	0,031	0,162	-0,006	0,216	0,031	0,103	0,036	0,248
	Min Increase Percentage	-0,017	0,163	-0,048	0,160	0,089	0,369	0,020	0,200
	Satisfaction Threshold	0,150	0,479	0,182	0,557	0,388	0,919	0,279	0,651
	TP Percentage	-0,042	0,242	-0,030	0,225	-0,020	0,286	0,132	0,390
	Uncertainty Threshold	0,442	0,762	0,431	0,759	0,326	0,653	0,343	0,769
	d					0,038	0,224		
	k							0,101	0,375
	m	0,013	0,154	-0,054	0,159				
	p			-0,078	0,257			0,047	0,407
Average Financial Uncertainty	Max Increase Percentage	0,067	0,374	0,038	0,542	-0,032	0,223	-0,059	0,531
	Min Increase Percentage	-0,028	0,383	-0,044	0,415	-0,013	0,513	-0,018	0,465
	Satisfaction Threshold	0,035	0,481	0,041	0,610	0,075	0,799	-0,066	0,782
	TP Percentage	-0,020	0,372	0,036	0,404	0,252	0,827	0,227	1,021
	Uncertainty Threshold	0,446	0,848	0,333	0,761	-0,138	0,464	-0,009	0,684
	d					-0,050	0,516		
	k							-0,052	0,658
	m	0,012	0,485	-0,022	0,414				
	p			-0,120	0,498			0,015	0,831
Average Personal Satisfaction	Max Increase Percentage	-0,010	0,113	-0,012	0,181	-0,019	0,217	-0,091	0,276
	Min Increase Percentage	0,011	0,169	-0,012	0,130	0,018	0,200	-0,046	0,236
	Satisfaction Threshold	0,293	0,680	0,225	0,732	0,289	0,835	0,248	0,902
	TP Percentage	-0,039	0,145	0,024	0,168	0,006	0,245	-0,033	0,316
	Uncertainty Threshold	0,244	0,717	0,343	0,735	0,142	0,622	0,006	0,618
	d					0,030	0,274		
	k							-0,074	0,344
	m	-0,023	0,236	-0,026	0,214				
	p			-0,031	0,189			-0,071	0,347
Average Personal Uncertainty	Max Increase Percentage	-0,001	0,761	0,075	0,777	-0,006	0,315	0,036	0,431
	Min Increase Percentage	-0,023	0,536	0,106	0,665	-0,088	0,367	0,095	0,455
	Satisfaction Threshold	-0,068	0,710	0,084	0,823	0,042	0,665	0,037	0,696
	TP Percentage	-0,032	0,666	0,087	0,581	-0,014	0,475	0,105	0,549
	Uncertainty Threshold	0,106	0,920	0,069	0,927	0,331	0,781	0,351	0,712
	d					0,013	0,317		
	k							0,134	0,574
	m	0,028	0,796	0,016	0,695				
	p			-0,008	0,680			0,068	0,423
Average Social Satisfaction	Max Increase Percentage	-0,003	0,021	0,009	0,019	-0,033	0,091	0,002	0,023
	Min Increase Percentage	-0,018	0,019	0,012	0,012	-0,034	0,087	0,002	0,024
	Satisfaction Threshold	0,132	0,488	0,240	0,452	0,221	0,593	0,175	0,219
	TP Percentage	0,071	0,314	0,191	0,351	0,184	0,413	0,077	0,164
	Uncertainty Threshold	0,219	0,462	0,261	0,572	0,134	0,403	0,023	0,150
	d					0,043	0,174		
	k							0,417	0,588
	m	-0,071	0,105	0,176	0,269				
	p			0,038	0,096			0,136	0,311
Average Social Uncertainty	Max Increase Percentage	0,001	0,122	0,070	0,283	0,053	0,161	0,055	0,243
	Min Increase Percentage	-0,020	0,120	0,101	0,248	0,058	0,154	0,003	0,335
	Satisfaction Threshold	0,020	0,287	0,129	0,330	0,045	0,247	0,083	0,363
	TP Percentage	0,412	0,733	0,440	0,712	0,568	0,852	0,628	1,002
	Uncertainty Threshold	0,134	0,447	0,197	0,499	0,043	0,342	0,042	0,354
	d					0,039	0,189		
	k							0,089	0,359
	m	-0,030	0,207	0,057	0,205				
	p			0,086	0,209			0,089	0,351

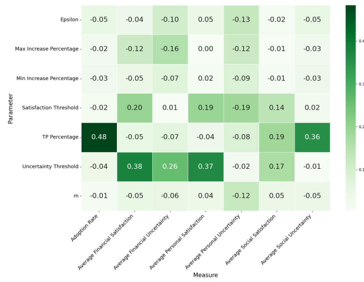
5.2.3. Submodel 2.2 - Dynamic Network with homophily based social comparison

Results

Global Sensitivity Analysis

(a) Barabasi-Albert - Budget

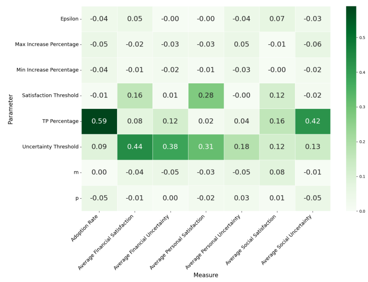
(b) Barabasi-Albert - Preference Conformity



(c) Barabasi-Albert - Preference Sustainability

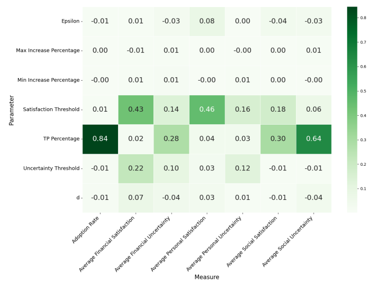
(d) Holme-Kim - Budget

(e) Holme-Kim - Preference Conformity

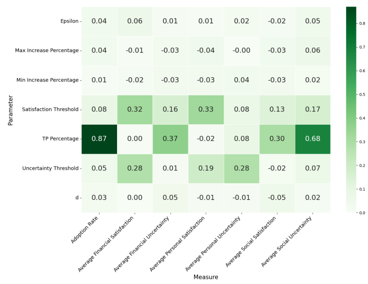


(f) Holme-Kim - Preference Sustainability

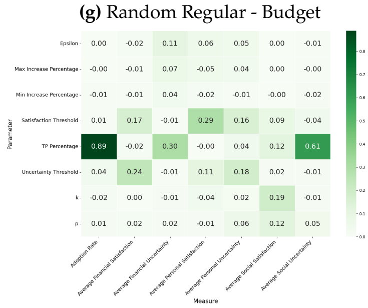
(g) Random Regular - Budget



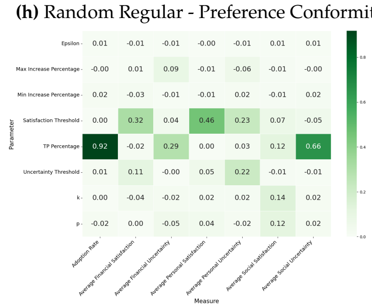
(h) Random Regular - Preference Conformity



(i) Random Regular - Preference Sustainability



(j) Watts-Strogatz - Budget



(k) Watts-Strogatz - Preference Conformity

(l) Watts-Strogatz - Preference Sustainability

Figure 5.12: First-order Sobol Indices from the global sensitivity analysis for Submodel 2.2 with homophily based social comparison

In the Barabasi-Albert network, the True Price (TP) percentage has the highest total-order Sobol indices across all homophily scenarios, indicating it accounts for a large portion of the output variance, particularly affecting the adoption rate. The total-order indices for the TP percentage on the adoption rate are notably lower in the Budget scenario compared to the Preference Conformity and Preference Sustainability scenarios. Epsilon, which controls the degree of similarity for social comparison, shows the highest total-order indices in the Preference Sustainability scenario across all measures. This indicates that agents' decision-making is more affected by their neighbours' sustainability preferences compared to budget or conformity preferences. Comparing these results to the original Barabasi-Albert model without homophily reveals notable differences. The original model has higher total-order Sobol indices for average financial uncertainty and average personal uncertainty compared to the Budget and Preference Conformity scenarios. However, the Preference Sustainability scenario displays similar patterns to the original model, with high sensitivity in these measures, suggesting that incorporating sustainability preferences in social comparison aligns closely with the dynamics observed in the non-homophily Barabasi-Albert model. Overall, the Barabasi-Albert network with homophily-based social comparison demonstrates that the attribute used for social comparison affects the model's sensitivity to parameter variations.

In the Holme-Kim networks, epsilon has the highest total-order Sobol indices in the Preference Sustainability scenario across most measures, except for personal and social satisfaction, where the Preference Conformity scenario has higher indices. Notable differences are observed when comparing these results to the original Holme-Kim model without homophily. The original model shows higher total-order indices for average financial uncertainty and average personal uncertainty compared to any of the new homophily scenarios. This suggests that the incorporation of homophily reduces the model's sensitivity to these parameters. However, the Preference Sustainability scenario shows somewhat similar patterns to the original model, particularly in parameters related to sustainability preferences.

In the Random Regular network, epsilon has the highest total-order Sobol indices in the Preference Sustainability scenario for adoption rate, a pattern that holds for most other measures. The exception is for average financial satisfaction, where epsilon is significantly higher in the Budget scenario. The TP percentage on average financial satisfaction and average personal uncertainty has moderate total-order indices in both the original Random Regular network and the Random Regular Preference Sustainability scenario. In contrast, these indices are negligible in the Random Regular Budget and Random Regular Preference Conformity scenarios. The minimum increase percentage shows negligible total-order indices on financial satisfaction and uncertainty in the Random Regular Budget and Preference Conformity scenarios, whereas they are moderate in the original Random Regular network and Preference Sustainability scenarios. Consistent with the Barabasi-Albert and Holme-Kim networks, the Preference Sustainability scenario in the Random Regular network shows higher total-order sensitivity indices in average financial uncertainty and average personal uncertainty measures compared to the Budget and Preference Conformity scenarios.

In the Watts-Strogatz network, epsilon shows negligible to minimal total-order Sobol indices across all measures and scenarios, with a notable exception in the Budget scenario, where it has moderate indices for personal uncertainty. The indices of other parameters remain consistent across the different homophily scenarios. The True Price percentage continues to have significant indices, particularly impacting the adoption rate. The scenarios show similar patterns overall, indicating that the type of homophily for social comparison does not drastically change the sensitivity dynamics of most parameters. When comparing these results to the original Watts-Strogatz model without homophily, the original model exhibits much stronger total-order indices for the True Price percentage in the measures of financial and personal satisfaction and uncertainty. Overall, the original model also has far more moderate total order indices compared to the more negligible indices in this submodel.

Discussion

Across all networks, epsilon generally has the highest total-order indices in the Preference Sustainability scenario, indicating that agents' decision-making is more affected by their neighbours' sustainability preferences compared to budget or conformity preferences. In the Holme-Kim, the Preference Conformity scenario has higher indices for personal and social satisfaction. This indicates that while sustainability preferences are important, conformity preferences become more influential in personal and social contexts. This may be due to the clustered nature of the Holme-Kim network, where tightly knit groups amplify the effects of conformity within social interactions. In the Watts-Strogatz network, epsilon shows negligible to minimal total-order Sobol indices across all measures and scenarios, except for a moderate impact on personal uncertainty in the Budget scenario. The indices of other parameters remain consistent across the different homophily scenarios. Therefore, in the Watts-Strogatz network, similarity in social comparison has limited influence, and the type of homophily does not significantly alter sensitivity dynamics. This could be due to the small-world nature of Watts-Strogatz networks, where the high clustering and short path lengths facilitate interactions with a diverse set of agents, thereby reducing the impact of homophily on parameter sensitivity.

(a) Barabasi-Albert - Budget

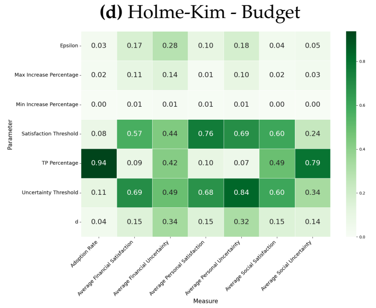
(b) Barabasi-Albert - Preference Conformity

(c) Barabasi-Albert - Preference Sustainability

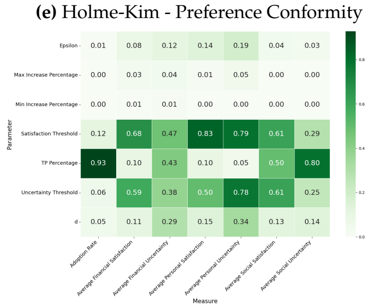
(d) Holme-Kim - Budget

(e) Holme-Kim - Preference Conformity

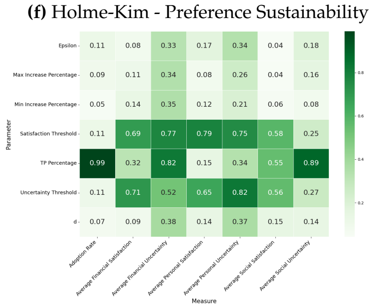
(f) Holme-Kim - Preference Sustainability



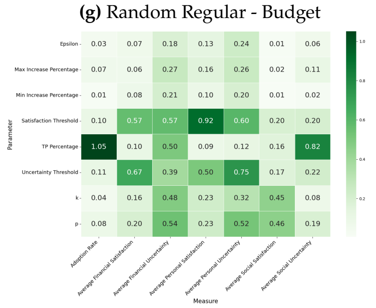
(g) Random Regular - Budget



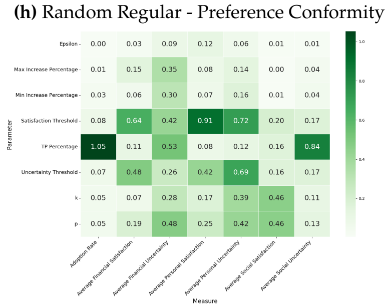
(h) Random Regular - Preference Conformity



(i) Random Regular - Preference Sustainability



(j) Watts-Strogatz - Budget



(k) Watts-Strogatz - Preference Conformity

(l) Watts-Strogatz - Preference Sustainability

Figure 5.13: Total-order Sobol Indices from the global sensitivity analysis for Submodel 2.2 with homophily based social comparison

Table 5.2: Summary of GSA results comparing the networks in terms of the parameter's first-order and total-order Sobol Indices for each measure

Measure	Parameter	Barabasi-Albert Budget		Barabasi-Albert Preference Conformity		Barabasi-Albert Preference Sustainability		Holme-Kim Budget		Holme-Kim Preference Conformity		Holme-Kim Preference Sustainability		Random Regular Budget		Random Regular Preference Conformity		Random Regular Preference Sustainability		Watts-Strogatz Budget		Watts-Strogatz Preference Conformity		Watts-Strogatz Preference Sustainability	
		S1	ST	S1	ST	S1	ST	S1	ST	S1	ST	S1	ST	S1	ST	S1	ST	S1	ST	S1	ST	S1	ST	S1	ST
Adoption Rate	Epsilon	-0,008	0,056	-0,005	0,046	-0,050	0,193	0,004	0,072	0,009	0,066	-0,035	0,104	0,012	0,027	-0,009	0,010	0,038	0,114	0,001	0,034	0,006	0,004	0,002	0,029
	Max Increase Percentage	-0,000	0,001	-0,002	0,017	-0,020	0,181	0,016	0,058	0,020	0,034	-0,051	0,106	-0,014	0,020	0,002	0,002	0,037	0,092	-0,002	0,065	-0,001	0,015	-0,006	0,022
	Min Increase Percentage	-0,000	0,000	-0,001	0,000	-0,028	0,131	0,003	0,044	0,013	0,030	-0,039	0,068	0,001	0,000	-0,002	0,000	0,009	0,053	-0,009	0,012	0,016	0,032	-0,003	0,002
	Satisfaction Threshold	0,006	0,158	0,028	0,158	-0,016	0,226	0,027	0,205	0,016	0,253	-0,009	0,204	0,030	0,082	0,010	0,119	0,081	0,114	0,010	0,103	0,003	0,080	0,031	0,041
	TP Percentage	0,465	0,670	0,538	0,796	0,483	0,808	0,555	0,838	0,617	0,825	0,590	0,962	0,843	0,937	0,845	0,928	0,870	0,990	0,888	1,051	0,918	1,053	0,912	1,063
	Uncertainty Threshold	0,065	0,330	0,016	0,215	-0,039	0,326	0,104	0,322	0,065	0,216	0,086	0,306	-0,016	0,107	-0,014	0,055	0,049	0,107	0,038	0,107	0,015	0,069	0,041	0,074
	d													-0,023	0,042	-0,011	0,051	0,025	0,070						
	k																			-0,019	0,044	0,001	0,049	-0,001	0,023
	m	-0,023	0,186	-0,007	0,154	-0,010	0,173	0,011	0,121	0,034	0,142	-0,000	0,146												
	p							-0,031	0,108	0,032	0,094	-0,053	0,134							0,015	0,083	-0,016	0,050	0,010	0,046
Average Financial Satisfaction	Epsilon	-0,014	0,077	-0,012	0,052	-0,035	0,145	0,035	0,087	0,001	0,096	0,046	0,206	-0,033	0,170	0,007	0,081	0,060	0,083	-0,020	0,070	-0,010	0,025	-0,013	0,070
	Max Increase Percentage	-0,032	0,036	-0,008	0,034	-0,118	0,196	0,046	0,089	0,023	0,084	-0,022	0,095	-0,007	0,106	-0,007	0,029	-0,009	0,109	-0,009	0,063	0,007	0,151	0,002	0,058
	Min Increase Percentage	-0,000	0,003	-0,003	0,002	-0,046	0,151	-0,002	0,028	0,003	0,052	-0,014	0,152	0,000	0,006	0,009	0,006	-0,020	0,136	-0,005	0,078	-0,025	0,057	0,006	0,018
	Satisfaction Threshold	0,241	0,447	0,358	0,524	0,198	0,485	0,214	0,500	0,272	0,581	0,163	0,563	0,255	0,568	0,432	0,680	0,320	0,694	0,166	0,567	0,315	0,643	0,295	0,600
	TP Percentage	0,013	0,099	0,012	0,129	-0,052	0,219	0,019	0,100	0,024	0,106	0,077	0,226	0,013	0,086	0,020	0,099	0,004	0,318	-0,020	0,105	-0,017	0,113	-0,017	0,103
	Uncertainty Threshold	0,542	0,739	0,426	0,635	0,380	0,643	0,399	0,715	0,271	0,484	0,438	0,697	0,307	0,695	0,223	0,586	0,282	0,709	0,241	0,674	0,114	0,485	0,152	0,615
	d													0,086	0,146	0,074	0,111	0,000	0,089						
	k																			-0,000	0,161	-0,035	0,068	-0,036	0,160
	m	0,036	0,190	0,029	0,303	-0,049	0,146	0,015	0,148	-0,037	0,173	-0,044	0,188												
	p							0,019	0,122	0,003	0,128	-0,013	0,197							0,020	0,201	0,002	0,192	0,019	0,214
Average Financial Uncertainty	Epsilon	-0,011	0,124	-0,053	0,155	-0,102	0,378	0,017	0,139	0,001	0,211	-0,003	0,255	-0,050	0,282	-0,026	0,118	0,014	0,331	0,106	0,185	-0,009	0,092	0,049	0,161
	Max Increase Percentage	-0,001	0,068	-0,011	0,054	-0,156	0,371	0,021	0,133	0,021	0,179	-0,034	0,230	-0,033	0,141	0,009	0,043	-0,032	0,345	0,071	0,269	0,093	0,349	0,059	0,157
	Min Increase Percentage	0,008	0,002	0,001	0,003	-0,075	0,371	-0,010	0,068	0,009	0,059	-0,022	0,324	-0,002	0,014	0,012	0,015	-0,031	0,352	0,038	0,211	-0,006	0,304	0,019	0,078
	Satisfaction Threshold	0,129	0,389	0,141	0,551	0,005	0,579	0,139	0,419	0,218	0,589	0,009	0,515	0,031	0,438	0,138	0,472	0,163	0,772	-0,007	0,574	0,037	0,418	0,096	0,522
	TP Percentage	0,075	0,106	0,084	0,148	-0,066	0,430	0,041	0,158	0,057	0,179	0,117	0,448	0,275	0,423	0,282	0,431	0,372	0,823	0,299	0,503	0,290	0,526	0,341	0,612
	Uncertainty Threshold	0,472	0,754	0,260	0,602	0,261	0,763	0,411	0,729	0,253	0,568	0,384	0,748	0,084	0,493	0,099	0,380	0,013	0,519	-0,008	0,389	-0,002	0,258	0,076	0,626
	d													0,072	0,339	-0,043	0,294	0,046	0,382						
	k																			-0,015	0,484	-0,024	0,284	0,012	0,336
	m	0,086	0,373	0,010	0,419	-0,056	0,382	0,072	0,319	0,010	0,363	-0,053	0,331												
	p							0,080	0,305	0,085	0,314	0,003	0,360							0,017	0,541	-0,050	0,478	0,109	0,388
Average Personal Satisfaction	Epsilon	0,016	0,092	-0,019	0,137	0,046	0,182	0,012	0,075	-0,060	0,195	-0,004	0,140	-0,021	0,100	0,080	0,139	0,007	0,169	0,055	0,133	-0,003	0,122	-0,057	0,116
	Max Increase Percentage	-0,011	0,010	0,012	0,028	0,004	0,191	0,035	0,056	0,038	0,080	-0,030	0,093	-0,029	0,012	0,002	0,014	-0,041	0,084	-0,049	0,160	-0,013	0,084	-0,010	0,049
	Min Increase Percentage	-0,002	0,001	-0,002	0,001	0,016	0,140	0,011	0,015	-0,009	0,018	-0,007	0,126	-0,010	0,006	-0,001	0,001	-0,030	0,119	-0,020	0,095	-0,012	0,072	-0,005	0,041
	Satisfaction Threshold	0,241	0,638	0,297	0,751	0,194	0,674	0,341	0,750	0,396	0,867	0,276	0,830	0,160	0,760	0,459	0,834	0,327	0,786	0,293	0,917	0,460	0,906	0,400	0,860
	TP Percentage	0,016	0,053	-0,004	0,076	-0,037	0,200	-0,002	0,052	0,004	0,064	0,018	0,168	-0,016	0,099	0,037	0,101	-0,016	0,150	-0,001	0,088	-0,000	0,083	0,004	0,108
	Uncertainty Threshold	0,396	0,722	0,281	0,657	0,366	0,797	0,300	0,708	0,271	0,540	0,314	0,714	0,105	0,677	0,029	0,501	0,190	0,654	0,112	0,504	0,054	0,423	0,055	0,564
	d													-0,009	0,148	0,033	0,148	-0,013	0,142						
	k																			-0,037	0,229	0,020	0,174	-0,030	0,211
	m	-0,030	0,144	0,005	0,222	0,038	0,203	-0,020	0,133	-0,036	0,256	-0,033	0,150												
	p							-0,010	0,037	0,023	0,131	-0,023	0,145							-0,014	0,235	0,037	0,248	-0,069	0,247
Average Personal Uncertainty	Epsilon	-0,005	0,160	0,007	0,134	-0,126	0,627	0,023	0,386	0,095	0,352	-0,044	0,514	-0,027	0,181	0,004	0,187	0,024	0,341	0,049	0,241	-0,005	0,064	0,015	0,146
	Max Increase Percentage	-0,019	0,057	0,023	0,127	-0,118	0,547	0,003	0,329	0,045	0,302	0,050	0,469	-0,032	0,102	-0,004	0,050	-0,002	0,255	0,035	0,259	-0,059	0,141	-0,024	0,136
	Min Increase Percentage	-0,001	0,000	-0,001	0,000	-0,086	0,680	-0,032	0,270	0,052	0,210	-0,033	0,609	0,002	0,012	0,008	0,003	0,037	0,211	-0,007	0,201	0,016	0,164	0,024	0,062
	Satisfaction Threshold	0,012	0,481	0,029	0,572	-0,187	0,824	0,157	0,671	0,219	0,636	-0,003	0,568	0,101	0,689	0,159	0,794	0,077	0,753	0,157	0,598	0,232	0,716	0,353	0,574
	TP Percentage	0,007	0,010	0,001	0,013	-0,084	0,588	-0,009	0,146	0,058	0,108	0,039	0,650	0,036	0,065	0,034	0,050	0,081	0,339	0,045	0,116	0,025	0,121	0,041	0,163
	Uncertainty Threshold	0,139	0,713	0,105	0,694	-0,021	0,811	0,291	0,702	0,263	0,662	0,180	0,838	0,219	0,836	0,120	0,778	0,280	0,825	0,185	0,752	0,216	0,685	0,314	0,721
	d													0,045	0,319	0,008	0,336	-0,015	0,367						
	k																			0,022	0,317	0,018	0,393	0,065	0,164
	m	0,048	0,648	0,134	0,731	-0,125	0,605	0,123	0,729	0,153	0,579	-0,053	0,653												
	p							0,110	0,604	0,178	0,567	0,025	0,648							0,057	0,523	-0,017	0,418	0,095	0,365
Average Social Satisfaction	Epsilon	0,017	0,065	-0,014	0,107	-0,016	0,101	0,023	0,056	0,067	0,107	0,067	0,077	-0,025	0,041	-0,039	0,043	-0,020	0,043	0,001	0,013	0,005	0,012	0,013	0,016
	Max Increase Percentage	0,007	0,006	0,004	0,004	-0,006	0,042	-0,014	0,017	0,005	0,021	-0,005	0,042	-0,032	0,020	0,004	0,003	-0,034	0,043	0,002	0,016	-0,011	0,004	-0,011	0,008
	Min Increase Percentage	0,004	0,002	0,001	0,002	-0,014	0,040	-0,018	0,019	-0,001	0,031	-0,004	0,043	-0,003	0,002	0,003	0,002	-0,028	0,057	-0,002	0,005	-0,011	0,007	-0,000	0,005
	Satisfaction Threshold	0,167	0,517	0,139	0,588	0,142	0,543	0,118	0,384	0,097	0,422	0,116	0,397	0,110	0,601	0,179	0,612	0,133	0,581	0,085	0,197	0,070	0,204	0,104	0,204
	TP Percentage	0,205	0,405	0,213	0,434	0,187	0,443	0,137	0,254	0,183	0,327	0,163	0,282	0,269	0,491	0,297	0,497	0,300	0,550	0,116	0,159	0,120	0,162	0,138	0,162
	Uncertainty Threshold	0,243	0,667	0,166	0,708	0,168	0,667	0,136	0,494	0,084	0,516	0,118	0,524	-0,015	0,601	-0,006	0,610	-0,022	0,560	0,017	0,168	-0,011	0,164	0,007	0,140
	d													-0,024	0,151	-0,007	0,128	-0,052	0,148						
	k																			0,188	0,449	0,143	0,459	0,193	0,434
	m	0,075	0,107	0,055	0,080	0,047	0,100	0,108	0,178	0,090	0,150	0,082	0,224												
	p							-0,000	0,111	0,008	0,117	0,007	0,108							0,123	0,458	0,118	0,462	0,185	0,536
Average Social Uncertainty	Epsilon	-0,018	0,078	-0,017	0,073	-0,054	0,233	0,001	0,079	0,006	0,122	-0,033	0,124	0,008	0,053	-0,032	0,032	0,050	0,185	-0,009	0,061	0,007	0,014	0,004	0,061
	Max Increase Percentage	0,005	0,006	-0,009	0,031	-0,028	0,188	0,006	0,074	-0,001	0,046	-0,061	0,130	-0,021	0,034	0,006	0,003	0,055	0,158	-0,004	0,111	-0,002	0,036	-0,011	0,044
	Min Increase Percentage	-0,003	0,002	0,000	0,002	-0,034	0,150	-0,013	0,037	0,018	0,050	-0,023	0,076	0,002	0,001	-0,003	0,001	0,022	0,084	-0,017	0,020	0,018	0,045	-0,005	0,004
	Satisfaction Threshold	0,054	0,167	0,047	0,219	0,020	0,239	0,038	0,259	-0,014	0,301	-0,018	0,263	0,080	0,238	0,064	0,291	0,168	0,247	-0,043	0,204	-0,051	0,168	-0,024	0,095
	TP Percentage	0,330	0,607	0,400	0,708	0,356	0,741	0,379	0,662	0,469	0,725	0,424	0,792	0,619	0,792	0,638	0,795	0,680	0,887	0,609	0,823	0,661	0,838	0,645	0,840
	Uncertainty Threshold	0,141	0,496	0,042	0,352	-0,006	0,472	0,156	0,461	0,067	0,346	0,132	0,414	-0,008	0,335	-0,005	0,250	0,069	0,269	-0,012	0,220	-0,007	0,167	0,005	0,177
	d													-0,062	0,136	-0,038	0,140	0,017	0,140						
	k																			-0,012	0,079	0,017	0,114	-0,002	0,067
	m	-0,049	0,241	-0,003	0,167	-0,046	0,208	0,027	0,148	0,058	0,159	-0,005	0,182												
	p							-0,018	0,182	0,054	0,153	-0,049	0,202							0,048	0,191	0,023	0,133	0,037	0,172

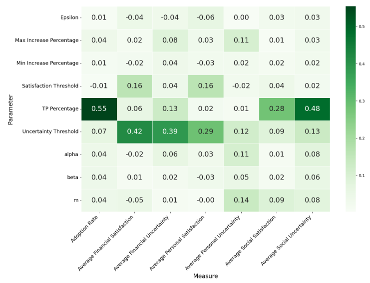
5.2.4. Submodel 3 - Homophily network model

Results

Global Sensitivity Analysis

(a) Barabasi-Albert - Budget

(b) Barabasi-Albert - Preference Conformity

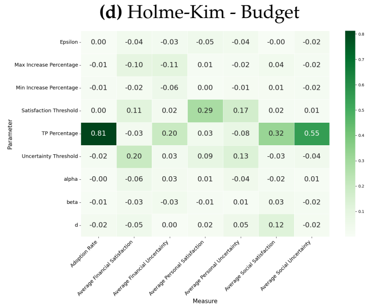


(c) Barabasi-Albert - Preference Sustainability

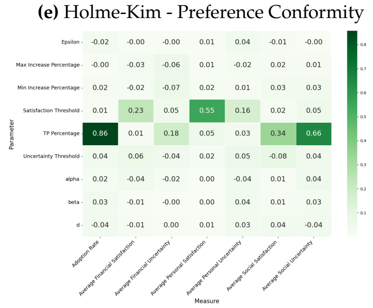
(d) Holme-Kim - Budget

(e) Holme-Kim - Preference Conformity

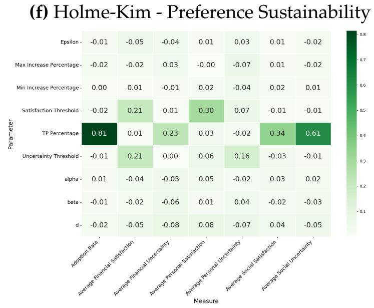
(f) Holme-Kim - Preference Sustainability



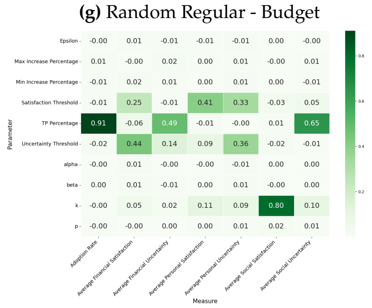
(g) Random Regular - Budget



(h) Random Regular - Preference Conformity



(i) Random Regular - Preference Sustainability



(j) Watts-Strogatz - Budget

(k) Watts-Strogatz - Preference Conformity

(l) Watts-Strogatz - Preference Sustainability

Figure 5.14: Homophily Network S1 heatmaps for different network models and metrics

In the Barabasi-Albert network, the parameters alpha and beta exhibit negligible to moderate total-order indices, with the highest values observed for the measures of financial and personal uncertainty. This pattern aligns with the previous sub-models, where financial and personal uncertainty measures generally showed moderate to strong total-order indices for all parameters. Compared to the previous sub-model, there are no notable differences between the three homophily scenarios, indicating consistent sensitivity patterns across different contexts.

In the Holme-Kim networks, consistent with the previous sub-models, the measures of financial and personal uncertainty generally display moderate to strong total-order indices for all parameters. However, this time, the strongest indices are observed in the preference conformity scenario, contrasting with the preference sustainability scenario in the earlier sub-models. Alpha and beta generally have minimal total-order indices except for the measures of financial and personal uncertainty, where the indices are quite strong. The network parameter ’m’ shows high total-order and first-order indices for average social satisfaction in the budget scenario, whereas they remain low in the other scenarios.

In the Random Regular network, epsilon shows higher total-order indices than in the previous sub-model, except for the preference sustainability scenario. Alpha and beta exhibit negligible to moderate total-order indices, with higher values in the measures of financial and personal uncertainty. These measures, in general, have higher indices for parameters than other measures, similar to the previous sub-models. Alpha and beta have the highest total-order indices in the preference conformity scenario.

In the Watts-Strogatz network, the network parameters ’k’ and ’p’ have negligible total-order indices, with a few exceptions. This differs from the previous sub-model, where several indices were moderate. A notable exception is the total-order index of ’k’ for the measure of social satisfaction, which is very strong in the budget scenario and moderate in the other two scenarios. The first-order index of ’k’ r, the measure of social satisfaction, is also extremely high in the budget scenario compared to the other two scenarios. The parameter ’p’ in these two scenarios has larger indices than the budget scenario but not nearly as high as in the previous sub-models. Epsilon across all three scenarios remains negligible, indicating minimal impact on the model’s output variance.

Discussion

In the Barabasi-Albert network, alpha and beta exhibit negligible to moderate total-order indices, primarily affecting financial and personal uncertainty measures. This aligns with previous submodels, indicating that financial and personal uncertainties remain sensitive to parameter variations. The lack of significant differences between homophily scenarios suggests that the preferential attachment mechanism in this network maintains consistent sensitivity patterns. The Holme-Kim network shows moderate to strong total-order indices for financial and personal uncertainty measures, consistent with previous submodels. However, the preference conformity scenario now shows the strongest indices, contrasting with earlier findings where preference sustainability was more influential. This shift can be attributed to the clustered nature of Holme-Kim networks, where tightly knit groups amplify the effects of social conformity. In these networks, the influence of conformity is enhanced due to frequent interactions within clusters, affecting agents’ financial and personal uncertainties more profoundly. The network parameter ’m’ significantly influences social satisfaction in the budget scenario, indicating that the degree of clustering impacts social outcomes. In the Random Regular network, epsilon shows higher total-order indices compared to the previous submodel, except in the preference sustainability scenario. Alpha and beta demonstrate negligible to moderate total-order indices, with the highest values in financial and personal uncertainty measures.

(a) Barabasi-Albert - Budget

(b) Barabasi-Albert - Preference Conformity

(c) Barabasi-Albert - Preference Sustainability

(d) Holme-Kim - Budget

(e) Holme-Kim - Preference Conformity

(f) Holme-Kim - Preference Sustainability

(g) Random Regular - Budget

(h) Random Regular - Preference Conformity

(i) Random Regular - Preference Sustainability

(j) Watts-Strogatz - Budget

(k) Watts-Strogatz - Preference Conformity

(l) Watts-Strogatz - Preference Sustainability

Figure 5.15: Homophily Networks ST heatmaps for different network models and metrics

6 | Experiments

In this section, we present the two experiments conducted using the ABM.

6.1. Gradual Introduction Rate

The gradual introduction of True Price (TP) products aims to understand how incrementally integrating TP products into the market, as opposed to a simultaneous introduction, affects consumer adoption and market dynamics. By varying the True Price introduction rate between 0 and 1 and the True Price percentage between 0% and 100%, we assess the impact of these parameters on various measures, primarily observing the adoption rate.

Across all network structures (Barabasi-Albert, Holme-Kim, Random Regular, and Watts-Strogatz), the True Price introduction rate showed moderate total-order Sobol indices for the adoption rate (Figure 6.1. This indicates that the rate at which TP products are introduced has a significant impact on the overall adoption rate.

(a) Barabasi-Alberts

(b) Holme-Kim (being re-run)

(c) Random Regular

(d) Watts-Strogatz

Figure 6.1: Total Order Indices resulting from GSA for the experiment of gradual introduction of TP percentage

6.2. Influencers

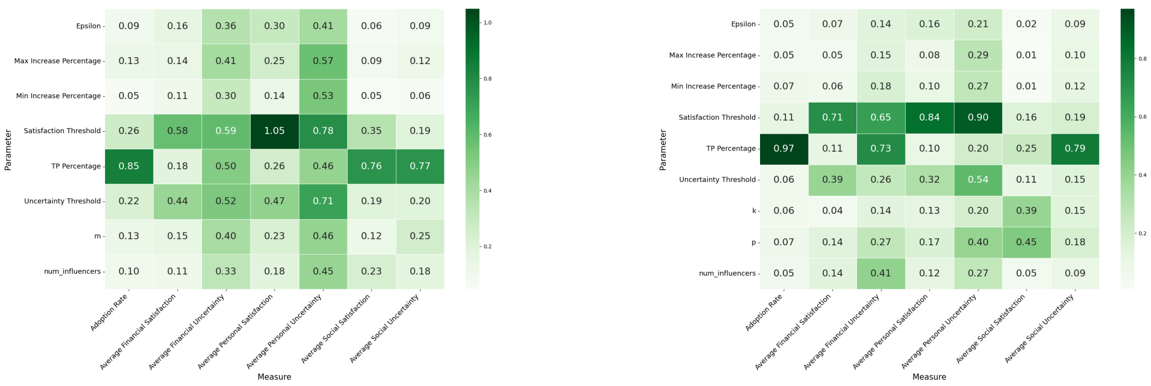
In this experiment, influencers are assigned TP products, leading to their automatic adoption. This adoption serves as an example for other agents, influencing their decision-making through social mechanisms such as imitation and social comparison.

In general, the analysis of total order indices for the number of influencers shows patterns consistent with previous sub-models regarding financial and personal uncertainty measures. Specifically, the total order indices for the number of influencers are moderate, indicating a significant influence on these uncertainty measures. For social satisfaction and uncertainty, the total order indices for the number of influencers are minimal to moderate. Conversely, the total-order indices for the number of influencers for adoption rate, personal satisfaction, and financial satisfaction are minimal, suggesting a limited effect of the number of influencers on these measures.

In the Barabasi-Albert network, the measure of social satisfaction shows a high total order index for the TP percentage parameter, while the index for the uncertainty threshold parameter is low and the satisfaction threshold parameter is moderate. This suggests that the percentage of True Price products is a crucial factor in determining social satisfaction when influencers are present. Influencers adopting True

Price products likely amplify their visibility and desirability, making the initial market penetration more significant for social satisfaction. In contrast, sub-model 2.2 showed higher indices for the uncertainty and satisfaction thresholds, indicating that without influencers, agents' satisfaction was more dependent on their individual uncertainty and satisfaction levels. For social uncertainty, the total-order index for the uncertainty threshold is low, while in sub-model 2.2, it was moderately high. This suggests that uncertainty plays a lesser role in social satisfaction when influencers are present. The consistency provided by influencers' adoption reduces overall social uncertainty, making individual uncertainty thresholds less significant. In the experiment, the total-order index of the satisfaction threshold for the measure of personal satisfaction is extremely high, and the index for the uncertainty threshold is moderate. In the sub-model 2.2, the uncertainty threshold had a higher total order index than the satisfaction threshold index, with both being moderately high. This indicates that with influencers, the importance of products meeting sustainability expectations (satisfaction threshold) is significantly heightened, while personal uncertainty remains a relevant but less dominant factor.

In the Watts-Strogatz model the number of influencers has a low total order index for average personal uncertainty and a moderate index for financial uncertainty. For all other measures, the indices are negligible to minimal, indicating that the presence of influencers has a limited impact on these aspects. In the current model, the uncertainty threshold has a moderate total order index for average financial satisfaction, whereas in submodel 2.2, the index was high. For average financial uncertainty, the total order index for the uncertainty threshold is low in the current model, whereas it was high in sub-model 2.2. This indicates that the presence of influencers significantly reduces the impact of financial uncertainty. The total order indices of parameters for the measures of social satisfaction and social uncertainty display a similar pattern to sub-model 2.2, having a negligible to minimal impact. This similarity suggests that while influencers can significantly affect financial and personal dimensions by reducing uncertainty and enhancing satisfaction, their impact on social dynamics remains consistent with the patterns observed in sub-model 2.2.



(a) Barabasi-Alberts **(b)** Watts-Strogatz

Figure 6.2: Total order Sobol indices for the influencer experiment

By promoting TP products, influencers can help normalize the concept and reduce perceived risks associated with TP products among their followers. While influencers can help manage uncertainty, they alone are not sufficient to drive widespread adoption or significantly boost satisfaction levels. The differing impacts of influencers in the Barabasi-Albert and Watts-Strogatz networks can be attributed to their structural characteristics. In the Barabasi-Albert network, influencers are likely to be highly connected hubs, allowing them to quickly spread information and influence a large portion of the network. This leads to a pronounced effect on social satisfaction and reduced social uncertainty. In contrast, the Watts-Strogatz network's small-world properties, with more uniform and local information spread, result in a more distributed influence of influencers. This causes less dramatic changes in social satisfaction and uncertainty. The network's clustering and short path lengths maintain stable local groups, explaining why influencers have a limited impact on social dynamics compared to the Barabasi-Albert network. These findings underscore the importance of considering network topology when designing strategies for influencer interventions.

7 | Discussion

- Insights from iterative process of sub-models
- Network effects
- Homophily effects
- Link to evol. game theory
- Does Consumat framework apply nicely to this problem?
- Does the model reproduce key characteristics and behaviour from literature?
- Insights relating to the fact that the scope was the Dutch population
- Recommendations for True Price implementation strategies, using insights from the experiments

7.1. Limitations

- Model assumptions:
  - Simplified Consumer Behavior: The model relies on simplified assumptions about consumer behaviour, such as the Consumat framework, which, while robust, cannot capture the full complexity of real-world decision-making processes. Factors such as cultural influences, emotional responses, and irrational behaviors are not explicitly modeled.
  - Although various network models (Watts-Strogatz, Barabási-Albert, Random Regular, Holme-Kim) were employed, the assumptions about network structures may not fully represent the dynamic and multi-layered nature of real-world social networks. Real-life interactions are influenced by multiple overlapping networks (e.g., family, work, social media), which were not modelled.
  - Fixed Parameter Values: Certain parameters were assumed to be static throughout the simulation. In reality, these values can fluctuate based on external influences like policy changes, economic conditions, and social movements.
- Data limitations
  - Survey Data Constraints: The use of European Social Survey (ESS) data, while extensive, may not fully capture the nuances of individual preferences and behaviours specific to the Dutch population regarding sustainability. Additionally, survey data may be subject to biases, such as social desirability bias or inaccurate self-reporting.
  - The model's financial means representation is based on general income distribution data. This approach might not capture the entire economic diversity and spending patterns of individual consumers.

- Computational Constraints
  - Scalability: The computational resources required for simulating large populations and extended time frames are substantial. Consequently, the simulations were limited to manageable population sizes and time periods, which may not fully capture long-term dynamics and rare events.

7.2. Further Research

- Future models could integrate more complex psychological theories to better capture the emotional and irrational aspects of consumer behaviour.
- Developing models that incorporate multiple overlapping network layers (e.g., social media, family, professional networks) could provide a more realistic representation of social influences on consumer behaviour.
- Introducing adaptive parameters that change based on external factors (e.g., economic conditions, policy changes) could enhance the model's realism and predictive power.
- Using longitudinal data to capture changes in consumer behaviour over time would provide deeper insights into the long-term impacts of True Price adoption.
- Expanding the study to include multiple countries and cultural contexts could help generalise the findings and identify culturally specific drivers and barriers to True Price adoption.
- High-performance computing and parallel processing techniques could allow for larger-scale simulations capturing more complex interactions.

8 | Conclusion

8.1. Conclusion

8.2. Future Work

9 | Ethics and Data Management

This thesis adheres to the ethical code and research data management policies of the University of Amsterdam and the Informatics Institute.

The research utilizes data from the European Social Survey (ESS) and the Central Bureau of Statistics (CBS). Both data sources meet stringent data protection standards. ESS data is processed in accordance with the UK Data Protection Act 2018, the EU General Data Protection Regulation (GDPR), and applicable national data protection laws, ensuring strict confidentiality. CBS undergoes annual privacy audits by accredited external organizations, resulting in a Privacy Audit Proof certificate that demonstrates compliance with GDPR regulations.

The model's design and implementation are based on established social science theories and frameworks, and the results are shared in a public GitHub repository to ensure transparency and reproducibility.

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10 | Appendix

10.1. GSA Results: Submodel 1

Table 10.1: Sobol Sensitivity Analysis for Adoption Rate

Parameter	S1	S1_conf	ST	ST_conf
TP_percentage	0.3089	0.1275	0.6425	0.1385
satisfaction_threshold	0.0568	0.0704	0.1864	0.0755
uncertainty_threshold	0.2305	0.1271	0.5117	0.1224
min_increase_percentage	0.0011	0.0020	0.0002	0.0001
max_increase_percentage	-0.0001	0.0017	0.0001	0.0001

Table 10.2: Sobol Sensitivity Analysis for Average Financial Satisfaction

Parameter	S1	S1_conf	ST	ST_conf
TP_percentage	0.0064	0.0412	0.0525	0.0283
satisfaction_threshold	0.3567	0.1372	0.5362	0.1084
uncertainty_threshold	0.4363	0.1299	0.7208	0.1678
min_increase_percentage	-0.0003	0.0111	0.0059	0.0033
max_increase_percentage	-0.0012	0.0147	0.0077	0.0019

Table 10.3: Sobol Sensitivity Analysis for Average Financial Uncertainty

Parameter	S1	S1_conf	ST	ST_conf
TP_percentage	-0.0168	0.0515	0.0736	0.0267
satisfaction_threshold	0.0448	0.0862	0.1960	0.0648
uncertainty_threshold	0.6980	0.1337	0.8361	0.1380
min_increase_percentage	-0.0010	0.0184	0.0120	0.0042
max_increase_percentage	0.0130	0.0167	0.0102	0.0014

Table 10.4: Sobol Sensitivity Analysis for Average Personal Satisfaction

Parameter	S1	S1_conf	ST	ST_conf
TP_percentage	-0.0196	0.0416	0.0860	0.0438
satisfaction_threshold	0.2623	0.1512	0.7098	0.1450
uncertainty_threshold	0.1302	0.1259	0.5676	0.1423
min_increase_percentage	-0.0054	0.0127	0.0123	0.0232
max_increase_percentage	0.0015	0.0028	0.0002	0.0001

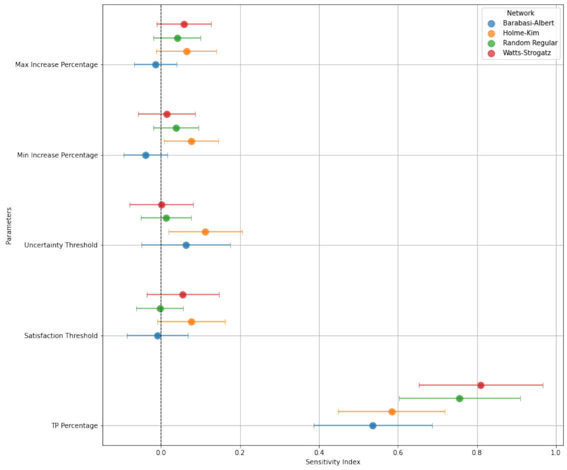
Table 10.5: Sobol Sensitivity Analysis for Average Personal Uncertainty

Parameter	S1	S1_conf	ST	ST_conf
TP_percentage	-0.0123	0.0353	0.0360	0.0269
satisfaction_threshold	0.1803	0.1003	0.3415	0.0894
uncertainty_threshold	0.6525	0.1173	0.8070	0.1246
min_increase_percentage	0.0029	0.0036	0.0004	0.0003
max_increase_percentage	0.0001	0.0031	0.0002	0.0002

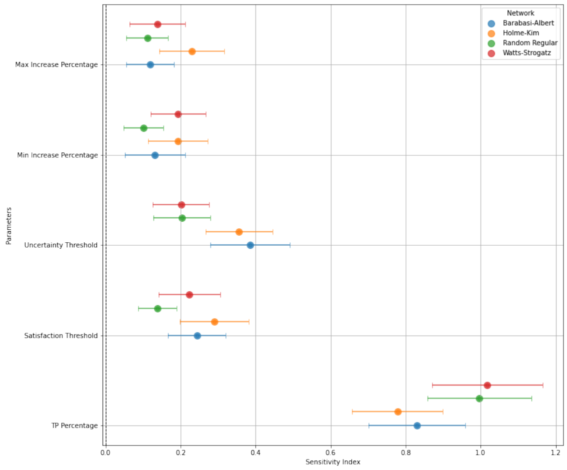
Table 10.6: Sobol Sensitivity Analysis for Average Social Satisfaction

Parameter	S1	S1_conf	ST	ST_conf
TP_percentage	0.1486	0.1033	0.3451	0.1034
satisfaction_threshold	0.1451	0.1122	0.4371	0.1260
uncertainty_threshold	0.3776	0.1353	0.7519	0.1730
min_increase_percentage	-0.0054	0.0113	0.0034	0.0014
max_increase_percentage	-0.0006	0.0038	0.0011	0.0009

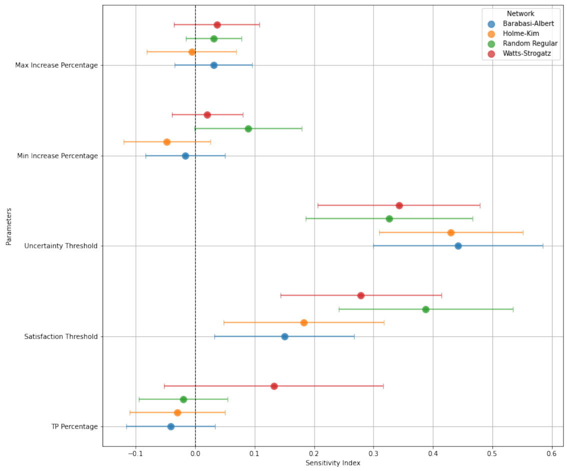
10.2. No Homophily



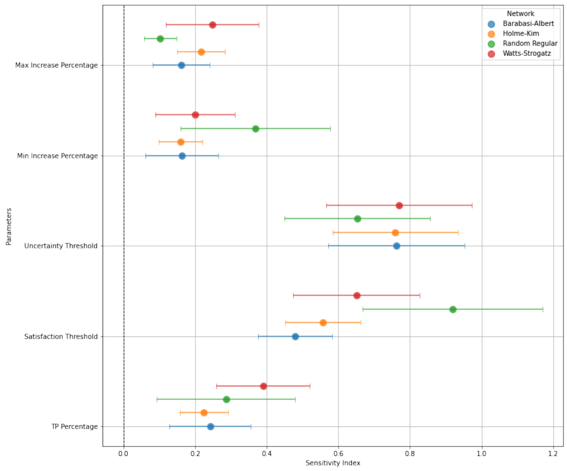
(a) First Order Analysis of Adoption Rate



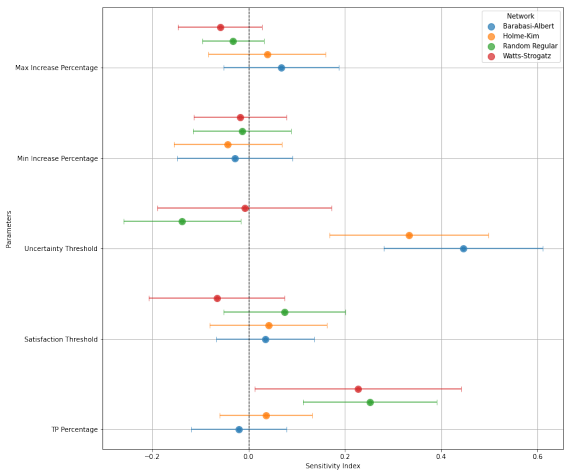
(b) Total Order Analysis of Adoption Rate



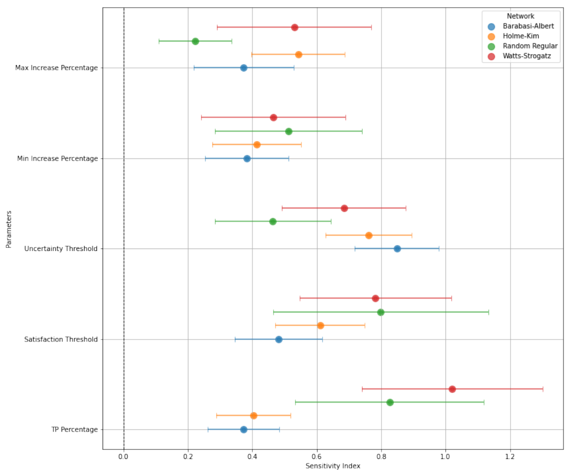
(c) First Order Analysis of Average Financial Satisfaction



(d) Total Order Analysis of Average Financial Satisfaction

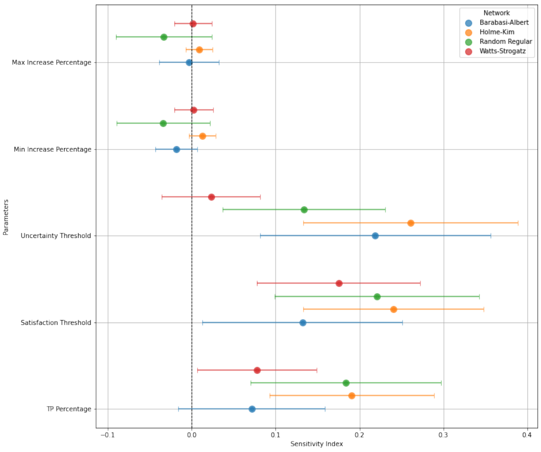


(e) First Order Analysis of Average Financial Uncertainty

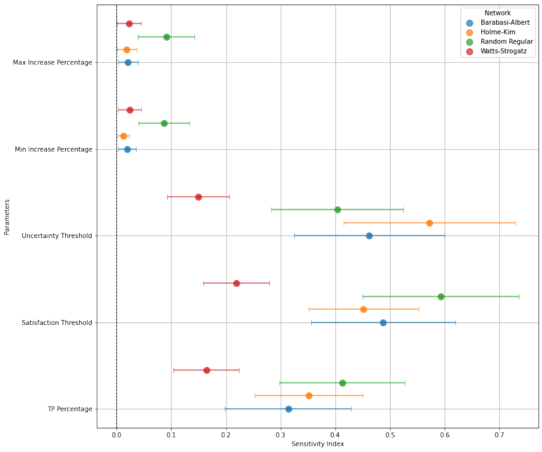


(f) Total Order Analysis of Average Financial Uncertainty

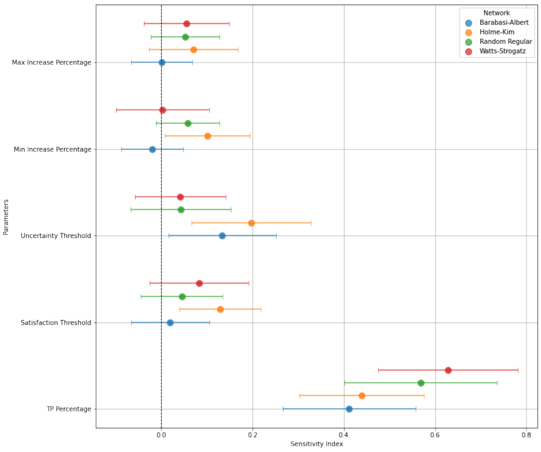
Figure 10.1: First and Total Order Sensitivity Analysis for Adoption Rate and Financial Measures without Homophily



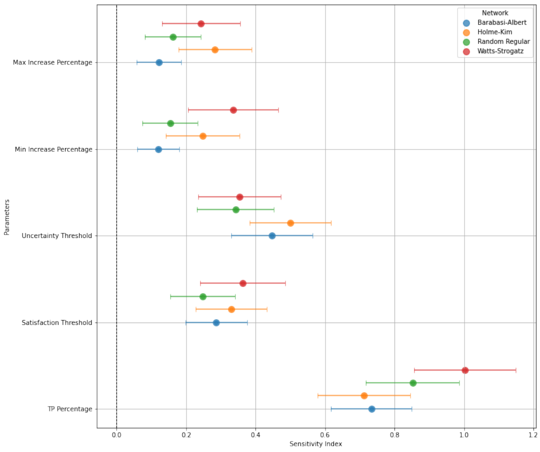
(a) First Order Analysis of Average Social Satisfaction



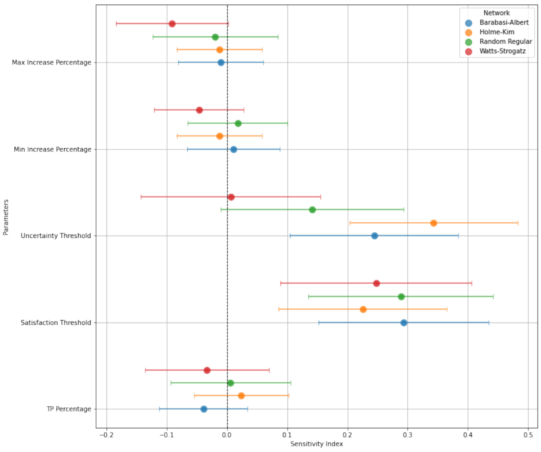
(b) Total Order Analysis of Average Social Satisfaction



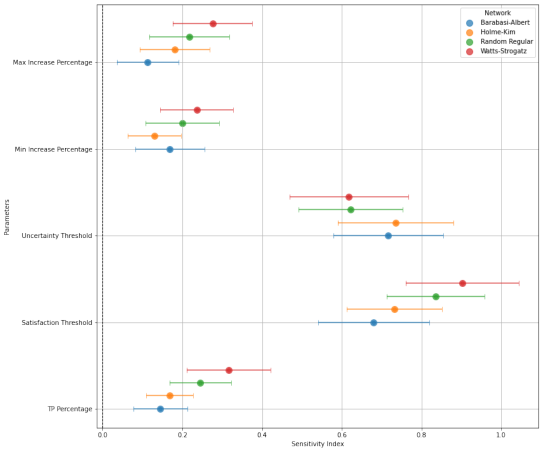
(c) First Order Analysis of Average Social Uncertainty



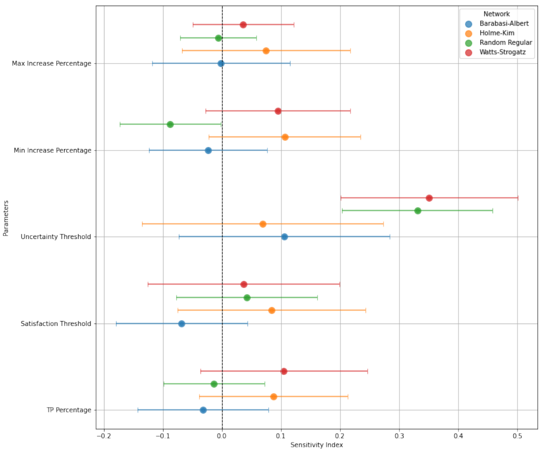
(d) Total Order Analysis of Average Social Uncertainty



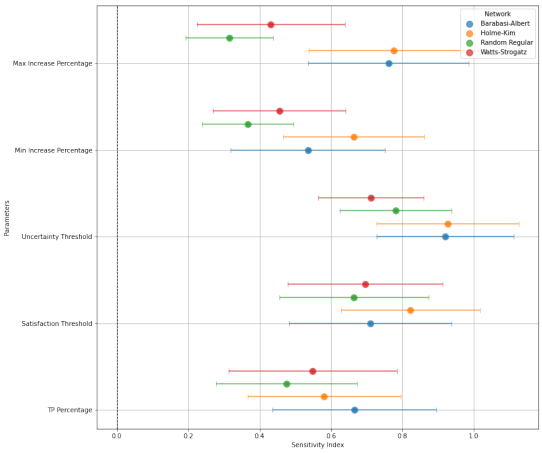
(e) First Order Analysis of Average Personal Satisfaction



(f) Total Order Analysis of Average Personal Satisfaction



(g) First Order Analysis of Average Personal Uncertainty



(h) Total Order Analysis of Average Personal Uncertainty

Figure 10.2: First and Total Order Sensitivity Analysis for Personal and Social Measures without Homophily

Table 10.7: Sobol Sensitivity Analysis for Average Social Uncertainty

Parameter	**S1**	**S1_conf**	**ST**	**ST_conf**
TP_percentage	0.1043	0.1116	0.3724	0.1033
satisfaction_threshold	0.0617	0.0823	0.2805	0.0765
uncertainty_threshold	0.4412	0.1356	0.6644	0.1133
min_increase_percentage	-0.0023	0.0104	0.0143	0.0184
max_increase_percentage	0.0100	0.0214	0.0101	0.0191