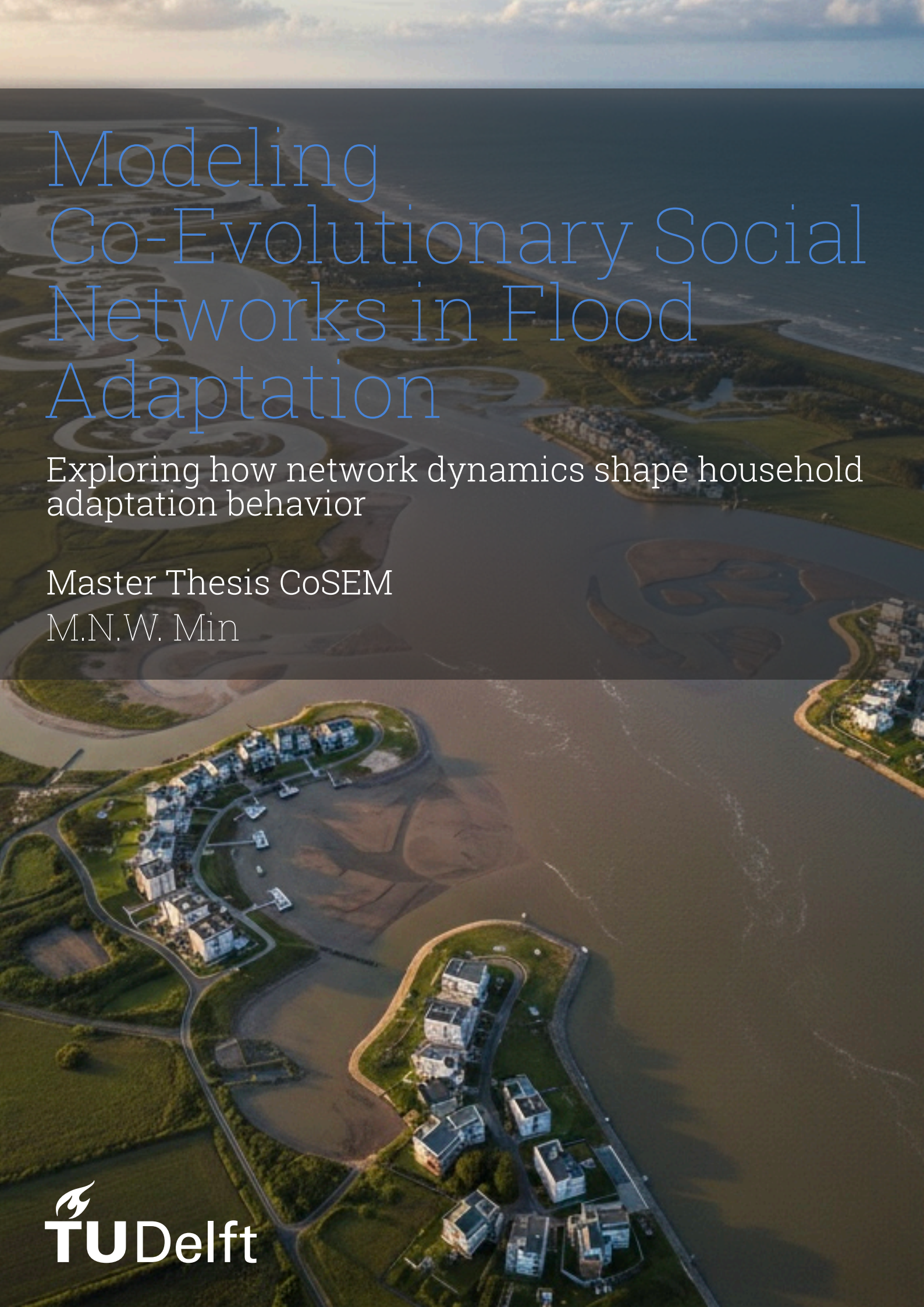


An aerial photograph of a coastal area during high tide. The water is a murky brown color, flooding the fields and surrounding the houses. The houses are clustered in small islands or peninsulas, with some roads visible. The sky is overcast with soft, grey clouds. The overall tone is somber and highlights the impact of flooding on the landscape and community.

Modeling Co-Evolutionary Social Networks in Flood Adaptation

Exploring how network dynamics shape household
adaptation behavior

Master Thesis CoSEM

M.N.W. Min

Modeling Co-Evolutionary Social Networks in Flood Adaptation

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by

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Cover: Coastal delta image generated by Google Gemini (March 2026)
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Executive summary

Despite increasing flood risks, household adaptation often remains below the level required to reduce vulnerability. Understanding how adaptation behavior spreads through communities is therefore an important research challenge. This thesis explores how changing social networks influence the spread of household flood adaptation behavior. In many real-world settings, social connections are not static: people form new relationships, lose contact with others, and interact with varying intensity over time. These processes, referred to as co-evolutionary network dynamics, may affect how households become aware of and decide to adopt flood protection measures. Despite their potential importance, their role in adaptation diffusion remains insufficiently understood.

To address this, this thesis extends the empirically grounded Flood Adaptation via Social Transformation (FAST) agent-based model with co-evolutionary social network dynamics. These include the formation and breaking of social ties as well as changes in the strength of interactions between households. The model is used to systematically explore how different configurations of these dynamics influence both the structure of the social network and the resulting adaptation behavior.

A series of computational experiments is conducted to examine the effects of network dynamism, initial topology, dynamic influence weights, and agent connectivity. The results show that co-evolutionary processes can substantially reshape the structure of the network, leading to either increased connectivity or fragmentation depending on the balance between tie formation and breaking. However, these structural changes do not translate into equally strong changes in adaptation uptake.

The influence of co-evolution is found to be moderate and highly dependent on context. Network restructuring contributes to adaptation primarily by changing local exposure to adaptive behavior. In particular, social norm dynamics play a key role: households are more likely to adapt when they are connected to others who have already taken protective measures. In contrast, internal decision mechanisms based on protection motivation theory appear less responsive to changes in network structure.

The experiments further show that the impact of co-evolution depends on how the network evolves. Tie formation dynamics support higher adaptation levels, while breaking ties reduces these effects, with the balance between the two being an important factor in affecting adaptation. Initial network topology also matters, with stylized networks showing stronger responses than empirical ones. Adding complexity in the form of dynamic interaction weights does not significantly improve model outcomes and can introduce instability.

Overall, the findings suggest that co-evolution should be understood primarily as a mechanism that shapes local patterns of social influence rather than as a direct driver of adaptation. While co-evolutionary dynamics can strongly alter network structure, these structural changes translate only weakly into additional adaptation uptake. The findings therefore highlight the importance of carefully specifying network dynamics in agent-based models and contribute to a more nuanced understanding of how social processes influence climate adaptation behavior.

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Introduction

1.1. The Societal Challenge

Climate change is increasingly exposing societies to more frequent and severe climate-induced hazards, such as flooding, forest fires and extreme weather events. While technological and infrastructural solutions are advancing, the capacity of societies to adapt does not keep up with the accelerating risks (Carr et al., 2025). A significant share of this adaptation gap is rooted in human behavior: even though climate risk awareness grows, many households delay or avoid investing in protective measures that could substantially reduce damage and vulnerability (Haer et al., 2016; Taberna et al., 2023).

Actions taken to reduce vulnerability to the impacts of climate change, are called climate change adaptation (UNDP, 2024). Climate change adaptation involves decision-making across several societal levels, from institutional planning down to individual household behavior (Noll et al., 2022). Current adaptation speed cannot keep up with the rate at which the severity of climate-induced hazards increases (Del Pilar Bueno Rubial et al., 2024). Therefore, there is a societal need to better understand the mechanisms influencing climate adaptation uptake, to help societies adapt to rapidly changing climatic conditions.

While institutional efforts are important, effective societal adaptation and resilience depends largely on the collective action of private (household) actors (Grothmann & Reusswig, 2006; Noll et al., 2022; Schubert et al., 2025). These individual level decisions directly shape the vulnerability of communities. However, the processes through which households decide whether and when to adapt remain insufficiently understood. The role of social networks in shaping adaptation behavior has only recently gained attention, despite evidence that individuals are strongly influenced by the actions and opinions of others (Flache et al., 2017; Haer et al., 2016; Wagenblast, Filatova, et al., 2026). Existing modeling approaches often treat social networks as static and external to the decision-making process. In reality, however, social networks evolve over time: individuals form new connections, lose contact with others, and the strength of their relationships might change (Gross & Blasius, 2007). Ignoring this co-evolution limits our ability to realistically capture how social influence affects adaptation behavior. By adding network dynamics to adaptation models, the interaction between individual behavioral factors and the network structure can be analyzed, leading to a more accurate representation of real-world adaptation behavior, which can help increase adaptation uptake (Wagenblast, Filatova, et al., 2026). As climate risks intensify, understanding these dynamic social processes becomes increasingly important, as they may help explain why adaptation spreads in some contexts while remaining stagnant in others.

Modeling adaptive social network structures is a complex but essential task that spans disciplines from mathematics and computer science to epidemiology and economics (Berner et al., 2023). By bridging social network theory (SNT) with simulation-based analysis, these models offer a sort of testing ground for understanding the complex social processes behind societal challenges such as climate change adaptation. Within this framework, agent-based modeling (ABM) has emerged as a particularly effective method for capturing the complex mechanisms behind climate adaptation behavior (Taberna et al., 2020). Combining insights from SNT and ABM could help to better understand behavior in social

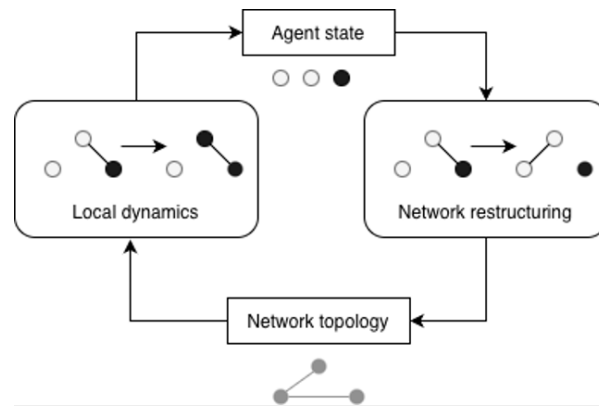


Figure 1.1: Overview of how co-evolutionary networks function. Adapted from Gross and Blasius (2007).

systems, specifically by modeling individual behavior as part of a dynamic social network (Bonabeau, 2002; Squazzoni et al., 2014). This thesis therefore aims to combine insights from SNT with exploratory modeling to investigate how co-evolutionary social networks influence household adaptation behavior.

1.2. The academic challenge

Climate adaptation is not only a physical or economic challenge, but also a social one. Household decisions regarding flood adaptation are influenced by interactions with others, including the exchange of information, observation of adaptive behavior, and the formation of social norms. As a result, adaptation behavior emerges through social processes rather than just through individual decision-making alone (Erdlenbruch & Bonté, 2018; Haer et al., 2016; Han et al., 2021; Taberna et al., 2023; Van Valkengoed & Steg, 2019).

Understanding these processes is challenging because households are embedded in social networks. These networks determine how information, experiences and influence spread between individuals. Social influence can occur through mechanisms such as social learning, imitation, persuasion and conformity, causing individuals to adjust their beliefs or behavior in response to others (Flache et al., 2017). In climate adaptation contexts these dynamics often manifest through social norms, where households form expectations about appropriate or effective actions based on the behavior of their peers (Constantino et al., 2022). Consequently, adaptation behavior cannot be understood independently of the social structures through which influence occurs.

A second challenge lies in distinguishing between the diffusion of information and the adoption of behavior. While information can spread rapidly through social networks, the adoption of costly adaptation measures often requires repeated exposure, social reinforcement and trust. Adaptation behavior therefore resembles a complex contagion rather than a simple diffusion process (Constantino et al., 2022; Zia et al., 2021). This means that changes in social structure do not always translate directly into behavioral change, making it difficult to predict adaptation outcomes from network characteristics alone.

The complexity of these processes is increased further by the fact that social networks are not static. Individuals can form new relationships, strengthen existing connections and break contact with others over time. Such changes can be driven by social mechanisms such as homophily, which explains that individuals preferentially interact with similar others, or preferential attachment, referring to highly connected individuals being more likely to gain additional connections (Barabasi & Albert, 1999; Kossinets & Watts, 2009). At the same time, these changing social structures influence the future spread of information and behavior.

This creates a feedback process between individuals and the networks in which they are embedded. On the one hand, social networks influence household perceptions, intentions and adaptation decisions. On the other hand, household behavior can influence the structure of the social network itself (see figure 1.1). Capturing this interaction requires moving beyond static representations of social systems and viewing adaptation as a co-evolutionary process in which network dynamics and behavioral dynamics

develop simultaneously (Gross & Blasius, 2007; Gu et al., 2017).

Representing this feedback loop poses a significant modeling challenge. Traditional modeling approaches are often insufficient to capture heterogeneous decision-making, social influence and dynamic interactions simultaneously. Agent-based modeling offers a suitable framework because it allows individual households, behavioral processes and social network structures to be represented within a complex adaptive system (Will et al., 2020). Combining agent-based modeling with co-evolutionary networks therefore provides a promising approach for exploring how social structure and adaptation behavior influence one another over time.

The following literature review examines how social networks have been incorporated into climate adaptation research and assesses the extent to which existing studies account for these co-evolutionary dynamics.

1.3. Literature review

This literature review positions this thesis project within the field of social network modeling in climate adaptation models. Based on the societal challenge and theoretical concepts introduced in the previous section, relevant studies applying social network modeling to climate change adaptation were selected. These studies were screened for relevance to dynamic and co-evolutionary social network modeling, as well as their applicability to household-level flood adaptation behavior. Based on the findings from this review a knowledge gap has been observed that forms the basis for the research approach.

1.3.1. Social networks in climate adaptation research

In recent years, developments in climate adaptation research have led to a focus on integrating human behavior into climate and flood risk assessment. Climate adaptation models have shifted from physical systems to socio-environmental systems modeling (Taberna et al., 2020). An important aspect of this integration, is the use of social networks as critical determinants of the adaptive capacity of a system (Barnes et al., 2020). Through these networks individuals are influenced on how they share information, perceive risks and how they implement adaptation strategies (Chaudhury et al., 2017; Cunningham et al., 2016; Haer et al., 2016).

1.3.2. Empirical approaches to social networks in adaptation behavior modeling

Shifting the focus from purely physical systems (e.g. modeling hydrological systems) to socio-environmental systems, has moved climate adaptation research into the domain of complex adaptive systems. Current empirical research on social networks in climate adaptation contexts consistently treats network structures as static and exogenous factors. Several empirical studies rely on cross-sectional data to represent social networks (Barnes et al., 2020; Chaudhury et al., 2017; Cunningham et al., 2016; Eise et al., 2021; Parks, 2022; Salgueiro-Otero et al., 2022), while broader socio-hydrological models often exclude explicit social network structures altogether (Carr et al., 2025).

In these studies, network structures are treated as static representations of social relationships. While these studies demonstrate that network structure plays a crucial role in diffusing adaptation-related knowledge and behavior, they do not capture how social ties evolve over time. The empirical data underlying these studies represent a single point in time, thus capturing only a snapshot of a complex social system. As climate adaptation is inherently a complex adaptive systems problem, assuming static social networks overlooks the dynamic and emergent nature of social interactions.

Cunningham et al. (2016) therefore specifically call for longitudinal data-collection to better understand network evolution. Almost all of these authors discuss cross-sectional compared to longitudinal data-collection as a limitation to their research. However, large-scale longitudinal data collection remains resource-intensive, making it difficult to empirically capture the evolution of social networks. This creates a methodological challenge: how to represent dynamic and stochastic social behavior in the absence of detailed longitudinal data.

1.3.3. The use of ABM in climate adaptation models

ABM offers a powerful approach to simulate the dynamics, stochasticity, and emergent properties of complex adaptive systems. Within climate adaptation research, ABMs have been used to incorporate bounded rationality and social influence mechanisms, proving that social influence, descriptive norms, and peer-to-peer learning amplify adaptation outcomes far more than purely rational financial calculations (Erdlenbruch & Bonté, 2018; Haer et al., 2016; Han et al., 2021).

Several studies embed agents in stylized social networks to examine how social influence shapes adaptation behavior (Erdlenbruch & Bonté, 2018; Haer et al., 2016; Han et al., 2021; Ruohan et al., 2025; Taberna et al., 2023). In addition, studies on network-based group decision-making show how social structures influence consensus formation in risk contexts (Ma et al., 2025). These models consistently show that social norms, peer-to-peer learning, and indirect experiences significantly affect adaptation decisions. However, in most of these models the network topology remains fixed over time. While behavior evolves, the social structure through which influence is mediated does not. This implicitly assumes that flood events, shifting opinions, and adaptation actions do not affect the structure of the social networks themselves (Erdlenbruch & Bonté, 2018; Haer et al., 2016; Han et al., 2021).

1.3.4. Emerging work on dynamic and co-evolutionary networks in climate adaptation modeling

Recent advances in ABM suggest that co-evolutionary network structures can in principle be modeled. For example, Van Den Ende et al. (2024) introduce a general framework for simulating co-evolutionary network dynamics across multiple domains. However, this framework is not specifically tailored to climate or flood adaptation contexts. In most of the research applying social networks in climate adaptation, static network structures are used for the sake of simplicity or a lack of data (see overview table 1.1). Even though social network analysis has become a core methodology in climate adaptation research, most climate adaptation models still treat social networks as a static structure or exogenous influence. Consequently, they fail to capture the feedback between network structure and agent behavior over time (Barnes et al., 2020; Saeedian et al., 2024; Taberna et al., 2020).

1.3.5. Examples of applications of social network co-evolution

In reality, social networks are dynamic, co-evolving structures in which behavior and relationships continuously influence one another (Juhola et al., 2022). A small number of studies illustrate the potential of modeling such dynamics. For example, Saeedian et al. (2024) model co-evolution between resource dynamics and social ties, while Entwisle et al. (2020) simulate how extreme climate events reshape social networks through migration processes. These studies demonstrate the feasibility of dynamic network modeling, but either lack behavioral specifics or focus on contexts different from household flood adaptation.

The lack of integration between co-evolutionary network dynamics and empirically grounded models of household adaptation represents a key gap in the literature. While theoretical frameworks and modeling tools for co-evolutionary networks exist (Saeedian et al., 2024; Van Den Ende et al., 2024), their application to climate adaptation remains limited. This suggests the need to apply co-evolutionary network modeling within empirically grounded adaptation contexts. An overview of the analyzed articles for this review is given in table 1.1. The table explains in what context the research was performed, how social networks were applied in the respective study, what level of network-dynamism was applied and what elements were missing in regard to this research. These missing elements contribute to the knowledge gap that is discussed in section ??.

Table 1.1: Key literature and the knowledge gap that is observed for this research

Author(s) & Year	Context method	and	Application of social networks	Network dynamism	Contribution to knowledge gap
Barnes et al., 2020	Papua Guinea; Multi-level network modeling	New	Links specific social-ecological network configurations to transformative action.	Static	Does not model the evolution of these complex multilevel networks.
Carr et al., 2025	Socio-hydrological model of flood adaptation		Explores interactions between public/private measures.	Not explicitly modeled	Lacks modeling of social network structures or social influence in adaptation uptake.
Chaudhury et al., 2017	Ghana agriculture; Empirical SNA	agricultural	Maps bridging/bonding ties to assess household adaptive capacity.	Static	Relies on a single point in time; fails to capture how ties change dynamically after climate shocks.
Cunningham et al., 2016	Australia climate policy; Empirical SNA	climate	Identifies "boundary spanners" in knowledge diffusion networks.	Static	Only provides a snapshot; stresses the importance of longitudinal methods to understand network evolution.
Eise et al., 2021	Colombia coffee farmers; Ego networks	coffee	Maps ego (individual) networks to identify informal vs. formal information flows.	Static	Measures existing relationships without exploring how these ties might change over time.
Entwisle et al., 2020	Thailand migration; ABM	migration	Models how extreme weather causes migration, reforming social ties.	Dynamic	Highly dynamic, but focused on migration rather than in-situ flood adaptation measures.
Erdlenbruch and Bonté, 2018	France flood risk; ABM		Uses small-world networks to simulate diffusion of individual adaptation.	Static topology	Social network is initialized at the start after which no ties are formed or broken.
Haer et al., 2016	Netherlands flood risk; ABM & Protection Motivation		Simulates spread of risk communication via random normal social networks.	Static topology	Information spreads dynamically, but the social network ties between households remain fixed.
Han et al., 2021	USA (Florida) coastal risk; ABM & Bayesian learning	(Florida)	Evaluates flood adaptation where agents share indirect flood experiences via social links.	Static topology	Network generated via Poisson distribution. Ties are static while agents update risk perceptions.
Juhola et al., 2022	Conceptual Review; Systemic risks and adaptation	Re-view	Frames social tipping points as non-linear changes triggered by behaviors in a social system	Conceptual review	Argues that current socio-economic models fail to explicitly capture adaptive, dynamic feedbacks and changing social norms.
Ma et al., 2025	Flood disaster chains; Social Network GDM	disaster	Uses trust networks among decision-makers to reach consensus during disaster chains.	Dynamic	Decision-maker risk preference influences tie formation, but focuses on short-term decision-making, not long-term socio-ecological adaptation.

Table continues on next page

Table 1.1 – Continued from previous page

Author(s) & Year	Context method	& Application of social networks	Network dynamism	Contribution to knowledge gap
Saeedian et al., 2024	Theoretical ABM; Human-environmental systems	Models co-evolution of resource feedback and social link dynamics in a .	Co-evolutionary	Directly models dynamic social networks, but applies this to a common pool resources game which has different social implications than a climate adaptation context
Salgueiro-Otero et al., 2022	Spain fisheries; Empirical SNA & Regression	Tests effect of bonding, bridging, and linking ties on adaptation/transformation.	Static	Network structures are fixed inputs for predicting hypothetical responses to future climate scenarios.
Taberna et al., 2020	Review of flood ABMs; Socio-Environmental Systems	Reviews how existing ABMs handle hazard exposure, vulnerability, and learning networks	Conceptual review	Concludes that the majority of current flood ABMs use static networks and specific behavioral rules, missing transformative dynamics.
Taberna et al., 2023	USA (Florida) coastal risk; Evolutionary ABM	Simulates how boundedly rational households update adaptation based on peer norms.	Static topology	Descriptive norms evolve dynamically, but the network structure mediating them does not co-evolve.
Van Den Ende et al., 2024	Software framework; ABMs and complex adaptive networks.	Introduces "DyNSimF", a python package to model the dynamics on a network as well as the dynamics of the network	Co-evolutionary	Provides a generic methodological tool for modeling complex state-topology co-evolution but lacks an empirical application directly testing these dynamics in a specific climate or flood adaptation scenario

1.4. Knowledge gap and main research question

The literature review demonstrates that social networks play an important role in shaping household adaptation behavior. Empirical studies consistently show that social influence, knowledge exchange and social norms affect how households perceive climate risks and decide whether to implement adaptation measures. Additionally, agent-based adaptation models increasingly incorporate social influence mechanisms and network structures to represent these processes.

However, most existing studies treat social networks as static structures. While adaptation behavior is allowed to evolve over time, the social networks through which information and influence spread generally remain fixed. Consequently, current models capture the effects of social influence, but largely overlook how households may simultaneously alter their social relationships. Processes such as tie formation, tie breaking, changing interaction strength, and network restructuring are therefore rarely represented in climate adaptation models.

This creates an important knowledge gap. Climate adaptation is viewed as a complex adaptive system characterized by feedback loops between social, behavioral, and environmental processes. However, current modeling approaches generally do not capture the potential feedback between household adaptation behavior and the social network structure through which that behavior spreads. As a result, it remains unclear how co-evolutionary social network dynamics influence the diffusion of household flood adaptation measures and whether accounting for such dynamics significantly changes model outcomes and behavior.

Based on this knowledge gap, the following research question has been formulated:

How can the co-evolutionary restructuring of social networks be modeled to better understand the diffusion of household flood adaptation behavior?

1.5. Research approach

To address the research question, this thesis adopts an exploratory modeling approach to investigate how changes in social network structure influence household flood adaptation behavior and how adaptation behavior can reshape social networks. Building on the academic challenges identified in the previous section, an existing agent-based model (ABM) is extended with co-evolutionary social network mechanisms that allow both household behavior and network structure to evolve over time.

The objective of the model is not to predict a single future outcome or identify an optimal solution, but rather to explore how different assumptions regarding network restructuring affect adaptation dynamics. This makes it possible to examine a range of plausible system behaviors and identify the mechanisms that drive or constrain adaptation uptake under different conditions. To assess the influence of network structure itself, both empirical and stylized network topologies are included in the analysis.

A Python-based ABM framework is used because household adaptation emerges from interactions between agents and their social environment. Such feedback processes are difficult to capture using top-down or purely analytical approaches. Agent-based modeling therefore provides a suitable framework for representing individual decision-making, social influence and dynamic social networks within a single modeling environment.

Furthermore, the model builds on the empirically grounded FAST-ABM developed by Wagenblast, Filatova, et al. (2026) and Wagenblast, Ghorbani, et al. (2026), resulting in an approach that combines empirical foundations with exploratory experimentation. More information on the model structure and empirical basis is provided in Chapter 2 and Appendix A. By extending this model with co-evolutionary network dynamics, this thesis aims to provide insight into the role of network restructuring in shaping the diffusion of household flood adaptation behavior.

1.5.1. Research objectives and sub-questions

The research approach is structured around two objectives, each associated with specific sub-questions and corresponding methods or data sources (see Table 1.2). Chapter 2 will explain the conceptual framework and on what literature base the model is built. Chapter 3 on the methodology will explain the base model and model extension, after which the different experimental setups are discussed.

1.5.2. Research pipeline

Figure 1.2 provides an overview of the research pipeline, illustrating how the theoretical framework, model development, and experimental analysis are interconnected throughout the thesis. The research is structured into five main phases.

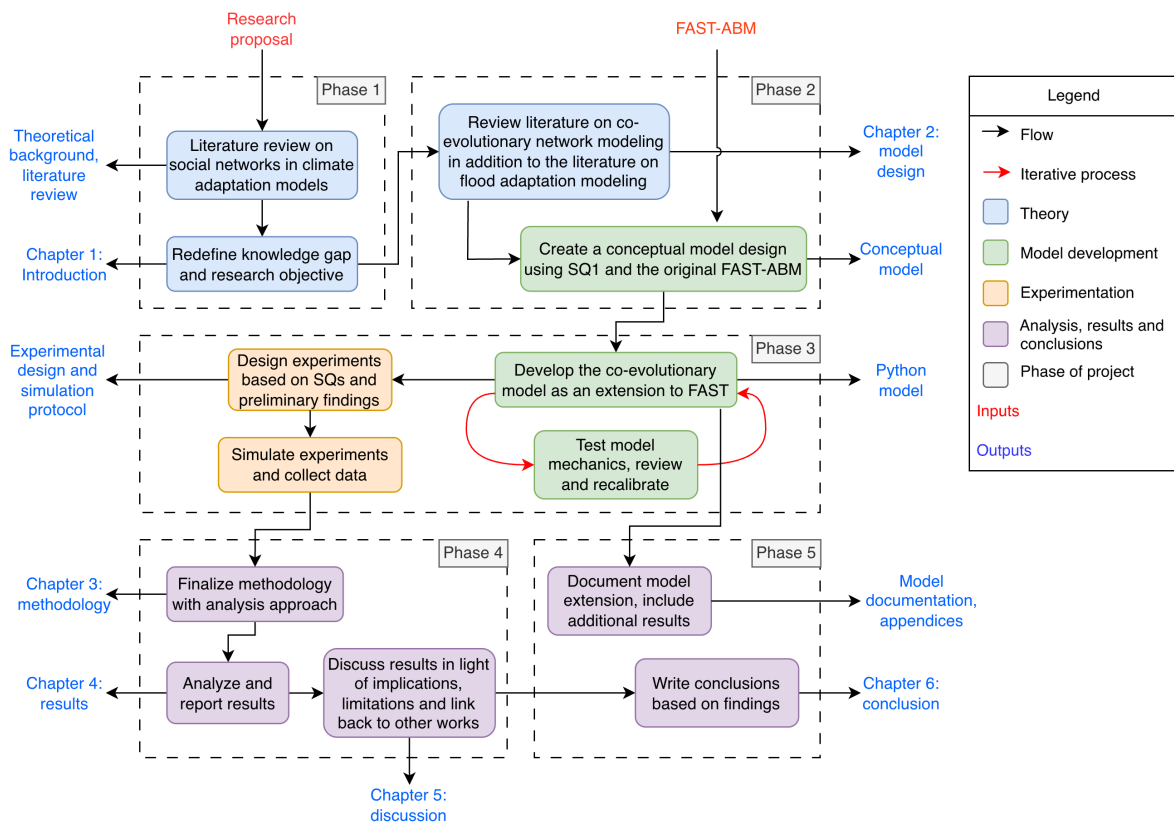
Phase 1 focuses on refining the research scope and establishing the theoretical foundation. Phase 2 develops the conceptual model. Phase 3 involves the implementation of the model and the execution of experiments. Phase 4 is dedicated to analyzing and discussing the results. Finally, Phase 5 synthesizes the findings and presents the overall conclusions of the study.

1.6. Relation to MSc program

This research focuses on modeling a dynamic social network, by adapting an existing model for household behavior in a flood adaptation context. The objective of this research relates to the CoSEM study program, since it involves a complex socio-technical system for which social, institutional, economic and technological factors are modeled and used to critically reflect on real-world implications of the findings. The approach is multidisciplinary and builds on insights from systems engineering, graph theory, computer science and the social sciences. Examples of courses that specifically relate to this research include Agent-Based Modeling and Design in Networked Systems.

Table 1.2: Research objectives, sub-questions, and methodology

Research Objective	Research Sub-Question(s)	Methods / Data
RO1: Develop and implement a co-evolutionary social network representation within FAST-ABM	SQ1: Which social mechanisms, behavioral assumptions, and interaction rules can explain the co-evolution between household adaptation behavior and social network structure in a flood adaptation context?	Literature review, desk research
RO2: Assess the influence of co-evolutionary social network dynamics on household adaptation behavior	SQ2: Under what conditions and through which mechanisms, do co-evolutionary social network dynamics influence household adaptation uptake? SQ2.1: How does the rate of network restructuring (tie formation versus tie breaking) influence adaptation uptake? SQ2.2: How does initial network topology moderate the effects of co-evolutionary dynamics on adaptation uptake? SQ2.3: What is the impact of adding dynamic weights on the network topology and subsequently on the resulting adaptation uptake? SQ2.4: How does household connectivity relate to individual adaptation behavior and how does this vary across setups?	Exploratory modeling; Use insights from preliminary experiments and model testing and insights from SQ1 as data inputs

**Figure 1.2:** Research flow diagram giving an overview of the thesis project and its important processes, inputs and outputs

Conceptual Framework and Social Mechanisms

2.1. Mechanisms of co-evolutionary social network dynamics

The goal of SQ1 is to identify the social processes and network restructuring mechanisms that are relevant for modeling co-evolutionary social networks in a household flood adaptation context. This section will address the findings from a literature review that has been performed to answer SQ1. Building on the literature review presented in Section 1.3, studies from climate adaptation research are combined with literature on co-evolutionary social network modeling from related domains such as network science, mathematics, and computer science. The objective is not to provide an exhaustive overview of all mechanisms described in the literature, but to identify the most relevant mechanisms for representing the interaction between household adaptation behavior and social network dynamics.

Following the classification of Berner et al. (2023), the reviewed studies mostly fall within two domains: opinion formation and information or knowledge diffusion. From these studies, mechanisms governing both behavioral change and network restructuring were extracted. For the purpose of this thesis, these mechanisms are organized into two categories: **network-to-household dynamics**, describing how social networks influence household behavior, and **household-to-network dynamics**, describing how households change their social connections. This distinction aligns with the conceptual structure of FAST, in which household and network processes are represented as separate but interacting layers (figure 3.2).

Not all mechanisms identified in the literature are incorporated into the model extension. Instead, the review is used to develop a theoretically grounded set of assumptions that can be tested within the scope of this research. Table 3.1 provides an overview linking the selected model assumptions and mechanisms to their corresponding literature sources.

2.1.1. Network-to-household

When relating the effect of (co-evolutionary) social networks to adaptation decisions, researchers in socio-hydrological modeling often rely on Protection Motivation Theory (PMT) to simulate how individuals decide whether to adapt or not (Carr et al., 2025; Erdlenbruch & Bonté, 2018; Haer et al., 2016; Han et al., 2021). Protection motivation consists of threat and coping appraisals (explained in section 3.1), which are not determined in isolation. The social network in which individuals (agents) are embedded diffuses “indirect flood experiences”, allowing them to dynamically update their adaptation preferences based on the decisions, experiences, and opinions of their neighbors (Han et al., 2021).

A mechanism that plays an important role in the behavior and opinion formation of individual agents is bounded confidence. This assumes that agents only compromise and move their opinions closer to one another if their current opinions are already sufficiently similar (Kozma & Barrat, 2008; Krishnagopal & Porter, 2024). Ioannidis et al. (2021) support the idea that bounded confidence limits agents’ social interactions. According to them, agents do not interact randomly, but instead select interaction partners based on bounded rationality. Interaction can involve the creation of new connections or the use of existing ones. How agents select interaction partners can be based

on different selection rules, such as homophily or preferential attachment.

Connections in a social network lead to the spread of behavior, opinions and information. The spread of behavior operates as a “complex contagion” (Zia et al., 2021). Unlike the simple diffusion of basic information, the adoption of (costly) adaptation measures requires social reinforcement, influence from prior adopters and repeated interactions between agents (Zia et al., 2021). Opinions on the other hand can converge and reach a state of consensus, but they can also polarize. This polarization mechanism can be described as agents reinforcing each other’s opinions (Flache et al., 2017). If an agent interacts with another agent who holds the same stance (e.g. both are positive or both are negative), they tend to move towards each other and mutually reinforce each other. Interacting with an agent holding an opposing stance can cause opinions to shift in a different direction (Baumann et al., 2020; Sole et al., 1975; Takács et al., 2016). This polarization can also occur at the group level, where opinions shift in different directions based on collective behavior. Gu et al. (2017) describe this “opinion momentum” as agents moving similarly to a flock of birds, where opinions move based on the average direction of neighbors. In addition to group-level opinion dynamics, it can also lead to “promotive” relationships where people feel tension to help or align with the other, which encourages supportive behavior and convergence of views (Sole et al., 1975; Takács et al., 2016). Perceiving another agent as similar increases social proximity and caring, which mediates more generous and prosocial choices toward them (Schütt, 2023) and more positive attitudes (Grigoryan, 2019), which in turn can facilitate opinion influence (reinforcing the idea of a confidence bound, or similarity bias, in opinion influence).

Not only opinions related to protection motivation diffuse through social networks in the context of climate adaptation. Households whose network partners are more engaged in adaptive or transformative actions are themselves more likely to take such actions, consistent with social influence operating alongside homophily and selection. When households observe their peers implementing protective measures, it directly amplifies their own threat and coping appraisals through observational learning and verbal persuasion. An agent’s intention to adapt is therefore strongly influenced by the descriptive social norms prevalent within their immediate network (Barnes et al., 2020; Haer et al., 2016).

Another important mechanism underlying co-evolutionary networks is the social influence exerted through the network and the way this influence scales. The connections a household has do not influence it uniformly; instead, the cognitive shift in an agent’s flood protection motivation is scaled by the strength (weight) of its connections. This is mostly modeled through weighted averaging of influence, scaled state contagion functions, or moderated knowledge absorption mechanisms (Aghbolagh et al., 2023; Lu & Yuan, 2026; Van Den Beukel et al., 2019). High-weight connections, representing strong ties such as family and close friends, act as efficient channels for opinion exchange, knowledge sharing and exerting a strong behavioral influence that can encourage an agent to adopt adaptation measures (Chaudhury et al., 2017; Lu & Yuan, 2026; Zia et al., 2021). Conversely, low-weight connections, representing weaker ties like acquaintances, primarily determine how much new information diffuses into the network, but often lack the influence needed to immediately push an individual past their intention threshold for adaptation (Erdlenbruch & Bonté, 2018; Ioannidis et al., 2021; Zia et al., 2021).

Taken together, these mechanisms indicate that network-to-household effects can be effectively represented through similarity-based interaction, bounded confidence, and weighted social influence. These principles form the basis for the behavioral dynamics implemented in the model.

2.1.2. Household-to-network

The strength of network connections and the influence agents exert on each other can be based on the distance between agents’ opinions. As discussed earlier, agents only tolerate a certain level of difference in opinion and may sever a connection based on a tolerance threshold (Kozma & Barrat, 2008). This tolerance threshold can be linked to a property of ties, where, instead of being discrete binary links, network connections can take the form of continuous weights. These weights can increase when agent opinions are within a similarity threshold and decay if they are too dissimilar, potentially dropping below the tolerance threshold (Van Den Beukel et al., 2019). If the weight drops below this threshold, the edge is probabilistically severed, leading the agent to rewire the connection to a new and more compatible partner in the network (Kozma & Barrat, 2008; Krishnagopal & Porter, 2024; Lu & Yuan, 2026).

In addition to opinions, other factors also play a role in connection strength. Salgueiro-Otero et al. (2022) relate connection strength to differences in the nature of the relationship between agents. Strong connections are characterized by frequent communication within a homogeneous group (e.g. family or close friends), which are better at sharing practices and providing social support for adaptive behavior. Chaudhury et al. (2017) emphasize the importance of weak ties that bridge structural holes between disparate groups to achieve transformational adaptation. Bridging ties can provide households with external resources such as novel technologies and diverse knowledge, which help to break out of local socio-ecological traps and diversify adaptation (Chaudhury et al., 2017; Salgueiro-

Otero et al., 2022). Eise et al. (2021) provide empirical evidence for the importance of informal connections in information diffusion, showing differences between family, friends, and acquaintances in interaction frequency.

Knowledge diffusion models sometimes also incorporate dynamic tie weights. According to Lu and Yuan (2026), tie strength can be adjusted based on a retrospective evaluation of bilateral utility. If the mutual knowledge gained by both agents increases, the tie is reinforced. As the knowledge gap closes over time, the marginal returns of the knowledge exchange decrease and the tie weakens. Similar to opinion dynamics models, if the tie strength falls below a critical threshold, the tie is severed. Luo et al. (2015) argue that links may also be dropped if the knowledge gap is too large and knowledge exchange becomes difficult. Zia et al. (2021) show that, in addition to determining the survival of a tie, connection strength also affects the extent to which information or opinions are exchanged.

When forming new connections, agents can follow several rules, such as homophily and preferential attachment. Agents are likely to establish social ties with peers who share similar socio-demographic attributes (such as age, income, and education) or who show alignment in their existing opinions and adaptation states (Baumann et al., 2020; Krishnagopal & Porter, 2024; Van Den Beukel et al., 2019). In addition to homophily, Van Den Beukel et al. (2019) and Chaudhury et al. (2017) propose that preferential attachment also plays an important role in tie formation in social networks. Households that are already highly central and visible within their community tend to form new connections more rapidly.

A related tie formation model uses a gravity-based approach. Gu et al. (2017) use a gravity function in which the probability of a connection increases based on the intrinsic "popularity" of the two nodes (identifying opinion leaders) and decreases based on the squared distance between their opinions. This opinion distance is also applied by Conrad et al. (2024) in a social space mobility model, where agents can move towards or away from each other based on their stance-point.

Overall, several authors suggest that hazard events can disrupt social systems and lead to qualitative changes with effects such as increased connectivity or interaction in the social network (Cunningham et al., 2016; Juhola et al., 2022; Parks, 2022; Saeedian et al., 2024). Saeedian et al. (2024) propose a co-evolutionary model of human-environmental systems that explicitly links environmental conditions to social link dynamics. In general, when resources are abundant, individuals are more likely to behave greedily or maintain negative/unproductive social links. Conversely, in conditions of scarcity or stress, people are more likely to self-organize and seek connection with others or resolve conflicting/negative connections. Parks (2022) provide empirical evidence that agents lacking experiential knowledge about specific hazards are actively seeking and maintaining connections with others to learn more about how to adapt. This suggests that the uncertainty and threat from changing environmental hazards actively drive individuals to look towards others, forming new connections in the process.

Finally, both spatial and structural considerations influence network evolution. Agents may form connections locally or globally, and their position within the network affects both influence and information flow (De Arruda et al., 2017; Holme & Newman, 2006; Jang et al., 2019). While these mechanisms are relevant, their implementation depends on model scope and complexity.

Overall, the examined literature suggests that household-to-network dynamics can be represented through similarity-driven tie formation, threshold-based tie breaking, and context-dependent rewiring. These mechanisms provide a tractable and theoretically grounded basis for modeling network evolution in the FAST-ABM.

2.2. Conclusion for SQ1

Based on the insights from the theoretical background and literature review in the introduction chapter, as well as the co-evolutionary social network literature (section 2.1), several core mechanisms of co-evolutionary network dynamics can be identified.

In a social network where households interact around flood adaptation behavior, three core dynamics can be identified: the formation of new ties based on homophily and preferential attachment, the breaking of existing ties that no longer serve the interests of the household, and the extent to which a connection influences a household. Influence in the network can be represented by the weight assigned to an edge. This weight can serve different purposes. It can represent connection strength and, with that, the level of influence exerted on or received from other agents. It can also serve as an indicator of 'viability' of the connection. If a connection is weak, interaction may no longer occur and the connection potentially breaks. This connects to the idea of tie breaking: if an edge has a low weight, it may be removed, reflecting low similarity between households and a reduced incentive to interact on a topic on which you disagree or do not feel like you can learn anything from the other.

Tie formation depends on the type of social network, but in a flood adaptation context there are a few rules that generally apply. First, homophily acts as an important gatekeeper for whether households will form connections.

Preferential attachment also plays an important role. In addition to rules describing who to connect with, external factors also influence tie formation. For example, flood events can trigger an increase in new tie formation as households look towards others for information and discussion. This suggests that the uncertainty and perceived threat associated with environmental hazards actively drive individuals to look toward others, thereby forming new edges to acquire essential response strategies.

Influence from the network to household agents is derived from both the network structure and its evolution over time. Relevant social rules relate to the strength of opinion influence, where perceiving someone as similar leads to increased exchange of views. Households exhibit bounded rationality and therefore have a confidence bound based on which they choose to exchange views (or not). This can be represented in the edge weight, where the weight is formed by a score of similarity between connecting households. Higher weights correspond to stronger influence on opinions. Furthermore, connection strength is not only determined by similarity, but also by the type of relationship that the households have. For example, family and friends generally have a stronger connection and thus influence on each others opinions than acquaintances or neighbors.

By synthesizing these mechanisms, the design of the ABM extension can be systematically grounded in existing literature. The integration of a dynamic weight system (driven by relationship types and PMT-based similarity), combined with homophilic tie formation and threshold-based tie severing, reflects key mechanisms identified in the literature. It reflects the idea that households do not adapt to floods as isolated, fully rational actors; rather, they are boundedly rational agents whose adaptive behavior is shaped by, and in turn shapes, the social networks in which they are embedded.

Having defined these social rules and network restructuring mechanisms, the next chapter presents the development of the FAST-ABM, in which these conceptual findings are formalized into an ABM framework.

3

Methodology

3.1. Foundations of the model

Before the co-evolutionary network dynamics model applied in this thesis is explained, the initial (base) model must be discussed. The Flood Adaptation via Social Transformation (FAST) ABM by Wagenblast, Filatova, et al. (2026), simulates an urbanized society which is located in a spatial context that is exposed to occasional flooding.

In this model, agents represent households and make decisions regarding private climate adaptation measures within their homes. Agents are characterized by diverse socio-demographic attributes and housing conditions, derived from empirical survey data from Wagenblast, Ghorbani, et al. (2026). Agent behavior and interactions in FAST are based on insights from environmental psychology and social norm theory. Agents are distributed across districts representing different neighborhoods and are embedded in a social network structure, through which opinions on their protection motivation (PMT) and social norms (SN) are exchanged.

At each simulation step, agents decided whether or not to invest in adaptation measures, based on their threat and coping appraisals which are grounded in protection motivation theory. Behavioral, social and economic attributes of agents have been empirically derived from survey distributions. In FAST the social network is generated prior to model initialization and has to be read into the model. Opinions are exchanged with connected households in the social network. In addition to individual protection motivation, perceived social norms influence private adaptation decisions. These social norms are updated dynamically as adaptation takes place and can be defined either based on the agent's local network, within their district, or globally. If an agent intends to adapt following their individual protection motivation and perceived social norm, and has sufficient financial resources at a specific time, the agent has a probability to take the intended adaptation decision and change adaptation status. Consequently, dynamic local and global social norms are updated each year, reflecting the number of adapted agents (see figure 3.1).

To clarify how this thesis builds upon FAST, figure 3.1 gives an overview of the additional components and flows of data (in red), showing how a feedback loop from household agents to the social network was created. The model extension integrates with the original model at several points, specifically by adding an influence from household agents to the network. This forms the basis for the tie and weight dynamics described earlier. While opinion exchange based on network connections was already present in FAST, it has been adapted here to incorporate dynamic weights.

Furthermore, there are a few concepts that will be discussed heavily in the results, which form the driving force behind household protection motivation. These are the threat and coping appraisals:

- **Risk perception** → Overall perception of flood risk.
- **Worry** → Concern about the potential impacts of flooding.
- **Perceived severity** → The extent to which a flood is expected to cause serious negative consequences.
- **Perceived probability** → The perceived likelihood of experiencing a flood event.
- **Self efficacy** → The perceived ability of a household to implement a specific adaptation measure.
- **Perceived response efficacy** → The perceived effectiveness of a specific adaptation measure in reducing flood risk or damage.
- **Perceived cost** → The perceived financial, time, or effort-related burden associated with implementing a specific adaptation measure.

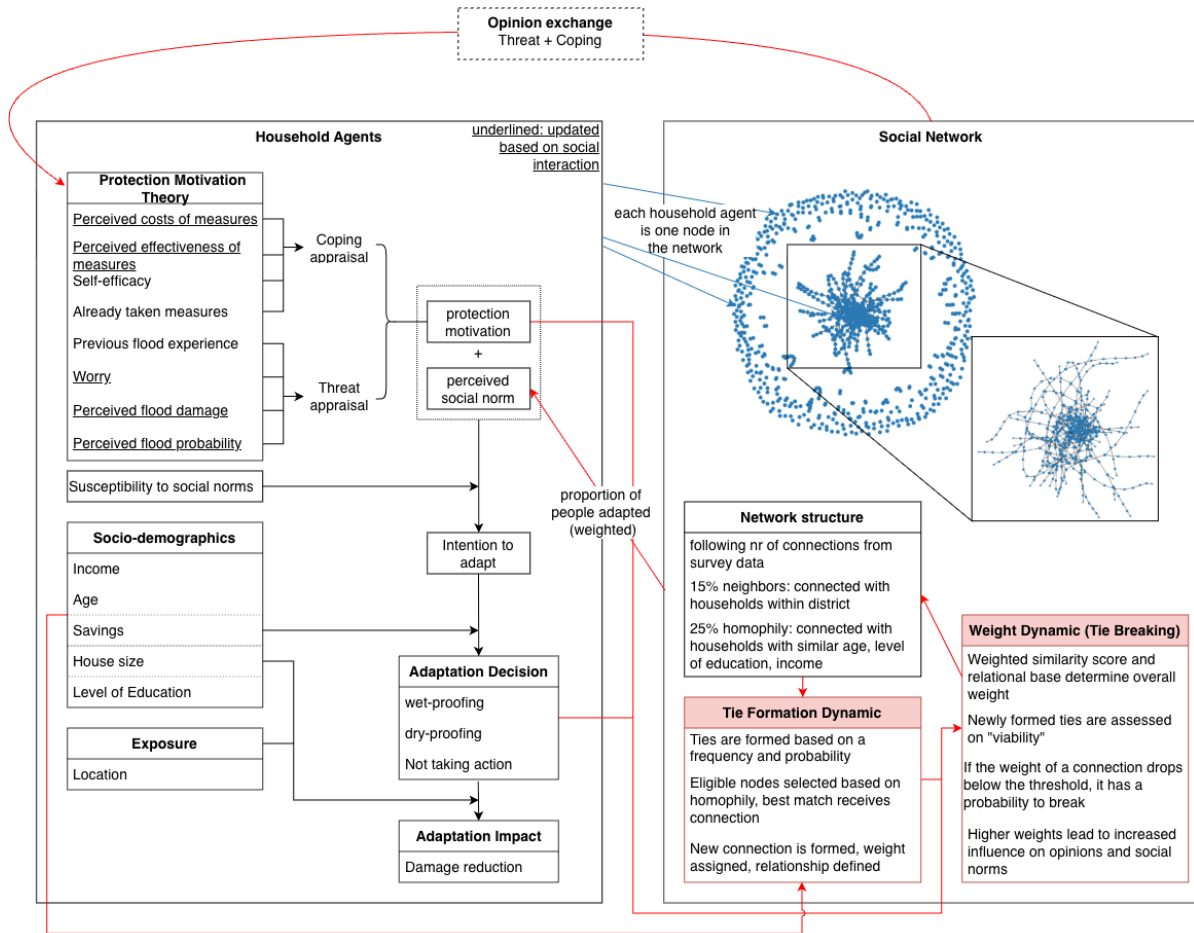


Figure 3.1: Connection of model extension to the original FAST-ABM. This shows how additional mechanics (red boxes) connect to the existing FAST-ABM (all black boxes and arrows), showing new information flows and influences with red arrows. Adapted from Wagenblast, Warnier, and Filatova (2026). This figure also depicts the feedback loop that makes the model extension co-evolutionary, with arrows flowing from the agents to the network and back.

Lastly, it is important to distinguish between adaptation intention and actual adaptation behavior in FAST. Protection motivation and social norm processes determine a household's willingness or intention to adapt, but this does not automatically result in the implementation of an adaptation measure. Actual adaptation also depends on additional model conditions, including whether the household considers a measure at that time step, whether sufficient financial resources are available, and the probabilistic decision rule through which intention is translated into action. As a result, high willingness to adapt does not necessarily lead to immediate adaptation uptake.

3.2. Model extension of FAST-ABM

The goal of this model extension is to incorporate co-evolutionary network dynamics into the FAST-ABM framework and apply these to household adaptation decision-making. Empirical evidence on human behavior in specific contexts is often limited, and therefore a number of assumptions must be made regarding the social dynamics introduced into the model. This aligns with the objective of this thesis, as defined by the main research question: "How can the co-evolutionary restructuring of social networks be modeled to better understand the diffusion of household flood adaptation behavior?"

3.2.1. Overview and purpose

Figure 3.2 provides an overview of the conceptual model and the feedback mechanisms that are central to this thesis. The model combines the original components of the FAST-ABM with newly introduced network dynamics to represent the interaction between household adaptation behavior and social network structure.

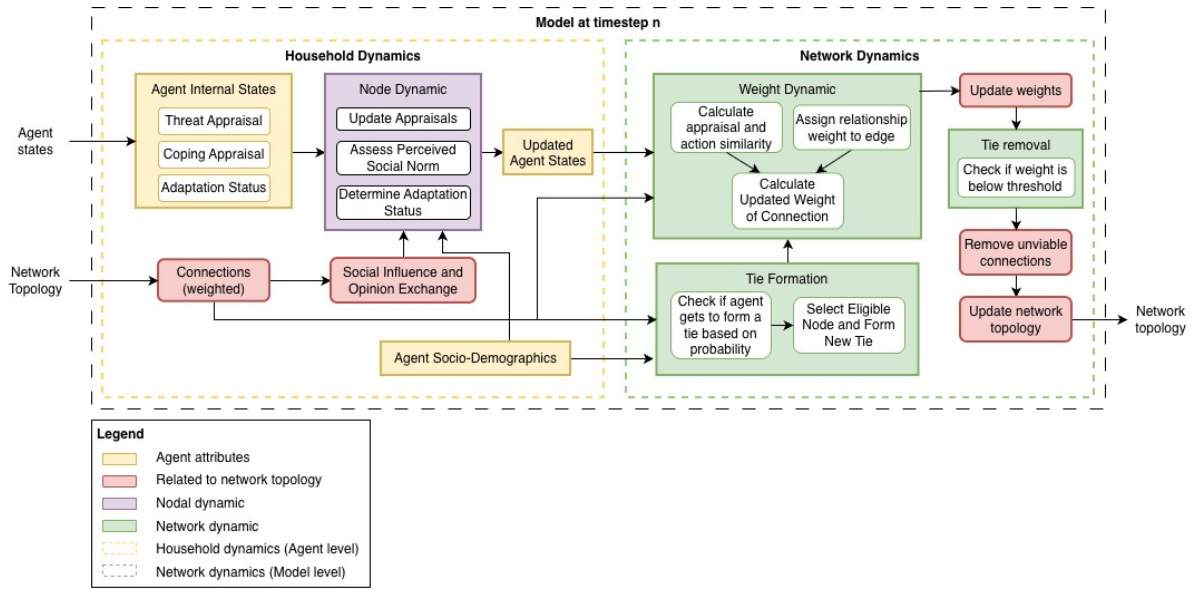


Figure 3.2: In-depth overview of the model extension made for this thesis project. This shows the same mechanics as figure 3.1, but in a flow diagram that depicts the logic of processes during each simulation step, starting with internal household dynamics (the Household Agents box in figure 3.1), followed by network changes and the added tie and weight mechanisms. To distinguish between the old model and newly added components, and understand where the two connect, see figure 3.1.

Within the model, connected households exchange information related to their threat appraisals, coping appraisals, and adaptation decisions. These interactions influence future household adaptation behavior, while adaptation-related similarities and differences simultaneously affect how social ties evolve over time. As a result, both household states and network structure change throughout the simulation, creating a continuous feedback loop between behavior and network topology.

The primary purpose of the model is to investigate how different network restructuring mechanisms influence the diffusion of household flood adaptation behavior. Three mechanisms are considered: tie formation, tie breaking (also called severing), and dynamic edge weights. Together, these mechanisms determine how households modify their social connections and how these changes affect the spread of adaptation-related influence. The rationale for selecting these mechanisms is discussed in section 2.1. The following sections describe the model components and their interactions in detail, building on figures 3.1 and 3.2.

3.2.2. Model inputs at $t=0$

The conceptual model is structured along the two levels: the agent level and the model level. Before the iterative process of agent and network dynamics begins, all agents are assigned attributes and the (weighted) network structure is initialized. All agents are initiated with socio-demographic characteristics, adaptation status and appraisals (protection motivation) based on empirical data from the original FAST model. The pre-generated network structure is then loaded into the model, which can consist of different network topologies depending on the experimental setup. Initial weights are assigned to connections based on agent attributes, ensuring that interactions during the first time step are stable and do not immediately result in excessive tie breaking.

It is important to note that, in the experimental analysis, different network configurations are evaluated independently. While this conceptual overview includes both structural dynamics and weight dynamics, specific experimental setups may disable certain mechanisms. In particular, the “static” and “tie-only” configurations use unweighted networks. Further details on these setups are provided in section 3.6.

3.2.3. Model step cycle: Household Dynamics

Household dynamics operate at the agent level, where internal states and attributes are updated. At the beginning of each step, the current network topology and agent states are used as input. A key mechanism in this process is the node dynamic, which originates mostly from the base FAST model. Here agents update appraisals based on opinion exchange (see figure 3.1, now also taking the weights of their social network into account if weights are enabled). This essentially means that agents interact with their network, taking into account their internal state

and socio-demographics.

Internally the agents will assess whether to adapt or not based on several factors (see section 3.1 and figure 3.1), but simply put if their eventual intention is above the predefined minimum threshold to adapt and the agent has the financial means to make the investment, there is a chance that the agent adopts a certain measure. After all agents have updated their states, the results are passed to the network dynamics. This ordering ensures that agent decisions are based on information from the previous step, after which the network responds to updated agent states.

3.2.4. Model step cycle: Network Dynamics

The network dynamics take place on the model level, and occur after all agent (node) dynamics have been completed. Using a simple probability factor, each step some agents are selected to form new connections. These connections are established based on homophily, consistent with the theoretical framework developed in section 2.1. Due to time and scope limitations, additional formation mechanisms were not implemented. In the weighted networks, new connections are immediately assigned a relationship type and corresponding weight. Subsequently, all agents evaluate the similarity between themselves and their neighbors, updating connection weights accordingly. This ensures that tie strength reflects the changing alignment between agents.

After all edge weights have been updated, the edge breaking mechanism is initiated. Edges that are below the set threshold have a probability of breaking during each step, which is scaled (linearly) with how far below the threshold the weight lies. Based on this some connections are removed and the network topology is updated and passed to the next step together with the updated agent states.

Two additional mechanisms affect tie formation. There is an increase in connectivity (formation of new ties) after a flood and a penalty for isolated nodes. After a flood has occurred, households will try to seek extra connections more actively, which is translated into a higher probability of forming ties. This increase of tie formation probability is scaled linearly to zero based on the "flood remembrance period" in FAST. Furthermore, agents that are isolated (i.e. who have no connections) receive a penalty to their ability to connect with others. This resembles the fact that these households are less likely to engage in conversations on the topic of flood adaptation.

3.3. Modeling choices and assumptions based on SQ1

To validate what modeling choices were made during the creation of the model extension, insights from chapter 2 and the results of SQ1 have been used. In table 3.1 an overview of the different model dynamics is shown, linking them to the literature that was reviewed.

For an overview of all other modeling assumptions that were made, see appendix A.7.

3.4. Methodological Approach

Exploratory modeling is a methodology that uses computational experiments to analyze complex and uncertain systems, supporting decision-making under conditions of deep uncertainty. It employs simulation as a testing environment to map a wide range of possible outcomes across diverse scenarios.

This thesis uses exploratory modeling because it enables the analysis of a wide range of outcomes given different model inputs. Instead of trying to predict what flood adaptation in country X will look like in 2050, the purpose is to explore the interaction of different mechanisms related to flood adaptation. Different co-evolutionary rules and assumptions are implemented, which have been discussed in section 3.2 and are based on the results from chapter 2.

Using exploratory modeling, these mechanics can be tested for different experimental setups in order to determine the range of possible outcomes given this model design, and to discover how adaptation behavior in the model is affected. Since exploratory modeling relies on computational experiments, ABM is a useful tool that serves as the laboratory in which the model is applied. This thesis also makes use of the Mesa library for ABM by Ter Hoeven et al. (2025) and NetworkX for network modeling in python.

The code developed for the model extension is made publicly available in a GitLab repository to support transparency and reproducibility of the modeling approach. The repository contains the implementation of the co-evolutionary network mechanisms, including tie formation, tie breaking, dynamic edge weights, and the scripts used to run the simulation experiments. The repository can be accessed at: <https://github.com/marijnmin/Master-Thesis>.

Table 3.1: Rationale for model design

Model component	Specific component	Theoretical logic	Supporting literature
Tie formation	Choice homophily	Agents connect to others with similar age, income, and education levels.	Barnes et al. (2020) and Van Den Beukel et al. (2019)
	Post-flood connectivity increase	Flood events trigger qualitative shifts in social systems, leading to new tie formation.	Cunningham et al. (2016), Juhola et al. (2022), Parks (2022), Saeedian et al. (2024), and Salgueiro-Otero et al. (2022)
	Isolation penalty	Isolated nodes in the social network receive a penalty as participation is significantly reduced	Salas-Peña and García-Palomares (2025)
Weight dynamics	Relationship hierarchy	Base weights are capped by tie type (Family/Friends > Neighbors > Acquaintances).	Eise et al. (2021), Haer et al. (2016), and Salgueiro-Otero et al. (2022)
	Similarity multiplier	Connection strength is a function of similarity in Protection Motivation and Adaptation Action.	Saeedian et al. (2024), Takács et al. (2016), and Van Den Ende et al. (2024)
Agent dynamics	Social influence (PMT)	Peer influence and descriptive norms directly update Threat and Coping Appraisals.	Haer et al. (2016) and Taberna et al. (2023)
	Social influence (weights)	Peer influence and opinion exchange is scaled by the strength of a connection or the weight assigned to it.	Aghbolagh et al. (2023), Chaudhury et al. (2017), Ioannidis et al. (2021), Lu and Yuan (2026), Van Den Beukel et al. (2019), and Zia et al. (2021)
	Bounded confidence	Agents are boundedly rational only adopt opinions from neighbors within a specific similarity threshold.	Ioannidis et al. (2021), Kozma and Barrat (2008), and Krishnagopal and Porter (2024)
Tie breaking	Sever threshold	Ties are severed when weight falls below a threshold due to dissimilarities or lack of utility.	Lu and Yuan (2026), Luo et al. (2015), Saeedian et al. (2024), and Van Den Beukel et al. (2019)

3.5. Baseline Model Configuration

In table 3.3 the baseline setup of additional input parameters in the model extension are shown. The baseline values for network dynamics-related parameters are determined based on preliminary experiments, with the aim of maintaining relatively stable levels of network growth and decay. This ensures that the resulting network structures remain within a realistic range for social interaction in a flood adaptation context. In the experimental setup these input parameters will be tested for their effect on the network topology. Within the experimental design, selected parameters are varied to analyze their impact on network topology and adaptation behavior. The notes provided in table 3.3 further explain the chosen default values and alternative parameter ranges. A complete overview of all model input parameters is provided in the model documentation in appendix A.6.

3.6. Experimental design

The goal of the experimental design is to test the assumptions underlying different model configurations and to analyze how adaptation behavior is influenced by co-evolutionary network dynamics. The solution space is explored given the co-evolutionary dynamics that were added, comparing different setups and analyzing on both aggregate and micro-level. Based on these results, the effects of incorporating co-evolutionary dynamics on adaptation behavior are assessed (chapters 4 - 6).

To design experiments that test the different aspects of the co-evolutionary model, SQ2 is divided into four sub-questions, each focusing on a specific level of analysis. For all sub-questions both an empirical and stylized network is tested. This approach is motivated by previous research and preliminary experiments, which indicate that initial network topology can have a significant varying effect on adaptation behavior.

The empirical network contains relatively few connections and includes many initially isolated nodes, reflecting the specific flood adaptation context represented in the empirical data. The stylized network is chosen to be a scale-free network type (Barabási-Albert) since this resembles many real-world social networks and allows for comparison with other fully connected network research. Both structures are first tested with a base parameter setup as in table 3.3. The following research sub-questions are addressed in the experiments:

SQ2.1: To what extent does the rate of network “dynamism” (ratio of tie-breaking to tie formation) determine the speed of adaptation uptake?

SQ2.2: How do different initial network topologies vary in their sensitivity to co-evolutionary rules, and how does this affect adaptation uptake?

SQ2.3: What is the impact of varying weight dynamics on network topology and subsequent adaptation uptake?

SQ2.4: How does agent connectivity relate to individual adaptation behavior, and how does this vary across setups?

Four different model configurations are used to perform the necessary experiments to answer these questions:

- Static network (no tie or weight dynamics)
- Tie dynamics only
- Weight dynamics only
- Tie & weight dynamics combined (“full” dynamics)

What input parameters are tested in what experiment can be found in table 3.5. The table shows parameters that are varied, and parameters that deviate from the default values that are shown in table 3.3 or the full input parameter table in appendix A.6. Table 3.5 also gives a concise description of the objective of each experiment.

Parameter ranges are selected carefully to balance model exploration with computational feasibility, as exhaustive parameter sweeps would result in a very large number of simulations. EXP1 and EXP2 both use a standard parameter sweep implemented through the Mesa batch runner. In EXP3, specific combinations of parameter values are tested instead of a full parameter sweep. Relational weight configurations are varied across four scenarios: *base*, *neighbor_focus*, *other_focus*, and *indifferent*. In addition, the relative importance of actions (social norms) versus opinions (protection motivation) is varied through different weight configurations (*weight_action_vs_opinion* and *weight_SN_vs_PMT*), using low, balanced, and high weighting scenarios. The specific parameter combinations used are summarized in Table 3.5.

EXP4 differs from the other experiments in that it does not consist of a batch run of Monte Carlo simulations, but instead focuses on a single run with detailed micro-level data collection at each time step. The objective of EXP4 is to trace how co-evolutionary dynamics affect individual agents by linking network changes to shifts in intentions

Table 3.3: Model parameters descriptions

Name	Type	Default value	Other value	Description	Notes
Formation_probability	Float	0.01	[0-1]	Determines the percentage chance each agent has each step to form a new connection	Network growth is sensitive to this, so low values are advised to ensure feasibility of simulation
Sever_threshold	Float	0.3	[0-1]	Sets the level of edge weight below which there is a probability of breaking	Probability of breaking linearly scales from 0% at threshold to 100% at 0
Breaking_probability	Float	0.009	[0-1]	Determines the percentage chance each agent has each timestep to break a random existing connection	Used instead of sever_threshold when weights are turned off
Base_family	Float	1.0	[0.5-1]	The weight ceiling set based on the type of relationship	1.0 means that the weight of this edge can reach 1.0 as a maximum
Base_neighbor	Float	0.7	[0.5-1]		
Base_other	Float	0.5	[0.5-1]		
weight_action_vs_opinion	Float	0.5	[0-1]	How much actions and opinions are valued respectively in calculation the similarity between agents	One value for all agents
Weight_SN_vs_PMT	String, Float	'empirical'	[0-1]	Determines how much SN intention is valued in household adaptation decision-making	When the value is high (e.g. 0.8), SN is weighted more than PMT; Original empirical value close to 0.5.
Set_hh_adapted_at_start	Boolean, Float	False	[0-1]	Sets the level of household agents that have adapted at the start of model simulation	False corresponds to the empirically found level, which is roughly 12%.
Weight_opinion_others	Float	0.5	[0-1]	Determines how much the PMT intention of the agent's network is taken into account when updating their appraisals.	A high value means higher influence from the network on the agent's appraisals.
Enable_tie_dynamics	Boolean	False	True	Tie dynamics (forming and breaking) can be switched on or off	When turned off the network structure remains the same
Enable_weight_dynamics	Boolean	False	True	Weight dynamics (changing weights after the edge is formed) can be switched on or off	When turned off, edges are unweighted, and thus social influence is no longer weighted

and adaptation decisions. Furthermore, agent-level appraisals, intentions, and adaptation behavior are analyzed jointly to identify potential behavioral patterns.

EXP5 focuses on high-adaptation scenarios identified through preliminary experimentation with FAST. This experiment uses a batch run with parameter sweeps to compare static and co-evolutionary configurations under conditions where adaptation levels are known to be high.

Table 3.5: Overview of simulation experiments and parameters

Input parameters	Type	Values	Notes	SQ addressed
EXP1: Baseline behavior				
<i>In this first experiment the baseline is run for each setup that is later used for comparison and sensemaking. What are the overall differences between levels of dynamism? Given a 'realistic' input parameter setup, how do the different levels of dynamics compare given differences in initial adaptation and network structures.</i>				
Enable_tie_dynamics	Boolean	True, False		SQ2.2, SQ2.3, SQ2.4
Enable_weight_dynamics	Boolean	True, False		
Network_type	String	'Empirical', 'Stylized'		
Set_hh_adapted_at_start	Float	False, 0.5, 0.75		
EXP2: Topology evolution				
<i>How do different levels of forming and breaking ties (in combination with weights or alone) affect opinions and adaptation? The goal is to first discover how the network structure changes given the additional parameters and different input values.</i>				
Enable_weight_dynamics	Boolean	True, False		SQ2.1, SQ2.2
Formation_probability	Float	0,005 – 0.0225 (steps of 0.0025)		
Breaking_probability	Float	0,005 – 0.0225 (steps of 0.0025)		
Sever_threshold	Float	0.015 – 0.5 (steps of 0.05)	Above 0.5 all 'other' type always have a probability to break (even at 100% similarity score)	
EXP3: Weight dynamics				
<i>How do dynamic weights affect behavior in the network? If we isolate weight dynamics and vary the inputs related to this, what happens with adaptation?</i>				
Relational weight scenarios (family_friend, neighbor, other)	List	base: [1.0, 0.7, 0.5] neighbor_focus: [0.6, 1.0, 0.6] other_focus: [0.6, 0.6, 1.0] indifferent: [0.7, 0.7, 0.7]	Family, neighbor other types edges each receive a different weight ceiling.	SQ2.2, SQ2.3
SN weight scenarios (weight_action_vs_opinion, weight_SN_vs_PMT)	List	low_SN: [0.25, 0.25] balanced: [0.5, 0.5] high_SN: [0.75, 0.75]	How much adaptation or PMT of other agents is valued in similarity calculation.	
Set_hh_adapted_at_start	Float	False, 0.5, 0.75		
Weight_opinion_others	Float	0.25, 0.5, 0.75		
EXP4: Micro-level analysis				
<i>Check individual agents in runs with high/low adaptation for a specific setup. How is adaptation on individual agent level affected, by whom and what are their connectivity characteristics? What triggers are there for agents to adapt? Can these adaptation triggers be linked to network co-evolution?</i>				
Enable_weight_dynamics	Boolean	True		SQ2.4
Enable_tie_dynamics	Boolean	True		
Set_hh_adapted_at_start	Float	0.25	Slightly higher value than base to boost adaptation levels for easier analysis	

Input parameters	Type	Values	Notes	SQ addressed
Enable_micro_logging	Boolean	True		
EXP5: High adaptation analysis <i>Run simulations where adaptation is known to be high, compare static with co-evolutionary setup to see the effect of adding co-evolution in situations where high adaptation occurs</i>				
Enable_tie_dynamics	Boolean	True, False		SQ2 overall
Set_hh_adapted_at_start	Float	0.25	Slightly higher value than base to boost adaptation levels for easier analysis	
Social_norm_calculation	String	'all', 'connections'	Allows comparison of global and local SN calculation	
Weight_SN_vs_PMT	Float	0.5, 0.8		
Per_HH_adapted_to_SN_prob_midpoint	Float	0.3, 0.5	See model documentation in appendix A for explanation	
Consider_measure_every_x_steps	Integer	5	Used to reduce computation time	
Formation_probability	Float	0.015		
Breaking_probability	Float	0.015		

3.7. Simulation protocol

Simulations are executed on the DelftBlue high-performance computing infrastructure (DHPC), 2024. Because the model contains stochastic processes, a single simulation run is insufficient to robustly analyze system behavior. Instead, each experimental configuration must be evaluated through multiple independent realizations to distinguish systematic effects from random variation in agent interactions and network evolution.

Stochasticity is handled by explicitly controlling the random number generator through fixed random seeds. For each combination of input parameters, the model is executed multiple times using different seed values, generating a set of independent stochastic realizations. In this thesis, 50 seed values are used for each experimental configuration, resulting in 50 Monte Carlo runs per parameter combination (with the exception of experiment 4, which focuses on an in-depth analysis of a single realization).

While this approach improves the robustness and reproducibility of the results, it also substantially increases the computational cost of the experiments. Each additional parameter, parameter value, or scenario multiplies the number of required simulation runs. As a result, the size of the experimental design is constrained by available computational resources, simulation time, and the volume of generated output data. To manage these constraints, batch experiment sizes were limited to the minimum required to answer the research questions while maintaining sufficient statistical robustness. Each simulation is run for 50 time steps and contains 1000 household agents. More information on the data analysis methodology is provided in section 3.8.

3.8. Measurement of outcomes and result analysis

Based on the research questions and experimental design, multiple levels of data analysis are applied to evaluate and communicate the results of the experiments. This section provides a concise overview of the analytical approaches used to interpret the model outcomes for each experiment.

All experiments generate data at different levels of aggregation depending on the objectives of the analysis. To keep data volumes manageable, only variables required for a particular experiment are collected and stored. For most experiments, aggregate model-level statistics and selected agent-level indicators are recorded using the standard Mesa DataCollector functionality. These outputs are subsequently processed, aggregated, and visualized using Python-based analysis workflows. Experiment 4 forms an exception, as it requires detailed micro-level information on individual agent trajectories, adaptation events, and network interactions. Therefore a custom data collection procedure was implemented to record additional agent-level data that are not available through the standard aggregate collection process (see appendix A.8). This distinction allows computational resources and storage requirements to remain proportional to the analytical needs of each experiment.

EXP1 Focuses on aggregate-level outcomes, directly examining adaptation levels in the network. Box plots and violin plots are used to compare different model setups, both relative to each other and to the baseline, in terms of achieved adaptation levels over time. In addition, correlations between network metrics and adaptation levels are analyzed to identify which network topology characteristics may influence adaptation dynamics.

EXP2 investigates changes in network topology and their relation to behavioral outcomes. Network evolution is visualized using heatmaps, linking parameter settings and structural changes to variations in average adaptation intentions. Furthermore, statistical analyses are used to explore relationships between topology changes and behavioral outcomes, allowing for the identification of significant associations between co-evolutionary dynamics and adaptation intentions.

EXP3 examines how different weight configurations and social influence scenarios affect intentions and adaptation uptake. Results are analyzed by comparing structured sets of parameter combinations across scenarios. Trajectory plots or Sankey-style diagrams are used to visualize transitions in adaptation or intention levels across different model configurations. Additionally, box plots are used to compare distributions of outcomes between scenarios. When clear patterns are not immediately observable, ANOVA-based analysis may be applied to identify statistically significant effects of different weighting mechanisms.

EXP4 focuses on micro-level dynamics within the model. Four types of analyses are conducted. First, influential agents are identified by ranking agents based on their impact on others, and their network position and connectivity are examined.

Second, adaptation 'triggers' are identified by linking network and intention changes with agent adaptation. This is done by tracing changes within a defined time window prior to adaptation events and applying thresholds to filter out noise. The network and intention changes are then linked to an adaptation and aggregated across all adaptations to show which changes preceded adaptation most often.

Third, changes in agent appraisals are analyzed across the entire simulation to identify aggregate behavioral patterns and validate the implemented mechanisms. Finally, individual agent trajectories are examined by plotting the evolution of appraisals, intentions, and adaptation status over time, allowing for comparison between agents who do and do not adapt. These analyses may be conducted across different experimental setups to explore how micro-level dynamics vary under different conditions.

EXP5 evaluates differences in adaptation trajectories between static and co-evolutionary model configurations under conditions of high adaptation. Times series plots are used to compare adaptation dynamics, while box plots can be used to compare adaptation gains over the static setup, across different levels of dynamics and different 'behavioral' setups (high vs. low adaptation).

3.9. Limitations and scope of the methodology

While the methodological approach applied in this thesis allows for a systematic exploration of co-evolutionary dynamics in social networks, several limitations should be acknowledged with respect to model design, experimental setup, and interpretation of results.

Model complexity and interacting mechanisms

The first limitation comes from the introduction of multiple interacting dynamics within the model, including tie formation, tie breaking, and weight updates. While this enables a richer representation of co-evolutionary processes, it also increases the difficulty of isolating the exact drivers of observed outcomes. Changes in adaptation uptake or network structure may result from the interaction of several mechanisms rather than a single identifiable factor. As a result, attributing causality becomes difficult and is dependent on the outcomes of the experiments.

Simplifying assumptions in behavioral and network dynamics

The model relies on a number of simplifying assumptions that are necessary due to limited empirical evidence from literature and computational feasibility. For example, tie formation is primarily based on homophily, while other relevant social processes such as triadic closure, spatial proximity, or institutional influences are not explicitly modeled. Similarly, weight dynamics are abstract representations of influence strength and do not fully capture the complexity of real-world social interactions. These simplifications imply that the model results should be interpreted as a representation of possible co-evolutionary dynamics, rather than exact simulations of real-world systems.

Sensitivity to parameter choices and initial conditions

The behavior of the model is sensitive to many input parameters beyond those analyzed in the experiments presented in this methodology. Examples are the chosen levels for flooding, connectivity boosts after floods and the time people remember flooding. Small variations in these parameters could lead to notable differences in how the network evolves and how households behave. While exploratory modeling is designed to address such uncertainty by scanning a wide parameter space, it also means that findings are conditional on the selected parameter ranges and scenarios.

Stochasticity and computational constraints

The model incorporates stochastic processes in both agent interactions and network evolution. Although multiple runs with different random seeds are used to capture variability, stochasticity also introduces uncertainty in the results. At the same time, computational limitations restrict the number of parameter combinations and runs that can be explored. This creates a trade-off between the extent to which different parameter setting can be explored and computational feasibility. This means that not all possible configurations of the model can be analyzed.

Scope of experimental design

The experiments performed in this thesis are designed to explore specific aspects of co-evolutionary dynamics, guided by the sub-questions of SQ2. However, the experimental design does not cover the full space of possible model configurations, nor does it include all potentially relevant mechanisms. For example, alternative formulations of weight dynamics or social influence rules could lead to different outcomes. Due to limitations in time and resources it is not possible to analyze each possible pathway that this model extension could take.

Interpretation and generalizability

Finally, the findings of this thesis are model-based and therefore subject to limitations in generalizability. The FAST-ABM framework and its extension are built on specific assumptions, empirical inputs, and simplified mechanisms. As such, the results should not be interpreted as direct predictions of real-world household adaptation behavior. Instead, they provide insight into how certain mechanisms may operate under controlled conditions and how different modeling choices influence system behavior.

Value of the methodology

Despite these limitations, the methodology provides significant value. By using an exploratory modeling approach, this thesis will be able to systematically investigate how different co-evolutionary assumptions affect both network dynamics and adaptation outcomes. The model serves as a computational testing ground that helps identify key mechanisms, sensitivities, and conditions under which co-evolutionary processes influence behavior. This makes it possible to generate insights that are otherwise difficult to obtain through empirical analysis alone.

4

Results

4.1. Co-evolution changes the network much more strongly than it changes adaptation

The results presented in this chapter explore the mechanisms that affect network structure and household adaptation behavior in the extension made to FAST. The analysis moves from aggregate-level findings to more detailed, micro-level insights.

A consistent pattern that is found across experiments is that co-evolutionary rules lead to substantial changes in network structure, while corresponding changes in household behavior remain comparatively limited. In particular, tie-based co-evolution systematically alters the number and distribution of connections, whereas the resulting increases in household adaptation are moderate in absolute terms. This suggests that changes in network structure and behavioral outcomes cannot be linked directly, nor can a simple causal relationship be inferred.

Network restructuring has varying effects, when compared between setups and when compared to a static baseline (figure 4.1). The largest absolute increases in adaptation uptake are observed in configurations with tie dynamics only. Differences across initial adaptation levels are relatively small, but noticeable when tie dynamics are present.

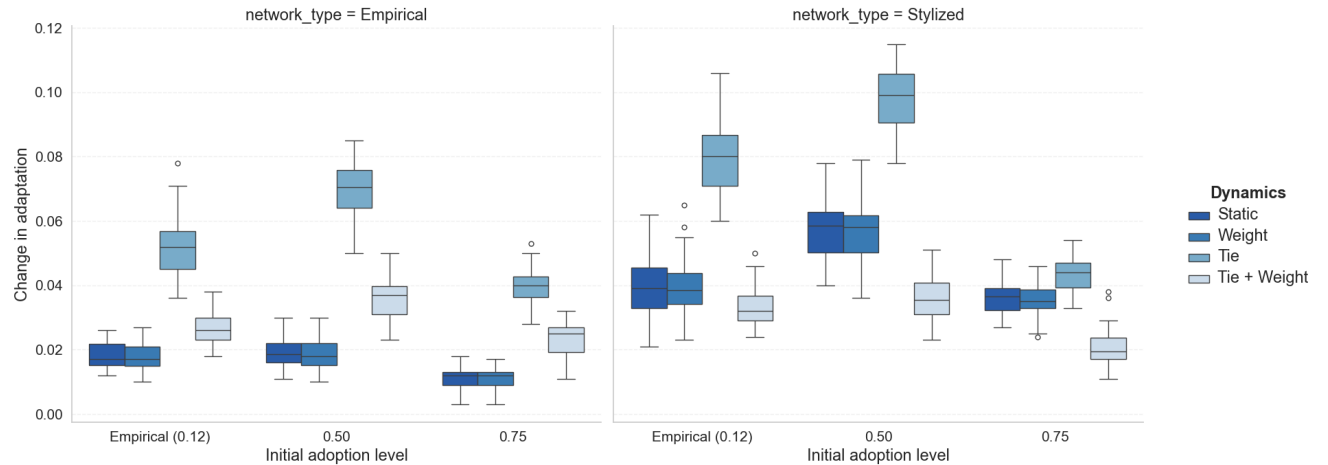


Figure 4.1: Changes in final adaptation levels under different initial network conditions. Network_type shows what initial topology has been used in the simulation runs, empirical being derived from Wagenblast, Ghorbani, et al. (2026) and stylized is a scale-free Barabási-Albert network. Change in adaptation shows fractional increases compared to the initial adaptation level (e.g. 0.06 change is a 6% increase in adaptation compared to start). Initial adaptation levels are in fractions of the total number of households. The empirical initial adaptation level is based on the survey data from Wagenblast, Ghorbani, et al. (2026). Static and weight-only dynamics perform similarly across configurations, tie dynamics reach the highest adaptation increases. Furthermore, the stylized topology generally achieves larger adaptation increases than the empirical topology. Each box is based on 50 Monte-Carlo simulations.

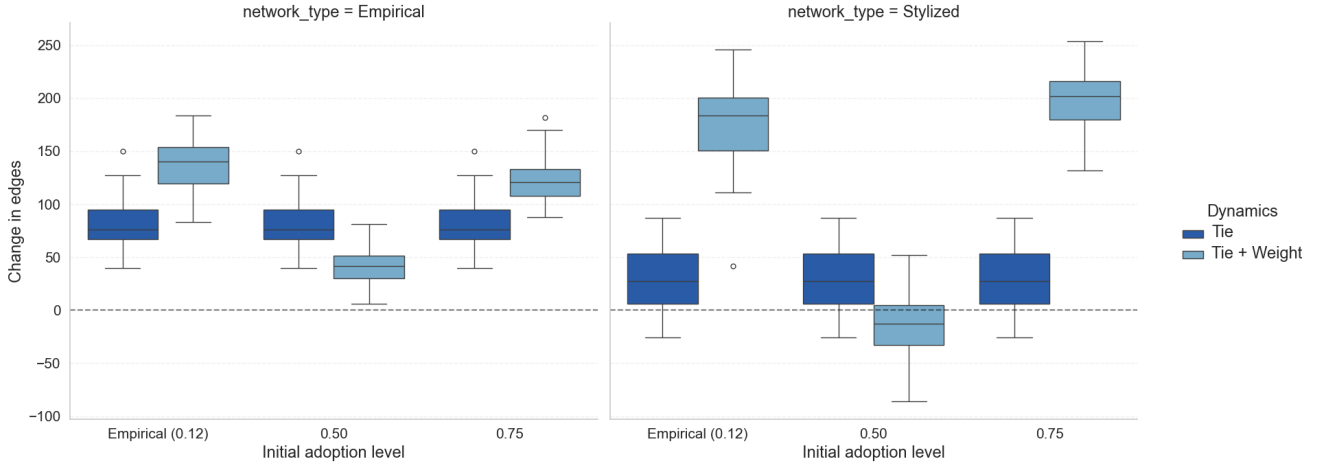


Figure 4.2: Absolute numbers of edges added or removed compared to initial number of edges, given different initial network conditions. Initial adaptation levels show the fraction of all the households that have already adapted flood measures at the start of the simulation. Only the configurations including tie dynamics are taken into account, as in the other configurations no ties are formed or removed. The tie dynamics only show a consistent network growth. When weights are added, a more diverse initial set of households (50% initially adapted) leads to more edges being removed due to differences in actions/opinions. Each box is based on 50 Monte-Carlo simulations.

Different configurations with different starting conditions and rules also lead to differences in network structure effects. Figure 4.2 shows the net change in the number of edges during simulation runs, indicating overall network growth or decay. If a simple linear relationship existed between network connectivity and adaptation uptake, this would be observable by comparing figures 4.1 and 4.2. However, this is not the case, which can be seen for e.g. the stylized network, where in the full dynamics (tie and weight) setups for empirical and 75% initial adaptation levels, the network growth is much higher than for the tie-only setup. The adaptation change compared to initial levels is on average higher in the tie-only setup than in the tie and weight setup, showing that network growth does not show a simple linear relationship with adaptation uptake.

When comparing co-evolutionary configurations to the static network baseline (see figure 4.3), only the tie-only setup consistently results in higher adaptation levels, and even then the increases remain modest (typically between 2% and 12%). Weight-only dynamics produce outcomes that on average are similar to the static network. When combining both dynamics, the stylized network reaches slightly lower adaptation increases than the static baseline, while the empirical network shows a modest improvement over the static model (see the striped lines in figure 4.3 for the mean and quartiles). The stylized network type generally outperforms the empirical network on adaptation increases, when compared within a certain dynamics setup.

To gain more insight in the relation of network topology with adaptation, correlations between various network metrics and adaptation changes were analyzed across all experimental setups. This correlation summary can be found in appendix B.1, but it reveals no consistent correlation between certain metrics and an increase or decrease in adaptation, and has therefore been left out of scope for the core results.

To better understand how co-evolution influences household adaptation behavior, the following sections analyze the specific parameters governing network restructuring.

4.2. The effect of co-evolution depends on the balance between tie formation and breaking

The next step is to assess how the rate of network dynamism (the balance between forming and breaking ties) affects household intentions and adaptation uptake. To understand this effect, the parameters that define the level of network restructuring are systematically varied. These include the formation probability, the breaking probability (when weights are disabled), and the sever threshold (when weights are enabled).

The direct effect of these parameters is that they determine how many ties are formed and removed each step, resulting in a net edge change between the start and the end of the model simulation. In figure 4.4 this is visualized in a heatmap where red indicates network growth and blue indicates network decay. In configurations with both tie and weight dynamics, the network shows a strong network decay. This reflects a threshold effect, where edge

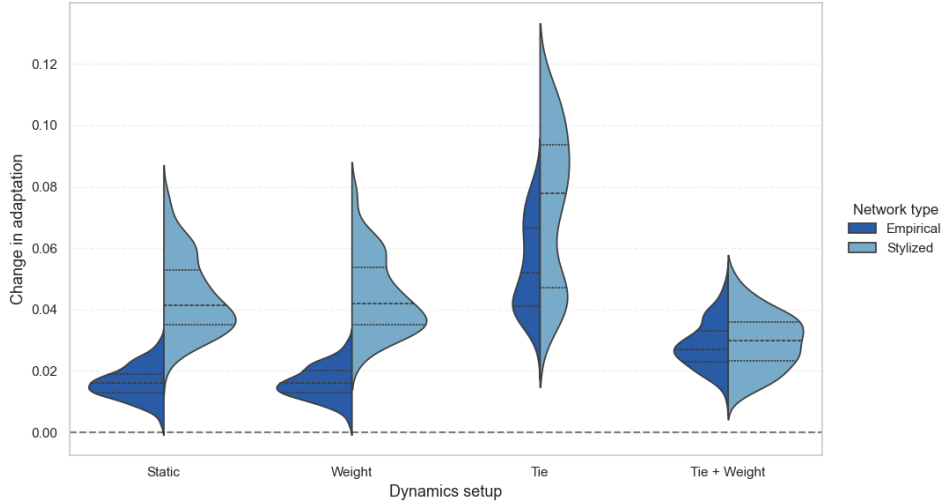


Figure 4.3: Violin plot showing how adaptation change in the other dynamics configurations compares to the static baseline (column on the left). The change in adaptation shows fractional increases compared to the initial adaptation level. The results of all initial adaptation levels are combined, as changes are relative to the initial level. Weight-only dynamics are almost identical to the static configuration. Tie dynamics again show higher changes in adaptation, just like the stylized network sees higher adaptation increases than the empirical network. Each column consists of 150 empirical and 150 stylized Monte-Carlo simulations.

weights fall below the sever threshold and connections start to break quickly. In contrast, when weight dynamics are disabled, edge removal is governed more directly by the breaking probability, resulting in a more gradual and linear pattern of network growth or decay. Overall these parameter sweeps provide a clear overview of the balance between forming and breaking edges in different contexts. In some settings the network can grow substantially, while in others it can fully dissolve. This has effects on the exchange of opinions and social influence in the network.

Similar heat maps can be made for the different intentions that underly adaptation in FAST, showing the relation between network changes and the driving behavioral forces behind adaptation. Figure 4.5 shows the resulting levels of protection-motivation (PMT) intention for dry-proofing measures across different combinations of formation and breaking parameters. Corresponding matrices for the other intentions and adaptation can be found in appendix B, including certain network metrics (average degree, average betweenness centrality) that have been tested across the parameter bounds. These visualizations reinforce the earlier finding that changes in network structure translate only weakly into changes in behavior. While substantial variation in network structure is observed across parameter combinations, the corresponding variation in behavioral outcomes remains limited.

In general, higher levels of tie formation relative to tie breaking are associated with higher social norm (SN) intentions, higher PMT intentions (particularly for dry-proofing), and higher adaptation uptake. On the other hand, increased rates of tie breaking and severing weaken these effects. The magnitude of these behavioral changes remains small to moderate.

For example, average PMT intentions for dry-proofing vary from only 0.118 in the empirical tie+weight (low sever threshold, low formation) to 0.239 in the stylized tie-only setup (high breaking, high formation). Comparing these results with the corresponding network structures shows that extreme differences in connectivity (from full network dissolution to moderate connectivity) do not translate into equally large differences in behavioral outcomes. This provides further evidence that increased connectivity alone does not lead to higher PMT or SN intentions.

To further investigate the relationship between network restructuring parameters and household intentions, correlation and regression analyses have been conducted on the data from experiment 2. A full overview of these statistical results is provided in appendix B in tables B1 to B6, the implications of these outcomes are discussed here.

Correlation matrix: Formation is correlated moderately (at 0.41-0.43) with all three intentions: social norm (SN), dry-proofing protection-motivation (PMT-DP) and wet-proofing protection-motivation (PMT-WP). The breaking and sever values are both presented as `param_y` in the correlation and regression analyses, since they both represent the "level" of tie breaking in different configurations. Breaking ties (`param_y`) shows a strong negative relationship with behavioral outcomes. This effect is present especially for SN (-0.62) and adaptation (-0.56). These results suggest that breaking connections in the network is more strongly associated with decreases in intentions and adaptation than tie formation is with increases. As expected, there is high correlation between the intentions and

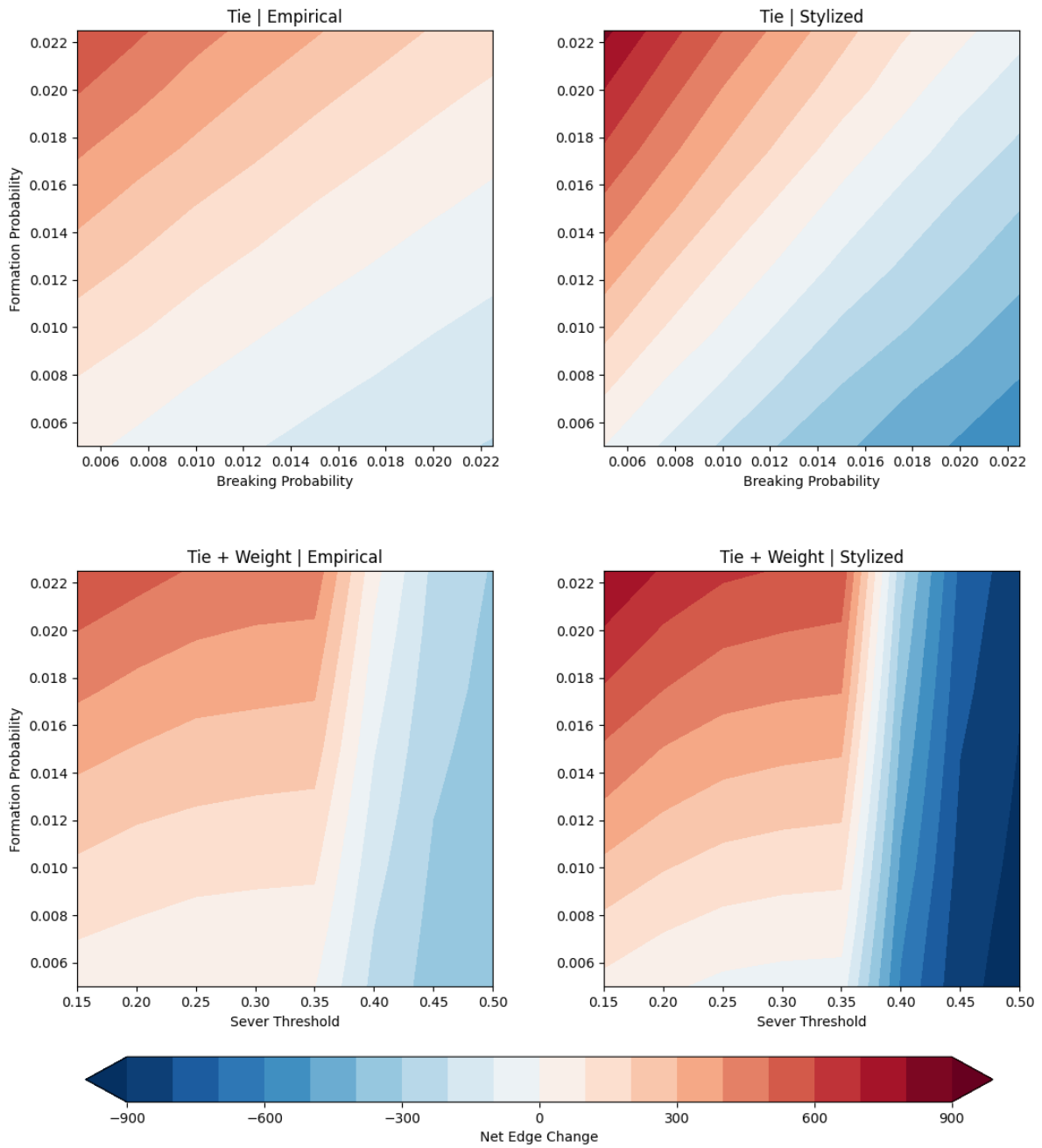


Figure 4.4: Heatmap showing the final net edge change in the network for different parameter combinations and configurations. The breaking and formation probability indicate the percentage chance each agent has each step to add or break a connection. The sever threshold is similar to the breaking probability, however, it indicates the value below which the weight of a connection leads to a probability of breaking, scaled to a 100% chance of breaking at a weight of 0. In the heatmap red indicates net growth of the network, blue indicates net decay. The initial adaptation level = 0.12 and each heatmap is based on 50 Monte-Carlo simulations.

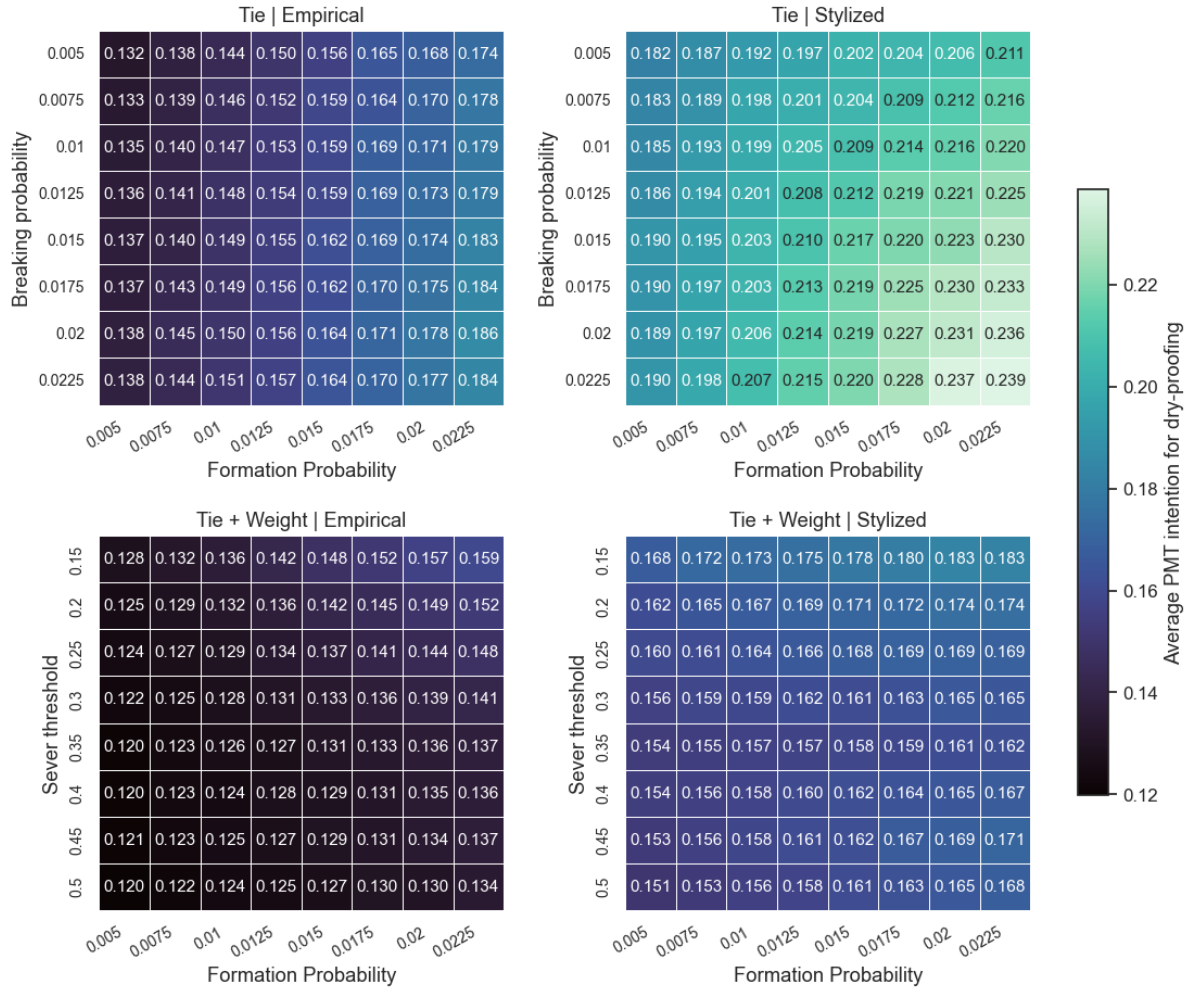


Figure 4.5: Average final protection-motivation intention for dry-proofing measures across all households. The breaking and formation probability indicate the percentage chance each agent has each step to add or break a connection. The sever threshold is similar to the breaking probability, however, it indicates the value below which the weight of a connection leads to a probability of breaking, scaled to a 100% chance of breaking at a weight of 0. A higher PMT intention leads to a higher chance of adopting a measure. The initial adaptation level = 0.12 and each heat map is based on 50 Monte-Carlo simulations.

adaptation, validating that intentions indeed form the adaptation decision together.

Regression analysis: Regression results consistently show that formation probability has a positive effect on intentions and adaptation, while `param_y` has a negative effect. The explanatory power of these simple models is moderate, with the following coefficients of determination:

- PMT-DP: $R^2 \approx 0.399$
- PMT-WP: $R^2 \approx 0.395$
- SN: $R^2 \approx 0.488$
- Adaptation: $R^2 \approx 0.407$

These results confirm that higher rates of tie formation are associated with increased intentions, whereas higher levels of tie breaking are associated with lower intentions and adaptation. However, the statistical significance comes partly from the large number of observations ($n=12,800$), so it is good to be cautious when interpreting these results. Interpretation should focus on the direction, consistency and magnitude of effects rather than significance alone.

To determine whether the effects of tie formation depend on the level of tie breaking, interaction models were estimated. For all four outcome variables, the interaction between formation probability and `param_y` is negative:

- PMT-DP: -4.20
- PMT-WP: -1.07
- SN: -5.45
- Adaptation: -5.33

This indicates that the benefits of increasing formation decrease as the breaking of ties is increased. The effect of dynamism is therefore not just additive but depends on the balance between forming and breaking ties. Higher formation leads to higher intentions and somewhat higher adaptation, while breaking ties lowers these outcomes. The regression analysis furthermore shows that breaking ties is more associated with lower outcomes than formation is with higher outcomes. It should be noted that the relatively strong negative influence of breaking ties may partly reflect model dynamics in which networks tend to dissolve under high sever thresholds in the tie + weight configurations.

The next step is to look at the fit of interaction models, which is only a slight improvement over the simple models:

- PMT-DP: $R^2 \approx 0.399 \rightarrow 0.416$
- PMT-WP: $R^2 \approx 0.395 \rightarrow 0.412$
- SN: $R^2 \approx 0.488 \rightarrow 0.497$
- Adaptation: $R^2 \approx 0.407 \rightarrow 0.426$

This suggests that interactions between formation and breaking ties are relevant, but do not substantially increase the explanatory power of the model. Finally, full regression models were estimated to account for the broader modeling context in which network dynamism operates. These models show substantially higher explanatory power:

- PMT-DP: $R^2 \approx 0.872$
- PMT-WP: $R^2 \approx 0.813$
- SN: $R^2 \approx 0.887$
- Adaptation: $R^2 \approx 0.874$

These results indicate that the broader co-evolutionary context (including network type and dynamics) plays a major role in shaping intentions and adaptation outcomes. Several patterns emerge: Stylized networks generally have higher intentions and adaptation (all else equal, PMT-DP = $+0.056$, PMT-WP = $+0.013$). Furthermore, for PMT-DP and PMT-WP, interaction terms involving tie + weight dynamics are often negative. This suggests that adding weights does not necessarily benefit behavioral outcomes, it can even dampen them in some contexts. The main value of these full regression models is showing that the dynamism effect differs substantially by network type and by whether weights are active.

Overall the results from this analysis show that while network dynamism clearly affects the network strongly, its translation into behavioral change is moderate and highly context-dependent. The balance between tie formation and breaking plays a key driver, but its effects are non-linear and depend on network structure and model configuration (see also figure 4.5). The role of initial network topology is explored further in the following section.

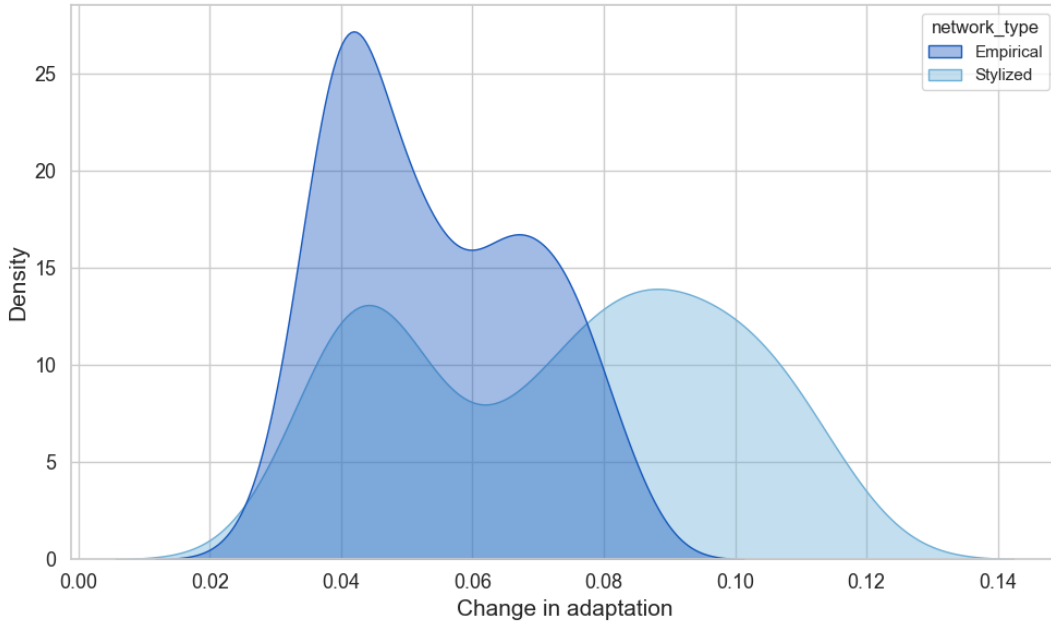


Figure 4.6: Comparison of adaptation change levels between topologies in the tie-only dynamics. The figure shows the frequency with which a certain adaptation increase is observed in the simulation results. The empirical network is based on Wagenblast, Ghorbani, et al. (2026), the stylized network is an Barabási-Albert style network. For the stylized network, higher adaptation increases are observed. These plots show 150 Monte-Carlo simulations per network type.

4.3. Topology moderates the sensitivity of the system to co-evolution

Co-evolutionary rules do not operate the same way across different initial topologies. A consistent result across experiment 1 and 2 is that stylized networks are more sensitive to co-evolutionary restructuring than empirical networks. Stylized networks tend to show larger changes in edge count and stronger restructuring under tie-based dynamics. In behavioral terms, they also tend to show somewhat stronger changes in intentions and somewhat higher adaptation gains under the same co-evolutionary conditions. Empirical networks on the other hand, appear more constrained and show smaller responses (see figure 4.1). This is also visible in the distribution of final adaptation increases across setups for stylized and empirical network topologies as seen in figure 4.3.

The topology effect is clearly visible under tie-based dynamics (figure 4.6). Weight-only dynamics have the same effect as the static setup in either topology but do show a clear differentiation, while tie + weight dynamics are more unstable and context-dependent: in some settings they still improve outcomes, but they often dampen the benefits seen under tie-only dynamics. This indicates that initial topology generally does not change the direction of co-evolutionary effects, but it does change their magnitude and stability.

An important distinction is that topology sensitivity is much stronger at the structural level than at the behavioral level. Stylized networks may exhibit large changes in connectivity, but these do not translate one-to-one into large additional gains in adaptation (see matrices in figure 4.5 and appendix B.4). The results therefore suggest that topology matters mainly because it changes how strongly co-evolutionary rules can alter local social influence and, through that, the behavioral environment in which adaptation decisions are made. This will be further elaborated upon in section 4.5.

4.4. Dynamic weights add limited value beyond tie restructuring

SQ2.3 poses the question whether adding dynamic weights to the network contributes meaningfully to adaptation behavior in the model. Across the experiments, the evidence for a strong added value of weight dynamics remains limited. Weight-only dynamics produce almost no difference relative to static baselines, and when weights are added to tie dynamics, the resulting outcomes are often more volatile and less stable than in tie-only configurations (see figure 4.1). In some cases tie + weight produces slightly higher adaptation than static, but in other cases it reduces the benefits of co-evolution compared with tie-only.

This suggests that, in the current model configuration, dynamic weights do not act as a strong independent driver

of adaptation diffusion. Rather than amplifying the benefits of co-evolution, they often introduce instability into network growth because dissimilarity and differing adaptation states can lower tie weights and thereby increase the likelihood of edges breaking. As a result, weight dynamics appear to contribute relatively little beyond what is already achieved by changing the connectivity structure itself.

In EXP3 different weight and social norm scenarios were tested. Their effect and the effect of weights in general are shown in figure 4.7. Here the change in social norm intention compared to the simulation start is shown, revealing only minimal differences between scenarios. The only large difference in this figure is between the tie + weight and weight-only dynamics, which can be explained by the fact that without rewiring of the network, changes in perceived social norms are limited. It is important to note that the same lack of effect from weights is observed for PMT intentions and adaptation changes (see figures B.10 and B.9).

Because the dedicated EXP3 weight analyses did not yield a comparably strong and stable pattern, they are treated here as supporting rather than central evidence. The main conclusion is therefore not that weights are irrelevant in principle, but that in the present experiments they add limited explanatory value compared with tie restructuring.

The ANOVA results largely confirm these observed patterns. While dynamics have a statistically significant effect on all outcome variables, the size of these effects differs per type. The strongest effect is observed for SN intention, where tie+weight dynamics result in higher and more variable changes. Effects on PMT-related intentions and adaptation uptake are relatively small (though statistically significant), indicating limited impact of the different input parameter setups. Scenario effects do exist but are generally smaller than the influence of dynamics and initial adaptation levels.

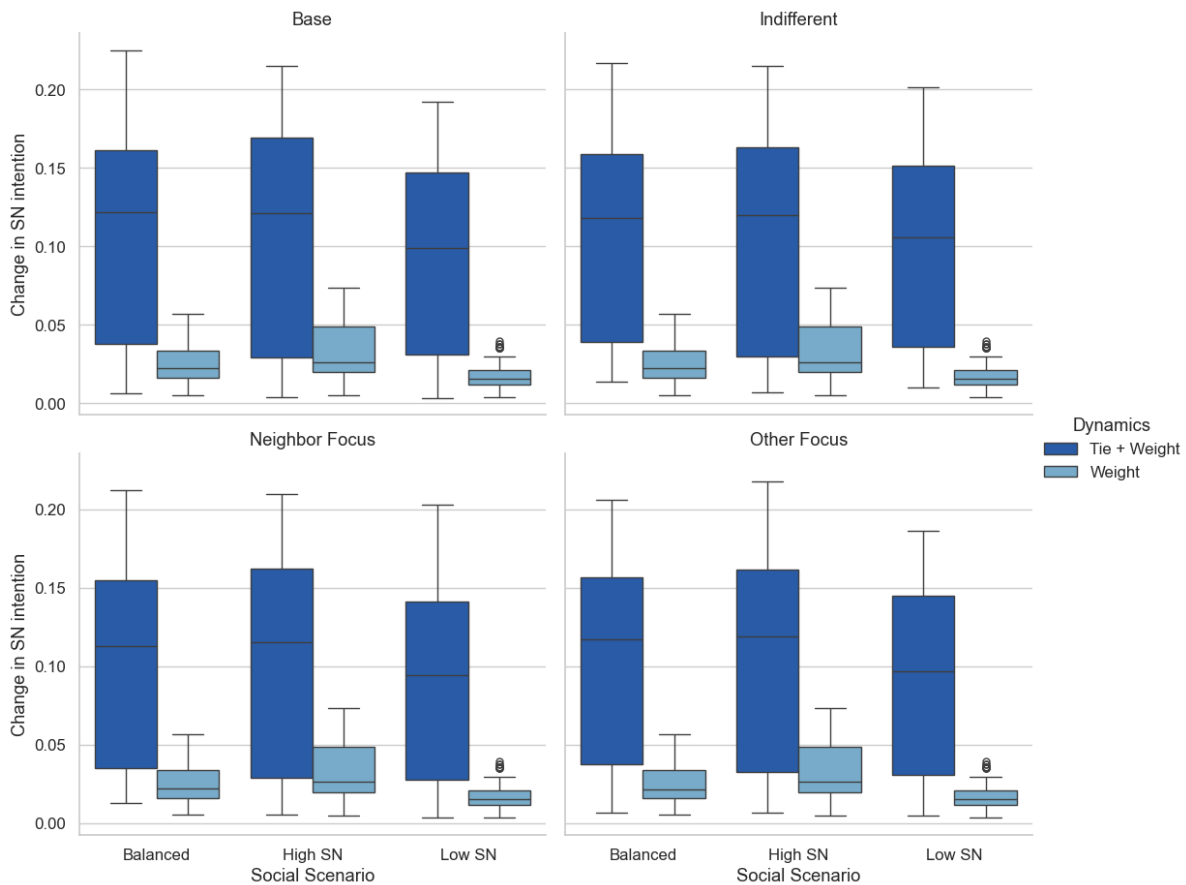


Figure 4.7: Box plot showing changes in social norm intentions, for different weight and social norm scenarios. The different scenarios are defined as follows: Base: family = 1.0; neighbor = 0.7; other = 0.5; Indifferent: family = 0.7; neighbor = 0.7; other = 0.7; Neighbor focus: family = 0.6; neighbor = 1.0; other = 0.6; Other focus: family = 0.6; neighbor = 0.6; other = 1.0; High SN: weight_action_vs_opinion = 0.75; weight_SN_vs_PMT = 0.75; Balanced: weight_action_vs_opinion = 0.5; weight_SN_vs_PMT = 0.5; Low SN: weight_action_vs_opinion = 0.25; weight_SN_vs_PMT = 0.25; Each box represents 50 Monte-Carlo simulations, meaning each scenario combination was run 50 times for different configurations. There is a clear potential for SN change in the tie + weight configuration, whereas in the weight-only configuration this increase is comparatively limited.

4.5. Micro-level implications: co-evolution operates mainly through local social norm influence

The last part of the experimentation focuses on answering SQ2.4, by linking co-evolution directly to adaptation by agents, and seeing if co-evolution can actually play a role in increasing adaptation even when we know that adaptation will be high based on the model input parameters.

First, adaptation "triggers" were traced by logging all network changes and agent attributes for a single run with 1.000 agents in a stylized network. The triggers have been split into behavioral and network triggers, where the behavioral triggers show changes in intentions, and network triggers log if a change occurred in the adapting agent's network. Because weight changes caused high levels of noise in the analysis, only tie formation and removal have been included as network changes for trigger tracing. Furthermore, a window of a certain amount of years is used and a threshold for flagging a PMT or SN change as trigger is added to reduce noise. The SN threshold is set at 0.1, as this can increase with large jumps as soon as one of the agent's neighbors adapts, or a connection is formed/broken. For the other values, see the histograms containing counts of each type of trigger. Each trigger can be explained as follows:

- No data: Agent adapted in the first step, so no prior step data to trace.
- No trigger: No significant change detected in either internal or social motivation prior to adoption.

Behavioral triggers:

- PMT: Adoption preceded by an increase in internal motivation (PMT) without detectable social or network influence.
- Social Norm: Adoption preceded by an increase in perceived social norm influence, without network change.
- PMT + SN: Adoption preceded by simultaneous increases in both internal (PMT) and social norm influences.

Network triggers:

- Network: Adoption occurs following network changes (e.g. tie formation or removal), without detectable changes in internal or social motivation.
- Network + SN: Adoption occurs following network change AND SN increase
- Network + PMT: Adoption occurs following network change AND PMT increase
- Network + PMT + SN: network change AND both PMT and SN increase

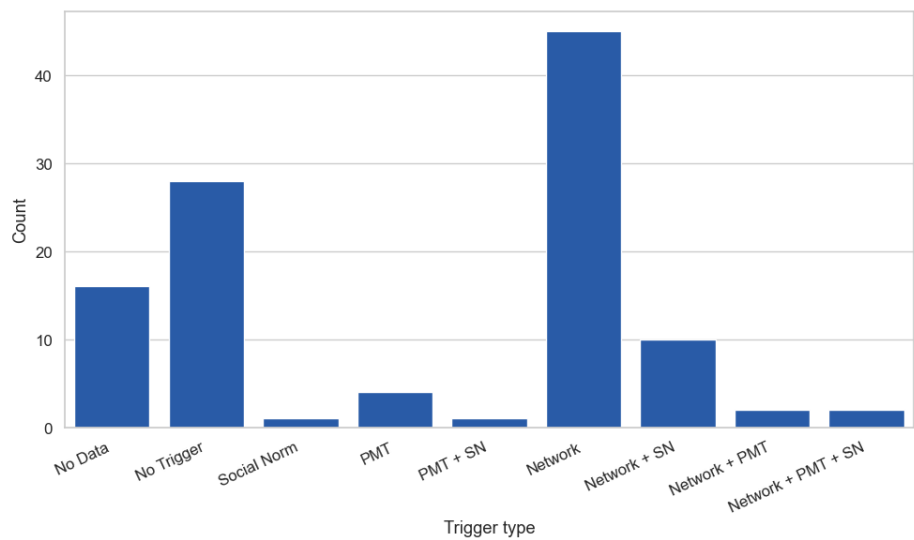
The counts of each type of trigger for one of the runs that was simulated can be found in figure 4.8. More of these histograms were made with different windows and threshold for PMT, these can be found in appendix B.11.

The trigger analysis does not show any causal chain between certain behavioral or network changes and adaptation, but it does show co-occurrence of these events. Overall, the result shows that many of the adoptions that occur after the first step do not show a clear trigger, or a network change occurred whilst not significantly changing the SN or PMT intention of the agent in question. This means that co-evolution cannot be linked as a reason for adaptation based on these results, nor does it indicate that there might be a clear relation to be found here.

The next step is to focus on individual agents and their appraisals, to see if this can explain more about the deep-rooted mechanisms that drive adaptation in FAST. For all agents the change in appraisals at each step was recorded, in order to show the aggregated change of appraisals across the simulation (see figure 4.9).

The trajectory plot (figure 4.9) shows that indeed appraisals change as expected, for example through the large spike in worry at step 15, which is when the flood occurs. This is followed by an increase in perceived severity of floods. Furthermore, initially most appraisals spike, as agents with different appraisals have been linked in the network creation and they will move opinions towards each other in roughly the first five steps. This movement of appraisals is shown in the absolute change levels in figure 4.9. Some appraisals remain constant and are therefore not visible in this change plot (*self_efficacy* and *risk_perception*). This can be combined with individual agent trajectory plots (figure 4.10), and the information on how appraisal values are used in a regression to calculate the PMT intention for a certain measure (see table A.2 in appendix B).

Combining these insights we can see that the resulting changes in PMT are highly dependent on the regression results, making PMT and exchange of opinions about appraisals only a weak driver of adaptation. To exemplify this, we can look at agent 19 in figure 4.10. Wet-proofing is adopted even when SN intention and PMT wet-proofing intention is low, which is possible due to the probabilistic nature of adoption of measures. PMT dry-proofing intention spikes after this, because of the intercept from the regression in table A.2 in appendix A. This shows that



PMT = Change in Protection Motivation intention. Social Norm = Change in Social Norm intention. Network = Tie formation or tie removal detected prior to adaptation.

Figure 4.8: Histogram showing counts of adoption triggers by type for each individual adaptation in a single simulation. Definitions of trigger labels can be found in section 4.5. The time window for tracing triggers in this plot is 5 years, the PMT change threshold for PMT triggers is set to 0.03. This does not show causality between network or intention changes and adoption, but it simply shows if said changes happened prior to adoption. This is used to determine whether certain (combinations of) triggers precede adoption. Overall most adaptation decisions seem to be preceded by network changes.

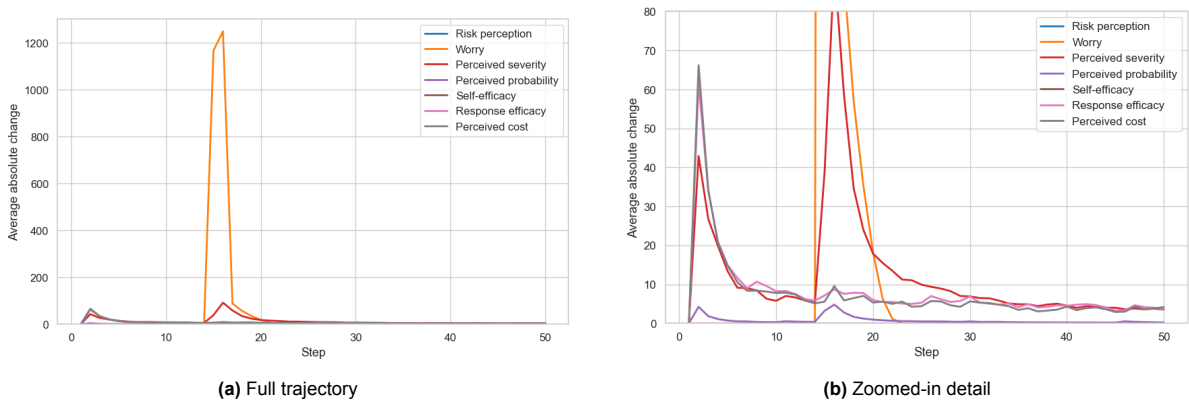


Figure 4.9: Trajectory plot of appraisal changes aggregated for all agents, showing both the full counts (a) and a zoomed-in focus on appraisals other than worry (b). A flood event occurs at step 15. Note that this plot counts absolute change in appraisals and does not say anything about their (average) values. This plot shows a single simulation. The spike of worry and perceived severity after the flood is clearly visible. Initial exchange of appraisals between households with differing views in the first steps is clearly visible, this stabilizes after step 5.

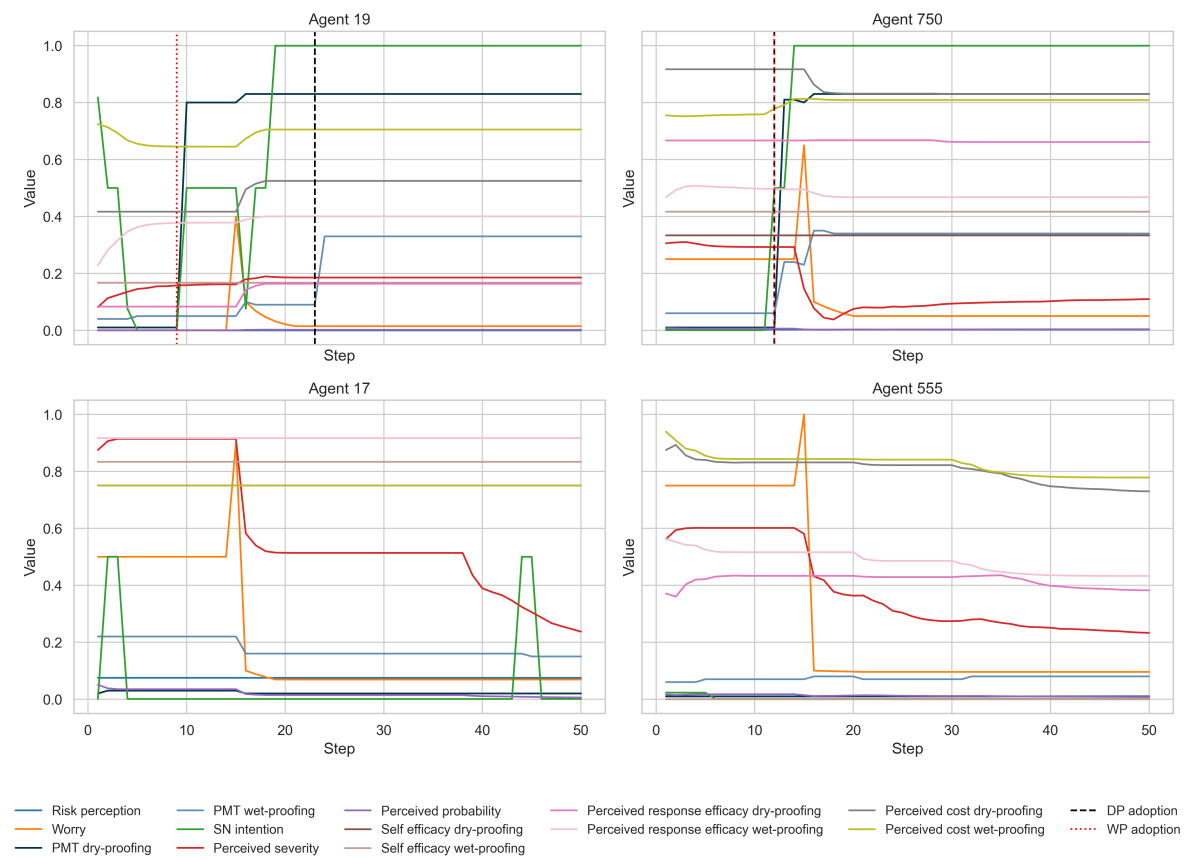


Figure 4.10: Individual agent appraisal trajectory plots over time, showing adoption of measures and individual appraisal levels. Agents have been selected randomly. DP = dry-proofing, WP = wet-proofing, PMT = protection motivation, SN = social norm. The different appraisals are explained in section 3.1. Appraisals together form the PMT intentions. A flood occurs at step 15. The plots visualize how intentions (SN and PMT) are formed, and sometimes lead to adopting a measure (agent 19 and 750), while in other cases it does not (agent 17 and 555).

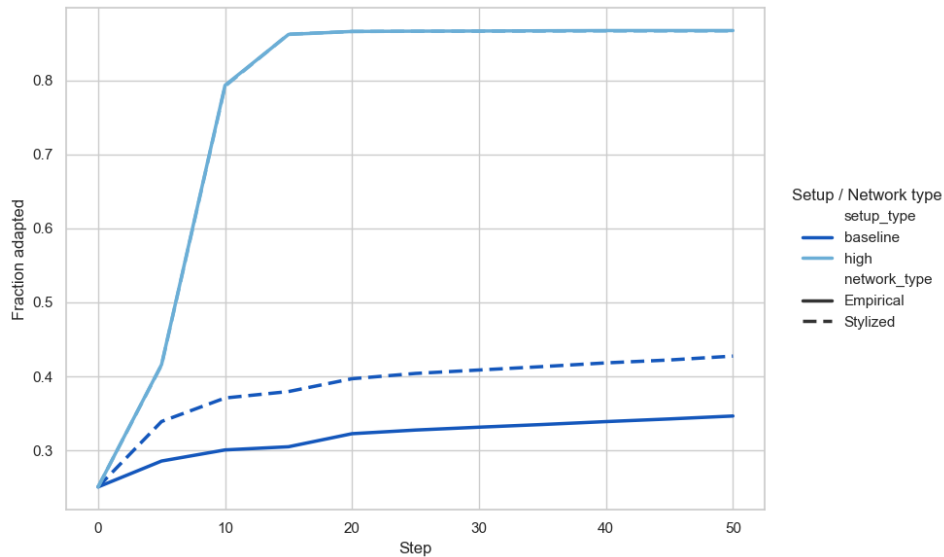


Figure 4.11: Trajectory plot of high and baseline adaptation setups. High setups focus on forcing adaptation through social norm calculation on a global scale, with initial adaptation level = 0.25. This means for many agents there is an initially probability close to 25% of adopting a measure. Note that stylized in the high setup is hidden behind the empirical network in the high setup as these have the exact same adaptation outcomes. This is due to adaptation being calculated globally, and the network structure no longer influences social norm intentions.

”done_other” has a strong positive influence on PMT dry-proofing intention, whereas other appraisals have much lower intercepts and thus less influence on wet- and dry-proofing intentions.

Overall these individual agent trajectories validate that the model works as intended. These plots show how stochastic adaptation decisions are, and that high intentions and appraisals do not necessarily lead to adaptation. Even when appraisals show a relatively high motivation for adaptation, this often does not take place. Take agent 17, with high appraisals for perceived cost-, response- and self-efficacy for wet-proofing, this household only has a PMT wet-proofing intention of around 0.2. This however does not lead to agent 17 adapting wet-proofing measures, and as connections that have adopted are broken due to differences in opinion, the local social norm of this agent also does not lead them to adopt a measure.

A much more direct effect on adaptation intentions is formed by the social norm and resulting SN intention, as this gives a flat boost to the overall intention to adopt a measure (see model documentation in appendix A). To indicate how social norms can quickly increase adaptation levels in FAST, a high level adaptation run was done with specific model input parameters (see table 3.5 in chapter 3). To show how adaptation in this run reaches high levels quickly, a trajectory plot can be found of the batch of simulations in figure 4.11. For the high adaptation run, the stylized network has an overlapping trajectory with the empirical network. This can be explained by the difference in input parameters. In the high adaptation setup, the social norm is calculated globally and independent of the network. As the focus in these runs is on the social norm and SN intention as a pathway to adaptation, if this is calculated independent of the network, the initial topology no longer matters. This can also be seen when comparing the dynamic vs. static setup for high and baseline adaptation settings (figure 4.12), where there is barely any difference in adaptation levels that are reached between static and dynamic in the runs with a high adaptation setup. However, in the baseline there is indeed an increase in adaptation over the static setup, both for the empirical and the stylized network.

This suggests that high adaptation levels can be reached independent of the network and thus regardless of network co-evolution.

4.6. Conclusion for SQ2

Taken together, the experiments show that co-evolutionary restructuring of social networks can be modeled in a way that helps explain the diffusion of household flood adaptation behavior. However, its influence is neither uniform across contexts nor equally strong across all layers of the model. SQ2 asks under what conditions and through which mechanisms, co-evolutionary social network dynamics influence household adaptation uptake. The results indicate that co-evolution affects adaptation uptake to a moderate and highly context-dependent extent,

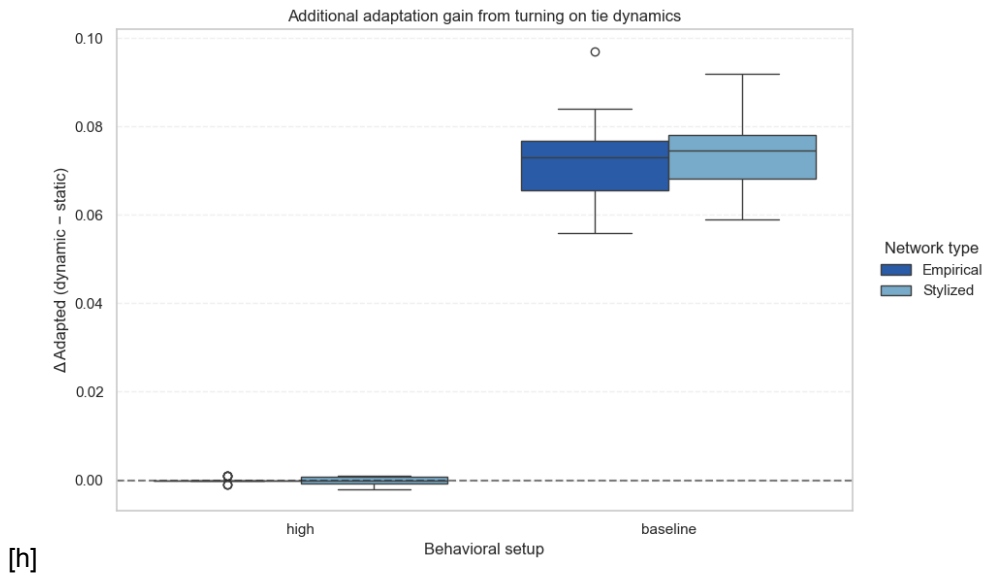


Figure 4.12: Boxplot showing the additional adaptation that is achieved when adding tie dynamics to the same setup. The delta adapted on the y-axis shows the adaptation levels that are reached compared to those in the static configuration, therefore showing adaptation compared to what happens in a static network. This shows that in the high adaptation setup there is no longer any difference between a static or a co-evolutionary model configuration. This is due to the decoupling of the social norm intention from the network, and the social norm being the main behavioral pathway to adaptation.

primarily through its influence on local social norm influence rather than through large-scale changes in individual decision-making processes. The rest of section will elaborate the conclusion to this sub-question.

In most of the aggregate analyses, the clearest structural effect of co-evolution is produced by tie-based dynamics, while weight-only dynamics contribute little beyond static baselines and often fail to generate meaningful behavioral gains. Tie + weight dynamics introduce more volatility than tie-only dynamics and often dampen or destabilize the benefits of simple tie restructuring. This indicates that, in the present FAST-ABM configuration, changing who is connected to whom matters more than changing how strongly households influence one another. Together with the insights from varying weight and social influence input parameters, this contributes to answering SQ2.3 by indicating that adding dynamic weights does not substantially change the impact of co-evolution beyond what is achieved through tie restructuring alone.

A second consistent finding is that co-evolutionary rules affect the network itself much more strongly than they affect household adaptation. Across the broad setup comparisons and the dynamism parameter sweeps, the network can grow substantially, fragment, or nearly dissolve depending on the balance between tie formation and tie breaking/severing. However, these large structural differences do not translate into equally large differences in final adaptation uptake. Instead, the behavioral effects of co-evolution remain moderate and strongly context-dependent. Formation-oriented dynamism is associated with higher intentions and somewhat higher adaptation, whereas breaking connections in the network weakens these effects. However, the resulting changes in household behavior are much smaller than the changes observed in the network structure itself. This suggests that structural sensitivity is a necessary condition for co-evolutionary effects, but not by itself sufficient to produce large behavioral change.

The results further show that initial topology strongly moderates the sensitivity of the system to co-evolutionary rules. Stylized Barabási-Albert networks respond more strongly to tie-based co-evolution than empirical networks, both structurally and behaviorally. They tend to show larger changes in edge count, stronger shifts in household intentions, and somewhat larger gains in adaptation uptake. Furthermore, topology changes the magnitude and stability of co-evolutionary effects rather than their overall direction. In both network types the formation of ties tends to support adaptation and breaking ties tends to weaken it, but stylized networks amplify these relationships slightly more than empirical ones. This finding answers SQ2.2 by showing that initial network topology moderates the sensitivity of the system to co-evolutionary rules, with stylized networks exhibiting stronger responses than empirical ones.

At the same time, the aggregate analyses show that topology and network dynamism do not affect all of the intentions to adapt equally. The clearest changes occur in social norm intention and, to a lesser extent, PMT dry-proofing intention. Correlation and regression analyses indicate that network growth is associated with higher

SN and higher adaptation, while breaking the network down is associated with lower values. Interaction models further reveal that the benefits of formation weaken as the breaking of ties is increased, meaning that the effect of co-evolution depends not simply on the presence of dynamism but on the specific balance between forming and breaking of the network. This directly addresses SQ2.1 by showing that this balance between tie formation and breaking determines both the direction and strength of co-evolutionary effects.

The micro-level EXP4 analysis helps to understand how this intention pathway operates. Trigger tracing and individual-agent trajectory analysis suggest that many adaptation events are not preceded by pronounced appraisal changes or gradual PMT buildups. Instead, the most consistent mechanism appears to involve network change and local social norm exposure. Social norm shifts are more frequently implicated in adoption than purely PMT-based changes, while many appraisal variables remain relatively stable except around flood events. This suggests that PMT is present in the model as a conceptual decision layer, but that it is less responsive to co-evolutionary dynamics than social norm influence. In other words, co-evolution does not primarily seem to increase adaptation by reshaping internal coping appraisals, rather it changes the local exposure conditions through which households observe the behavior of others and adjust their social norm related intentions.

This interpretation is reinforced by the additional high-adaptation comparison. When the model is given a certain parameter setup for which high adaptation levels are very likely, the difference in adaptation uptake between static and dynamic network conditions practically disappears. Under this setup, adding tie dynamics adds little additional adaptation in either empirical or stylized networks. This provides strong support for the conclusion that co-evolution matters mainly when the social norm viewed by an agent is local and thus network dependent. If norm information is global and uniform for all agents, restructuring the network adds little, because the main social diffusion mechanism is effectively being bypassed. The results from this high-adaptation analysis and those from the micro-level analysis relate to SQ2.4, suggesting that connectivity can affect individual adaptation behavior mainly through local social norms rather than through stable PMT patterns or specific topology related effects.

Taken together, these findings point to a consistent underlying mechanism of co-evolution in the model. The experiments suggest that co-evolution in FAST functions primarily as a mechanism that can enhance local social influence, rather than strongly increasing overall adaptation uptake. Tie restructuring changes the structure through which households encounter the adaptation behavior of others, and this primarily affects the model through social norm dynamics. Dynamic weights add little beyond this process. The model therefore contributes to understanding flood adaptation diffusion not by showing that co-evolution universally increases uptake, but by showing under which structural and behavioral conditions network change can amplify or constrain local norm diffusion and thereby shape household adaptation behavior.

5

Discussion

This thesis set out to investigate how co-evolutionary social network dynamics can be modeled to better understand the diffusion of household flood adaptation behavior. Two sub-questions structured this research. SQ1 focused on identifying the social mechanisms and network restructuring rules that can explain the co-evolution between household adaptation behavior and social network structure. SQ2 then explored under what conditions, and through which mechanisms, these co-evolutionary dynamics influence household adaptation uptake.

The answer to SQ1 showed that co-evolutionary social network dynamics can be represented through two interacting pathways. First, network-to-household dynamics describe how the social network influences household behavior through mechanisms such as opinion exchange, bounded confidence, weighted social influence and social norm influence. Second, household-to-network dynamics describe how households reshape the network through tie formation, tie breaking and changing connection strength. These mechanisms formed the conceptual basis for extending the FAST-ABM with co-evolutionary network restructuring.

The results for SQ2 show that co-evolutionary dynamics can significantly change the network structure, but that their influence on adaptation behavior is moderate and highly context-dependent. Tie formation and tie breaking strongly affect network topology, while the resulting effect on adaptation uptake is much smaller. The most consistent behavioral pathway is not a direct transformation of internal protection motivation, but rather through local social norms influencing adaptation intentions. In other words, co-evolution matters mainly because it changes which households are influenced by adapted others, rather than changing the appraisals and protection motivation held by these households.

This discussion reflects on these findings in relation to the literature, the main research question, the limitations of the model, and the societal challenge introduced at the start of this thesis.

5.1. Implications of findings in relation to existing literature

5.1.1. Co-evolution changes structure more than behavior

A central finding of this thesis is that co-evolutionary dynamics affect network structure much more strongly than household adaptation behavior. Networks can experience substantial growth, decay, or restructuring depending on the balance between tie formation and breaking. However, these structural changes do not translate into equally large changes in adaptation uptake.

This distinction is embedded in the FAST-ABM itself. The model separates willingness to adapt from actual adaptation behavior. Both protection motivation and social norm intentions influence the probability of adaptation, but they do not guarantee that a household implements a measure. This helps explain why even scenarios with higher intentions do not necessarily produce proportionally higher adaptation uptake. Network evolution may increase exposure to adapted households and raise social norm intentions, but actual adaptation remains filtered through financial constraints, timing, and stochastic decision-making (see section 3.1).

This finding relates directly to the distinction between information diffusion and behavioral adoption discussed in the literature. Zia et al. (2021) argue that diffusion and absorption should not be treated as the same process. Information can spread through a network, but this does not automatically mean that individuals absorb it and act upon it. The results of this thesis show a similar pattern in the flood adaptation context. Co-evolutionary

restructuring can increase opportunities for interaction and influence, but actual adaptation remains constrained by behavioral thresholds, financial hurdles, and decision-making mechanisms.

It also aligns with Taberna et al. (2023), who emphasize the role of bounded rationality and the intention-action gap in household adaptation. Even when households have access to adaptation-related information or if they interact with adapted peers, this does not guarantee that they will take protective measures. The results therefore confirm that social network structure matters, but they also show that structural change alone cannot fully explain adaptation uptake.

Furthermore, this finding can be connected to the academic challenge introduced in chapter 1. The issue is not only that current models often treat networks as static, but also that adding dynamic networks does not simply lead to a certain type of behavioral change, since this change is highly conditional and context dependent. Co-evolutionary modeling is useful because it helps reveal where network change matters, but it should not be interpreted as a direct solution to the adaptation gap.

5.1.2. Social norms are more responsive to network changes than individual protection motivation

A second important finding is that social norm influence is more responsive to co-evolutionary dynamics than PMT-related appraisals. PMT intentions change more gradually, because they are partly driven by internal appraisals and empirically derived relationships in the model. Social norm intentions, on the other hand, can change more abruptly when an agent becomes connected to adapted households or when neighbors adopt measures.

This finding supports the role of peer exposure identified in empirical adaptation research. Barnes et al. (2020) show that exposure to adaptive behavior within a social network can be an important driver of adaptation. The results of this thesis confirm this mechanism in a modeling context, where co-evolution primarily influences adaptation when it changes connections to households that have already adapted.

The results also align with Meylahn and Searle (2024), who argue that social influence should not necessarily be understood as directly overwriting internal beliefs. In the present model, co-evolution does not strongly reshape household protection motivation. Instead, it changes the social environment in which households make decisions. This means that the network mainly affects adaptation through perceived social norms, rather than through large shifts in internal threat and coping appraisals.

This finding also reflects back on the conceptual framework developed in Chapter 2. The household-to-network mechanisms are clearly visible in the results: households form and lose ties, and this substantially changes the network structure. However, the network-to-household pathway is more selective than expected. Some of the literature (Aghbolagh et al., 2023; Chaudhury et al., 2017; Haer et al., 2016; Ioannidis et al., 2021; Taberna et al., 2023; Van Den Beukel et al., 2019) suggests that social influence through the network takes effect both on individual decision-making (PMT) and on social norms. The results from this project show that social norms are much more sensitive to network co-evolution than PMT appraisals.

5.1.3. Additional model complexity does not automatically improve explanation

Another important implication relates to the role of model complexity. The literature on co-evolutionary networks often focuses on representing increasingly realistic mechanisms, such as dynamic tie strengths (Van Den Beukel et al., 2019), evolving interaction weights (Ioannidis et al., 2021), and more complex, multi-layer network structures (Aghbolagh et al., 2023; Krishnagopal & Porter, 2024; Yin et al., 2023; Yu & Huo, 2025). However, the results of this thesis suggest that additional complexity does not automatically improve the explanatory value of the model.

A specific example of this, is the fact that dynamic weights add limited value beyond tie restructuring. Weight-only dynamics produce outcomes that are close to the static baseline, while combining tie and weight dynamics often introduces instability and can dampen the benefits observed under tie-only dynamics. This suggests that, in the current model setup, changing who is connected to whom matters more than changing how strongly households influence one another.

This finding is consistent with work by Saeedian et al. (2024), who show that increasing complexity in co-evolutionary human-environment systems can reduce system performance under certain conditions. In this thesis, the addition of dynamic weights appears to increase volatility without producing clear behavioral gains. This does not mean that weights are irrelevant in principle. It suggests that dynamic weights require strong theoretical and empirical grounding before being added to adaptation models.

A key modeling decision that likely influences this outcome, is the decision to not scale social norm influence by edge weights. Since social norm influence emerged as the dominant behavioral pathway, the effect of dynamic

weights is likely suppressed in the current model configuration. This implies that the limited value of weights should be interpreted cautiously. Future model versions may find stronger effects if connection strength is also allowed to influence social norm perception.

5.1.4. Initial topology moderates the effect of co-evolution

The comparison between empirical and stylized networks also contributes to the literature on network representation in agent-based models. The results show that stylized Barabási-Albert networks are more sensitive to co-evolutionary restructuring than empirical networks. They show stronger growth, stronger decay, and larger changes in adaptation outcomes. Empirical networks, in contrast, appear more constrained and stable.

This finding supports the idea that topology influences diffusion dynamics, but it also informs modelers not to interpret results based only on stylized networks. Stylized networks are useful for mechanism exploration because they make structural effects more visible. However, their response to co-evolutionary rules may be stronger than what would be observed in empirically grounded networks. In this thesis, the empirical network acts as a stabilizing structure that limits extreme network growth or fragmentation.

This reinforces the need for empirical grounding in social network modeling. If the objective is to understand possible mechanisms, stylized network topologies are useful. If the objective is to assess the likely magnitude of effects in real-world adaptation contexts, empirical network structures are necessary. The results therefore support the broader call in the literature for better empirical data on social networks and their evolution over time (Carr et al., 2025; Conrad et al., 2024; Flache et al., 2017; Taberna et al., 2023; Will et al., 2020).

5.1.5. Synthesis of the contribution

Taken together, these findings both confirm and refine existing knowledge on social influence and climate adaptation. The results support the broader literature showing that co-evolutionary social networks are an important factor in understanding adaptation behavior (Chaudhury et al., 2017; Entwisle et al., 2020; Juhola et al., 2022; Saeedian et al., 2024; Taberna et al., 2023; Will et al., 2020). However, they also show that the effect of network co-evolution on adaptation behavior operates primarily through local social norms rather than through large-scale structural change alone.

The main research question is aimed at understanding how co-evolutionary social networks can be modeled and how this can help understand adaptation behavior. This thesis shows that the co-evolutionary restructuring of social networks can be modeled as a feedback process between household adaptation behavior and network structure. In this model, households influence the network through tie formation, tie breaking, and changing connection strength, while the network influences households through the connections they hold and scaling exchange of appraisals by connection strength. This modeling approach helps to better understand adaptation diffusion by showing how social influence is mediated through changing local network contexts.

The main contribution of this thesis is therefore not that co-evolution universally increases household adaptation uptake. Instead, the contribution lies in showing under what conditions co-evolution matters, and through which mechanisms. This distinction is important because it clarifies the role of co-evolutionary networks in flood adaptation modeling. Network restructuring can shape the diffusion environment, but it does not by itself guarantee widespread adaptation. The added value of modeling co-evolution lies in revealing when network change amplifies or constrains local social influence, particularly through social norms.

An additional implication is that the behavioral outcomes of the model appear relatively robust under network evolution, which is not accidental. The model contains several filters between internal decision-making, social influence and actual adaptation. Network change can alter who households interact with and can affect local social norm intentions, but actual adaptation depends on whether this willingness is translated into action. This translation is mediated by the behavioral structure of FAST, including financial constraints, measure consideration and stochastic adoption. Therefore, network evolution certainly affects the diffusion of adaptation intentions, but it does not lead to rigid behavioral changes, unless forced to do so through specific model settings.

5.2. Model sensitivity, limitations and future work

The model shows sensitivity to several initial conditions and parameter settings. In particular, initial levels of adaptation can lead to path-dependent outcomes, where small differences early in the simulation result in diverging trajectories over time. Several assumptions also have a strong influence on results, including the increase in connectivity following flood events, the number of flood events simulated, and the scaling of weights.

This path dependence is an important characteristic of FAST-ABM and is also observed in the extended model developed in this thesis. Early adaptation decisions, initial network structure, and early tie formation can influence the later trajectory of both social norms and network evolution. Because adaptation decisions affect the perceived social norm, and because social norms in turn influence future adaptation decisions, small differences early in a simulation can be reinforced over time. This means that the model should not be interpreted as producing deterministic predictions, but as generating possible adaptation pathways under specific initial conditions and assumptions. This is consistent with the behavior of the original FAST-ABM, in which early adaptation decisions and evolving social norm perceptions can shape later adaptation trajectories (Wagenblast, Filatova, et al., 2026).

More generally, the results should be interpreted as conditional rather than universal. Outcomes vary depending on the specific parameter combinations used, even if these variations are often moderate in size. It is important to note that a meaningful sensitivity analysis was not carried out due to time constraints. This limits the ability to formally assess the robustness of the results, particularly in relation to input parameter uncertainty and resulting path dependence.

Another limitation of the model extension is that network restructuring is implemented through addition or removal of edges, rather than explicitly controlling the total number of ties in the network by only rewiring connections or by setting a limit to network growth or decay. As a result, total network size can fluctuate stochastically due to probabilistic formation and breaking. While this is acceptable (and maybe even preferable) within an exploratory modeling context, it introduces noise when comparing scenarios with different levels of network growth and decay. In more focused studies, it may be useful to constrain the total number of connections (e.g. through minimum/-maximum bounds) to isolate social influence effects more clearly.

Furthermore, the potential impact of weight dynamics remain underexplored within this study. The results suggest that weights have limited direct impact beyond introducing instability in certain configurations. However, social norm influence was not weighted by connection strength. Given that SN is the primary driver of adaptation in the model, this likely suppresses the effect of weight dynamics.

Future work should focus on three areas. First, additional empirical research is needed to better understand how social influence operates in flood adaptation contexts, particularly how households perceive and respond to local social norms. Second, longitudinal data collection is needed to observe how adaptation-related relationships evolve over time, allowing co-evolutionary rules to be grounded in observed behavior rather than theoretical assumptions. Third, future model development should explore alternative formulations of PMT and social norm influence, including weighted social norms and different network restructuring mechanisms, to better understand how behavioral and structural dynamics interact.

5.3. Societal and practical implications

Chapter 1 described an adaptation gap between climate adaptation behavior and the rate at which climate-induced hazards increase in severity and frequency. This adaptation gap poses a societal need to better understand household adaptation behavior and the mechanisms that drive it. By modeling the co-evolution of the social network in which these households are embedded, some of these mechanisms have been analyzed. The results suggest that simply increasing opportunities for social interaction is not enough to substantially accelerate household flood adaptation. Although co-evolutionary dynamics can greatly alter the network structure, the resulting behavioral gains are modest at best. This implies that the adaptation gap cannot simply be explained by a lack of connectivity between households. Instead, the way social influence operates within these networks appears to be more important than the network structure itself.

This practical insight suggests that policymakers should be careful not to assume that increased social connectivity automatically translates into higher household adaptation uptake. It furthermore suggests that policy interventions that strengthen visible adaptive behavior and social norm formation may be more effective than interventions focused on increasing interaction between households.

6

Conclusion

This thesis investigated how co-evolutionary social network dynamics can be modeled to better understand the diffusion of household flood adaptation behavior. To do so, the FAST-ABM was extended with mechanisms for tie formation, tie breaking, and dynamic edge weights. These mechanisms were used to explore how changing social network structures influence adaptation uptake across different network configurations and experimental settings.

The main research question asked:

How can the co-evolutionary restructuring of social networks be modeled to better understand the diffusion of household flood adaptation behavior?

This thesis shows that co-evolutionary restructuring can be modeled as a feedback process between household behavior and social network structure. Households influence the network through tie formation, tie breaking, and changing connection strength, while the network influences households by shaping the connections that influence their perceived social norm and protection motivation. This approach helps to reveal how adaptation diffusion depends not only on individual decision-making, but also on the changing local social context in which households are embedded.

The results lead to four main conclusions. First, co-evolutionary dynamics affect network topology much more strongly than they affect household adaptation behavior. Networks can grow, decay, or restructure substantially, but these structural changes translate into only small to moderate changes in final adaptation uptake. This indicates that the behavioral outcomes of the model are relatively robust under network evolution.

Second, the effect of co-evolution is highly context-dependent. Initial topology, initial adaptation levels, and the balance between tie formation and tie breaking all influence the magnitude and stability of model outcomes. Formation-oriented dynamics generally support adaptation, while excessive tie breaking weakens these effects.

Third, tie formation and tie breaking matter more than dynamic weights in the current model configuration. Dynamic weights add limited explanatory value beyond tie restructuring and can increase network instability. This suggests that, in this model setup, changing who is connected to whom matters more than changing how strongly connected households influence one another.

Fourth, co-evolution primarily influences adaptation through local social norm influence. Changing who is connected to whom matters because it changes which households are exposed to adapted others. PMT-related appraisals are less responsive to network restructuring. The discrepancy between willingness and actual adaptation is important here: co-evolution can increase exposure or intention, but this does not automatically translate into implemented measures.

Together, these findings show that co-evolutionary network dynamics are valuable for understanding the social diffusion environment of household flood adaptation, but they should not be interpreted as a direct or universal driver of higher adaptation uptake. The main contribution of this thesis is therefore the distinction between structural sensitivity and behavioral impact: a network may change strongly, while adaptation behavior changes only moderately.

The findings should be interpreted as model-based insights rather than direct predictions of real-world adaptation behavior. The results depend on the assumptions and parameter choices used in the FAST-ABM extension, and

further work is needed to empirically ground dynamic social network mechanisms, especially the role of local social norms and weighted social influence.

Overall, this thesis contributes to a more nuanced understanding of how social networks shape household flood adaptation. Co-evolutionary dynamics can amplify or constrain existing diffusion pathways, but their effect depends on how network change interacts with behavioral mechanisms. For adaptation modeling, this means that dynamic networks should be specified and evaluated carefully. For the broader societal challenge of household flood adaptation, the results suggest that increasing social connectivity alone is unlikely to close the adaptation gap; what matters most is how social influence is translated into visible and meaningful local adaptation norms.

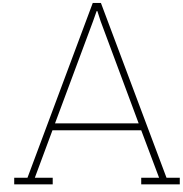
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Model Documentation

A.1. General Description

This model is an extension of the Flood Adaptation via Social Transformation (FAST) ABM by Wagenblast, Filatova, et al. (2026), which simulates an urbanized society that is located in a spatial context, exposed to occasional flooding. The agents in this model are individuals representing their household by making decisions on private climate adaptation in their home. Agents consist of a diverse socio-demographic with different homes (based on survey data). Agent behavior and interactions in FAST are based on several sociological insights from environmental psychology and social norm theory. Agents are divided over several districts representing different neighborhoods, and they connect through a social network structure through which opinions on their protection motivation and social norms are exchanged. Each timestep, agents decide whether or not to invest in adaptation measures, based on their threat and coping appraisals which are grounded in protection motivation theory. Behavioral, social and economic attributes of agents have been empirically derived based on the survey distributions. In FAST the social network is generated before model initialization, based on the empirical survey data. A similarity-biased opinion dynamics model is used for opinion exchange, and on top of the individual protection motivation of agents, perceived social norms affect private adaptation decisions. The perceived social norm affects decision-making, which is updated as adaptation takes place. This perceived social norm can be both locally (within an agent's district) or globally. If an agent intends to adapt following their individual protection motivation and perceived social norm, and can financially afford investing at a specific time step, they take the intended adaptation decision and change adaptation status. Consequently, dynamic local and global social norms are updated each year, tracing the number of adapted agents. For an overview of FAST and the extension made in this thesis, see figure 3.1

A.1.1. Model Extensions

This model extends FAST by revising the social network dynamics:

- Instead of using a static network structure, connections in the network change dynamically.
- Agents use specific rules to determine who to talk to about flood adaptation measures, and with whom they no longer want to discuss them.
- Neighbor influence is no longer uniform but is scaled with the weight agents attribute to their connections.
- The protection motivation of agents and their historical adaptation decisions determine how others view them.
- The explicit types of relationships agents share determine how their connection is valued.

A.2. Model Initialization

A.2.1. Creating the Grid

The spatial landscape is initialized as a grid of 5×5 cells, containing one column of water and four columns of residential area (as can be seen in figure A.1).

- **Population Distribution:** Provided per grid cell as a nested list. The sum must match the total number of household agents modeled. Adjusting household counts per cell allows for customized population distributions.
- **Flood Depth:** Given as a list where every value represents the explicit flood depth for one column.
- **Agent Placement:** Household agents are placed randomly on the grid, taking into account the maximum

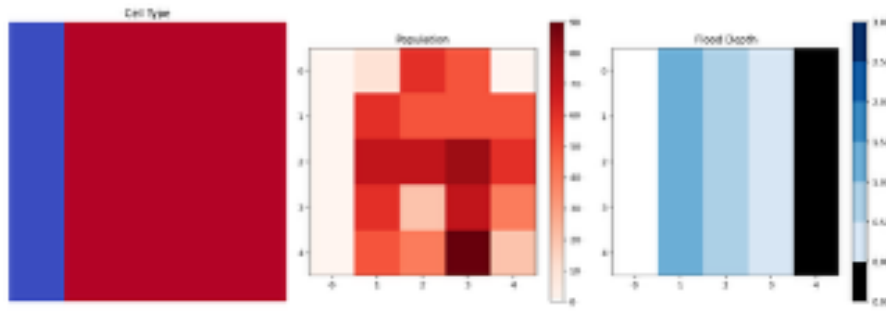


Figure A.1: Model landscape. Left: cell type (blue - water, red - residential). Middle: Population distribution. Right: Flood depth. Note: all are set in the initial setup

population that can be placed in each cell.

A.2.2. Network Initialization

1. **Structure Reading:** The network structure is generated externally and read in via a `.graphml` file. If the node count does not correspond with the total number of household agents, an error is given.
2. **Node Matching:** Node IDs and agent IDs are synchronized for consistency, allowing easy access to agents in the network.
3. **Spatial Proportioning:** To match empirical survey findings, 15% of connections are assigned to households that exist within the same cell. How many households in the end are connected within the same cell depends on the number of households and the number of cells, as the rest of the households are assigned to nodes randomly and might also be placed in the same cell
4. **Socio-Demographic Homophily:** 25% of connections are established between households sharing similarities in income category, education level, and age (≤ 10 years difference). Attributes (annual income, education, age, house size, and savings) are assigned using indices from `Sociodemographics.csv`.
5. **Edge Attributes and Weights:** This is an additional step added in the co-evolutionary extension of FAST. Each initialized edge is assigned a relationship type based roughly on empirical survey division. Edge weights are computed right at step 1 to ensure all core dynamics function immediately.

A.3. Model Step Dynamics

A.3.1. Core Step Sequence

Each simulated year, the model executes the following sequence:

1. Check if a flood occurs (only at specified input timesteps).
2. Advance individual household agents (see step in Agent Class).
3. Execute Tie Formation (if tie dynamics are enabled).
4. Update Edge Weights (if weight dynamics are enabled).
5. Execute Tie Breaking (if tie dynamics are enabled).
6. Update global model variables (all the model level metrics that can be collected through the mesa data collector).
7. Perform micro-logging (if enabled)

A.3.2. Tie Formation Rules

New edges are added to the network probabilistically based on a defined formation probability. To optimize computational efficiency, an agent randomly selects 10 candidate nodes and ranks them based on a homophily score. The connection is formed with the highest-ranked candidate, immediately assigning a relationship type and weight base.

Special context exceptions include:

- **Isolation Penalty:** Isolated nodes face a penalty (assumed 90% reduction), making them much less likely to form ties.
- **Post-Flood Boost:** During the flood remembrance period, nodes receive a formation probability boost scaling linearly from 1 (immediate) to 0 (end of period). The isolation penalty is completely deactivated during this window.

A.3.3. Weight Dynamics Equation

Network weights are updated by looping through all existing edges. The formula multiplies the relational base ceiling by a weighted similarity score:

$$\text{weight}_{i,j} = \text{relational_base} \times (\alpha \cdot \text{opinion_similarity} + (1 - \alpha) \cdot \text{action_similarity}) \quad (\text{A.1})$$

Where:

- α controls the relative importance between opinion and action similarity.
- **Opinion Similarity** evaluates threat and coping appraisals for wet- and dry-proofing:

$$\text{opinion_similarity} = 1 - \frac{\text{diff}_{\text{wet}} + \text{diff}_{\text{dry}}}{2} \quad (\text{A.2})$$

- **Action Similarity** applies a Jaccard similarity metric across implemented measures, meaning an exact match is not required to generate positive similarity.

A.3.4. Tie Breaking Rules

Ties are broken probabilistically using the `sever_threshold` parameter. If an edge weight drops below this threshold, the chance of it breaking scales linearly from 0% (at threshold) to 100% (at a total weight of 0).

A.4. Data Collection Variables

A.4.1. Model Data Collector

The following macro-level metrics are tracked dynamically:

Category	Collected Variables	Comment / Calculation
Network Metrics	edges, avg_clustering, density_nw, degree centrality, betweenness centrality, avg_degree, nr_isolated_agents, new_ties_this_step, ties_removed_this_step, net_edge_change	Tracks structural evolution and step-by-step edge generation adjustments.
Adaptation Rates	fraction_wet_proofed, fraction_dry_proofed, fraction_adapted_any, fraction_adapted_both	Monitors total societal protection thresholds.
Intentions	avg_intention_SN, avg_intention_PMT_DP, avg_intention_PMT_WP, avg_intention_overall_DP, avg_intention_overall_WP	Tracks underlying motivation shifts prior to household physical adaptations.
Appraisals	avg_perceived_severity, avg_perceived_probability, avg_cost_dp, avg_cost_wp, avg_re_dp, avg_re_wp	Captures cognitive risk processing metrics.
Micro Logging	micro_adoption_events	Dict of adoption events and neighbor influence shares.

A.4.2. Agent Data Collector

Collected conditionally (`collect_agent_data = 1`) due to size constraints:

- **Financials:** savings, income (Damages/adaptations are paid directly from savings).
- **PMT Appraisals:** risk_perception, worry, PMT_intention_DP, PMT_intention_WP, perceived_severity, perceived_probability, flood_experience, self_efficacy_DP/WP, perceived_re_DP/WP, perceived_cost_DP/WP.
- **Social Influence:** nr_connections, SN_intention.
- **Connectivity:** Initial_degree, Initial_connectivity_class, Current_degree, Is_isolated_now, Ever_connected, Ever_isolated, Betweenness, Weighted_degree.

A.5. Agent Step Dynamic

A.5.1. Agent Initialization

1. **Get Location**
2. **Collect PMT Parameters**
3. **Set Measure Age:** a random number is set between 0 and the level set for measure aging.
4. **Retrieve Agent Socio-demographics**
5. **Initialize PMT:** In order to calculate edge weights at initialization, agent protection motivation has to be initialized for it to be updated and used in weight calculation.
6. **Calculate PMT intention:** Use the `calculate_probability_to_take_measure_PMT` function to calculate protection motivation

A.5.2. Core Step Sequence

1. **Save Money:** Save money based on the model savings rate (5% of annual income, can be modified).
2. **Get Connections and Neighbors:** Identify current node connections and neighbors within the same grid cell.
3. **Calculate Worry:** If inside a `personal_flood_remembrance_period`, step-by-step worry values decay until baseline levels are restored. This is only applicable if people experienced damage and therefore updated their worry with the flood shock.
4. **Network Influence:** Apply either an *assimilative* or *similarity-biased* opinion dynamics model to adjust internal risk perceptions. PMT appraisals are updated based both on internal dynamics and opinion exchange from the network. To what extent the opinions of others are taken into account is determined by `weight_opinion_others`.
5. **Social Norm Intention:** Compute current adaptation fractions based on chosen social norm configurations:
 - *Connections*: How many of the connecting agents have adapted. Fraction of adapted connections to all connections. If no connections, probability from social norm is 0.
 - *Neighbors*: how many of the neighbors (i.e. agents within the same district) have adapted. Fraction of adapted neighbors to all neighbors.
 - *All*: How many in total have adapted. Fraction of adapted overall to number household agents.

Based on the chosen configuration, the fraction is translated to a SN intention via a logistic function.
6. **PMT Intention:** The regression on PMT appraisals is based on the survey data. The logistic regression is built from the variables worry, perceived probability, perceived severity, perceived response efficacy of measures, self-efficacy related with measures, perceived costs of measures to the implementation of these. A summary of the regression weights is presented in table A.2. The final PMT intention is based on the internal appraisal updates, and the influence from other households through opinion exchange (as explained before in step 5).
7. **Overall Intention:** Compute overall adaptation probability:

$$\text{Intention_to_adapt}_m = \text{protection_motivation}_m \cdot (1 - w) + \text{perceived_social_norm} \cdot w \quad (\text{A.3})$$

8. **Decide to Take Action:** If it is a step to consider measures: Evaluate intention against a minimum constraint which is set with `minimum_intention_to_consider_measure`, check available personal savings against costs of taking the measure, execute if possible and then deduct costs from savings.

Table A.2: Logistic Regression PMT NL-UK

	wet-proofing	dry-proofing
Intercept	-2.38289	-4.67177
worry	0.83516	0.35241
perc_damage	0.15866	0.34518
Perc_probability	-0.34495	-0.0588
flood_experience	0.72487	0.2407
self_efficacy	0.64328	0.74314
resp_efficacy	0.42687	0.23785
perc_cost	-1.42589	-0.65049
done_other	1.63487	6.10513

A.5.3. Flood Shock Experience

When a flood occurs, households face certain impacts and damages:

- Flood damage computed via European depth-damage curves is subtracted from savings (allowing negative balances).
- `flood_experience` shifts to 1.
- Personal worry values jump immediately via a shock parameter.

A.6. Overview of Input Parameters

The complete set of input parameters that can be varied is shown in table A.3.

Table A.3: Running the model: complete set of input parameters

Name	Type	Default value	Possible other values	Notes
weight_action_vs_opinion	Float	0.5		
Formation_probability	Float	0.01	[0-1]	Standard running with 1000 now
Isolated_penalty	Float	0.1		Multiplier for formation_probability (e.g. 0.1 means 10% of the formation probability remains)
Flood_connectivity_boost	Float	1.0		Depends on scenario/focal event?
Sever_threshold	Float	0.15	[0-1]	Sets the level below which edges are able to break
Relation_types	String	['family_friend', 'neighbor', 'other']		General strong/mid/weak relation types
Base_family	Float	1.0		Based on relative importances of relationships in opinion exchange
Base_neighbor	Float	0.7		Based on relative importances of relationships in opinion exchange
Base_other	Float	0.5		Based on relative importances of relationships in opinion exchange
Enable_tie_dynamics	boolean	False	True	Turned off in the baseline
Enable_weight_dynamics	boolean	False	True	Turned off in the baseline
Enable_visualization	Boolean	False	True	Generation of network snapshots that can be used to create a gif/mp4 of the network evolution
Enable_micro_logging	Boolean	False	True	Used to create micro data for agents and network in single runs
Other important input values from FAST				
seed	Int	None		
nr_households	Int	1000		Standard running with 1000 now
Set_hh_adapted_at_start	Float or boolean	False	[0-1]	If False, just uses the adaptation from the empirical data. If value between 0 and 1, sets that amount of households as adapted at start
Prop_inc_for_damage_adaptation	Float	0.05		Percentage of income available for adaptation and damage each months. Accumulates.
Exchange_what	String	'threat+coping'	'coping', 'threat'	

Name	Type	Default value	Possible other values	Notes
Social_norm_calculation	String	'connections'	'all', 'neighbors'	Based on what population the proportion of adapted households is calculated to be considered in the decision-making of the household agent
per_HH_adapted_to_SN_prob_midpoint	Float	0.5	[0,1]	Midpoint of logistic regression for translating % adapted to the probability from social norm
Weight_SN_vs_PMT	Float or string	'empirical'	'empirical', [0,1]	Either using survey data to determine weight or the given weight for the consideration of social norm in the likelihood to act
Opinion_dynamics_model	String	'similarity_biased'	'assimilative'	
Weight_opinion_others	Float	0.5		If an agent has connections, they assign this weight to them
Threshold_similarity_bias	Float	0.4		Only used when using 'similarity_biased' opinion dynamics model
Grid_width	Int	5		
Grid_height	Int	5		
Flood_depth_in_m	List	[99, 3, 1, 1, 1]		Has to have length of grid_height, first value is waterfront.
Threshold_severe_flood_exp	Int	2		Above what water level HH agents are considered severely affected
Flood_time	List	[10, 50]		
Population_density	Listed list	[[0,5,5,5,5], [0,5,5,5,5], [0,5,5,5,5], [0,5,5,5,5], [0,5,5,5,5]]		Has to add up to nr_households. Has to be size of grid_width x grid_height
Network_structure_file_path	String	'../data/network_structures/ network_empirical.graphml'	'../data/network_structures/ barabasi_albert_1000.graphml'	Network structure that is used, needs to have same number of nodes as nr_households
Fraction_neighbors	Float	0.15		Connections between household agents in one grid cell
Fraction_homophily	Float	0.25		Connections between household agents with similar age, income, level of education
Flood_remembrance_period	Int	5		How long the increased connectivity effects and worry are active

Name	Type	Default value	Possible other values	Notes
Consider_measure_every_x_steps	Int	1	Min 1	Every how many steps households try to take a measure
Minimum_intention_to_consider_measure	Float	0.0001	[0,1]	Minimum intention needed to consider taking a measure
Worry_increase_with_flood	Float	0.4	[0, 1]	How much worry increases when experiencing a flood
Min_worry_after_flood	Float	0.1	[0,1]	Minimum worry after experiencing a flood
Max_damage_per_sqm	Float	950		From 4 in €, adjusted for inflation to 2023 value, EU based
CCA_costs	dict	{'dry-proofing': 10300, 'wet-proofing': 8000}		See brainstorm document (money) (in €), based on 5
Damage_reduction	Dict	{'dry-proofing': 0.5, 'wet-proofing': 0.4}		See brainstorm document (money), based on 5
Measures_aging	dict	{'dry-proofing': 0, 'wet-proofing': 0}	{'dry-proofing': 20, 'wet-proofing': 20}	If 0, no aging of that measure. Number of years after which measure loses effect and needs to be rebought
Transformative_threshold	Float	0.8	[0, 1]	Threshold above which transformative adaptation is reached
Collect_agent_data	Int	0	1	0: no data collection on agent-level, 1: data collection on agent-level

A.7. Summary of Core Model Assumptions

Table A.4: Summary of core model behavioral and structural assumptions

Assumption No.	Description
1	Tie formation is seen as probabilistic. The probability to form a new connection each step (year) is assumed to be 1%.
2	When selecting who to form a new connection with, an agent takes a set of 10 randomly selected candidates, from which an agent is selected with whom they will form a new tie.
3	A penalty exists for isolated agents, resembling that they are less likely to start interacting with others on flood adaptation. This penalty is assumed to be a 90% reduction of probability to form a new connection.
4	After a flood there is an increase of tie formation, resembling that households are more engaged on the topic and will talk to other (new) households. This increase is 100%, scaled linearly to 0% after the chosen flood remembrance period has passed.
5	For weights of connection, it is assumed that the type of relationship an agent has with the other household, sets a ceiling for how strong their connection can be. How much of the connection strength is achieved is based on how similar the agent perceives the other agent to be (on flood adaptation as a topic). This is translated as relationship weight and similarity weight being multiplicative in the model.
6	Opinions are resembled by the appraisals that form an agent's protection motivation, and their actions are resembled by the adaptation decisions taken by agents. This is assumed to be a 50/50 split in similarity score calculation.
7	There are three assumed types of relationship: family and friends, neighbors and others. These in turn have a high, mid or low weight, which is based on literature, but the levels of these weights are an assumption.
8	The weight of an edge below which the agents might stop interacting on flood adaptation is set by a threshold. The chance of this tie breaking is probabilistic and is assumed to scale from the threshold (0%) linearly to 100% at a weight of 0.
9	It is assumed that edge weights scale the influence from agents on each other's PMT, and this scaling is calculated through the weighted mean of all connections.
10	Social norms (adaptation taken by others) are not scaled by edge weight, but have kept the regression as in the original FAST-ABM. They are however calculated based on 'neighbors' as base value, so network topology effects affect the SN intention of agents.
11	Edge weights are present also in static and tie dynamics setups, however they are static weights (do not change after being set at edge formation or model initialization).
12	Opinion exchange is assumed to be similarity biased, with a threshold of 0.4 (tolerance of opinion difference).
13	The minimum threshold of intention needed to adapt, is removed (set to very low) to allow for easier analysis
14	It is assumed that adaptation measures taken do not age (so are permanent). This prevents time trajectories of adaptation to oscillate and spike.

A.8. Data collection methods

For experiments 1, 2, 3 and 5, model outputs were collected using the built-in Mesa DataCollector functionality. At each simulation step, aggregate statistics such as average PMT intentions, social norm intentions, adaptation uptake, and network characteristics were recorded. After each simulation run, these outputs were exported to .csv data files for further analysis in Python.

Experiment 4 required a different data collection approach because the objective was to identify the micro-level mechanisms preceding individual adoption decisions. Aggregate model outputs were insufficient for this purpose, as they do not preserve the temporal trajectories of individual households. Because storing complete trajectories for all agents across all Monte Carlo runs would generate datasets that are too large to handle efficiently (while also providing limited additional insight for the objectives of this experiment), the micro-level analysis is performed on selected simulations rather than a full set of stochastic repetitions.

A custom data collection procedure was implemented directly within the model code. At every simulation step, the state of each household agent was recorded, including:

- adaptation status,
- PMT intentions,
- social norm intentions,
- threat appraisals,
- coping appraisals,
- network connectivity,
- relevant network restructuring events.

To determine which mechanisms preceded adaptation events, a post-processing procedure was applied to the agent-level trajectories. For every adoption event, a retrospective analysis window of X simulation steps was examined (standard window of 5 steps). Changes in PMT intentions, social norm intentions, and network structure were evaluated within this window (using a threshold value to reduce noise).

Based on these observations, adaptation events were classified into categories such as:

- PMT-driven,
- social-norm-driven,
- network-driven,
- mixed-trigger events.

The data collection procedure produced three main output datasets:

1. Model-level outputs containing aggregate simulation statistics.
2. Agent-level trajectory data containing the state of every household at every simulation step.
3. Trigger-event datasets containing classified adaptation events and the variables associated with those events.

A.9. Code availability

The model extension developed for this thesis is made available through a public GitHub repository. The repository includes the Python implementation of the co-evolutionary network dynamics, the model configuration files, and scripts used for running and analyzing the experiments. The code can be accessed at: <https://github.com/marijnmin/Master-Thesis>

B

Additional results

Table B.1: Appendix Table B1 — Summary statistics for EXP2 variables

Variable	Mean	SD	Min	Max	N
Formation Probability	0.0125	0.0059	0.0025	0.0225	12,800
Breaking/sever Parameter (y)	0.1694	0.1755	0.0050	0.5000	12,800
Avg. Intention (SN)	0.1115	0.0558	0.0060	0.3204	12,800
Avg. Intention (PMT-DP)	0.1646	0.0327	0.1091	0.2959	12,800
Avg. Intention (PMT-WP)	0.1339	0.0081	0.1205	0.1684	12,800
Fraction Adapted (Any)	0.2055	0.0396	0.1410	0.3670	12,800
Net Edge Change	-2.00	356.68	-960.00	898.00	12,800

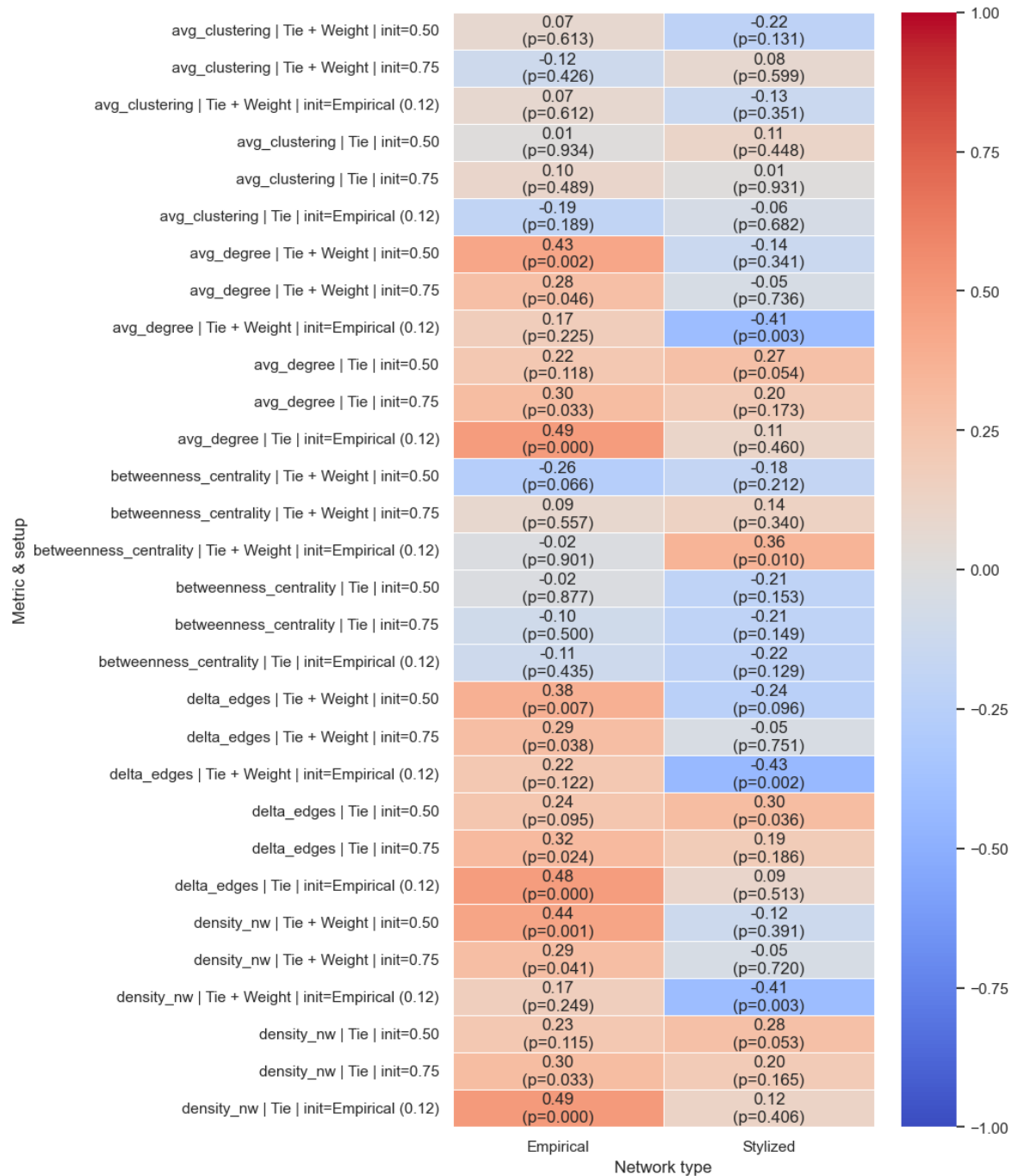
Table B.2: Appendix Table B2 — Correlation matrix for key variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) Formation Probability	1.000					
(2) Disruption Parameter (y)	-0.189	1.000				
(3) Avg. Intention (SN)	0.429	-0.622	1.000			
(4) Avg. Intention (PMT-DP)	0.413	-0.547	0.956	1.000		
(5) Avg. Intention (PMT-WP)	0.409	-0.546	0.935	0.987	1.000	
(6) Fraction Adapted (Any)	0.413	-0.556	0.955	0.999	0.988	1.000

Table B.3: Appendix Table B3 — Simple OLS regressions

Variable	SN	PMT-DP	PMT-WP	Adaptation
Intercept	0.1033*** (0.0010)	0.1576*** (0.0006)	0.1322*** (0.0002)	0.1975*** (0.0007)
Formation Probability	3.0713*** (0.0613)	1.7916*** (0.0390)	0.4399*** (0.0097)	2.1586*** (0.0468)
Disruption Parameter (y)	-0.1784*** (0.0020)	-0.0908*** (0.0013)	-0.0225*** (0.0003)	-0.1116*** (0.0016)
R^2	0.4877	0.3988	0.3946	0.4073
Adj. R^2	0.4876	0.3987	0.3945	0.4072
N	12,800	12,800	12,800	12,800

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.



Note: init = initial adaptation level at start of simulation. Avg_density = ratio of existing to possible ties. Avg_degree = average number of connections per agent. Avg_clustering = average clustering coefficient. Avg_betweenness = average betweenness centrality of agents in the network. Delta_edges = change in number of edges between start and end of simulation.

Figure B.1: Correlation between different network metrics and the levels of adaptation reached across runs, given different model configurations. The columns show the different network types, the rows show what model configuration and metric is presented. Correlation values are given plus the p-value for significance is shown.

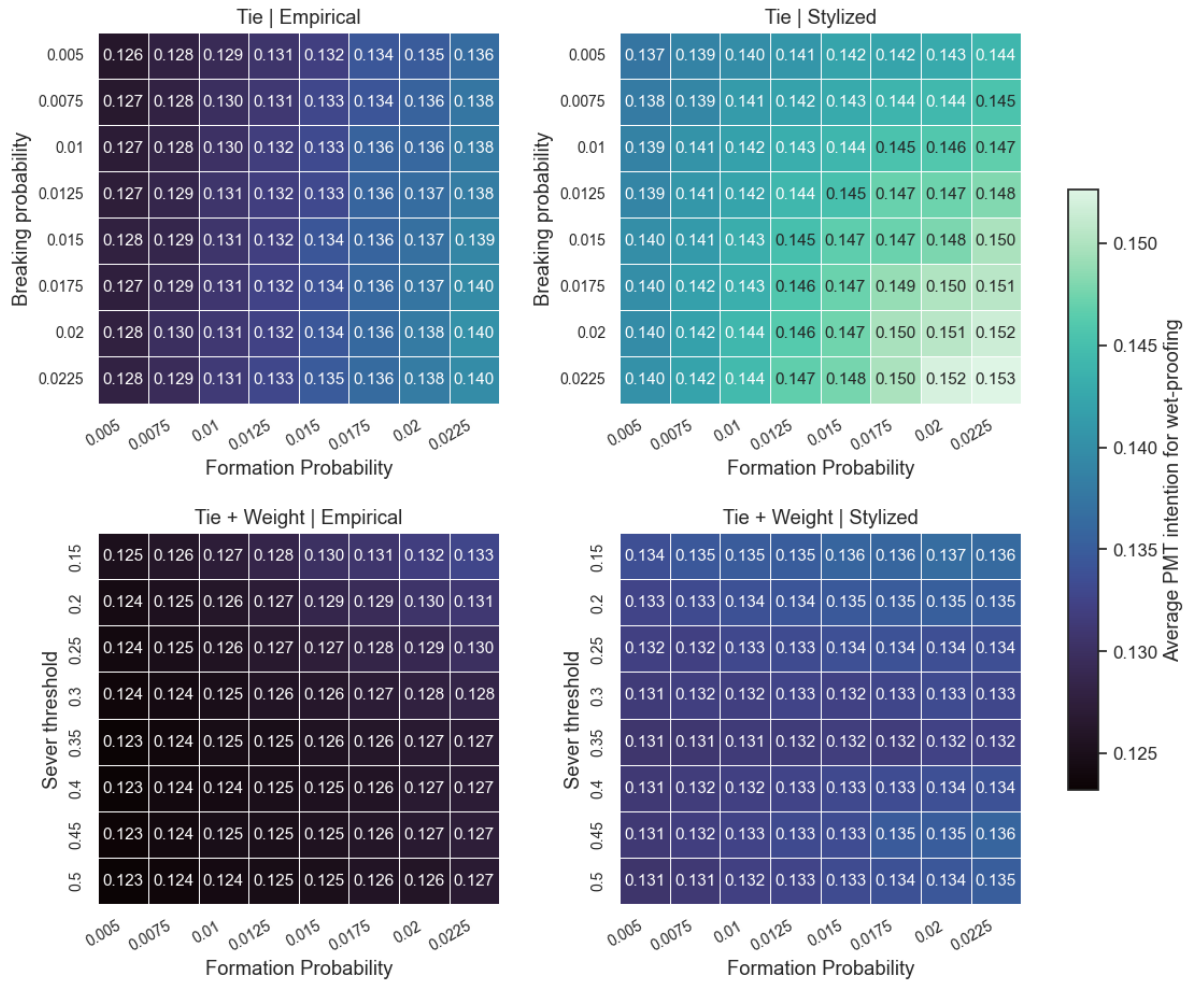


Figure B.2: Average final protection-motivation intention for wet-proofing measures across all households. The breaking and formation probability indicate the percentage chance each agent has each step to add or break a connection. The sever threshold is similar to the breaking probability, however, it indicates the value below which the weight of a connection leads to a probability of breaking, scaled to a 100% chance of breaking at a weight of 0. A higher PMT intention leads to a higher chance of adopting a measure. The initial adaptation level = 0.12 and each heat map is based on 50 Monte-Carlo simulations.

Table B.4: Appendix Table B4 — Interaction regressions

Variable	SN	PMT-DP	PMT-WP	Adaptation
Intercept	0.0911*** (0.0012)	0.1481*** (0.0008)	0.1298*** (0.0002)	0.1855*** (0.0009)
Formation Probability	3.9863*** (0.0841)	2.4962*** (0.0532)	0.6201*** (0.0133)	3.0530*** (0.0637)
Disruption Parameter (y)	-0.1118*** (0.0047)	-0.0394*** (0.0030)	-0.0094*** (0.0007)	-0.0465*** (0.0036)
Formation $\times$ Disruption	-5.4526*** (0.3464)	-4.1985*** (0.2192)	-1.0734*** (0.0546)	-5.3302*** (0.2627)
R^2	0.4974	0.4155	0.4123	0.4257
Adj. R^2	0.4973	0.4154	0.4122	0.4256
N	12,800	12,800	12,800	12,800

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

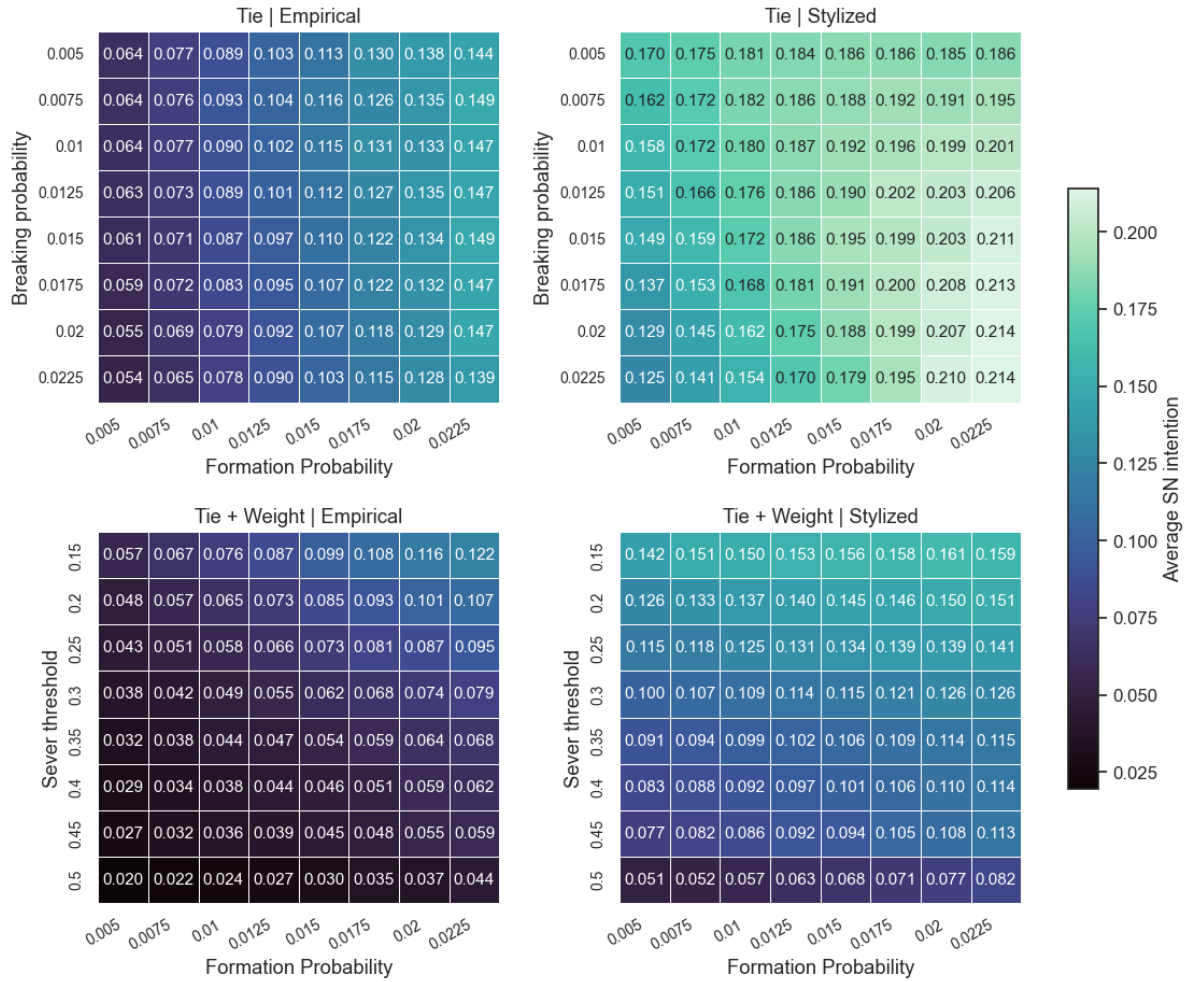


Figure B.3: Average final SN intention across all households. The breaking and formation probability indicate the percentage chance each agent has each step to add or break a connection. The sever threshold is similar to the breaking probability, however, it indicates the value below which the weight of a connection leads to a probability of breaking, scaled to a 100% chance of breaking at a weight of 0. A higher SN intention leads to a higher chance of adopting a measure. The initial adaptation level = 0.12 and each heat map is based on 50 Monte-Carlo simulations.

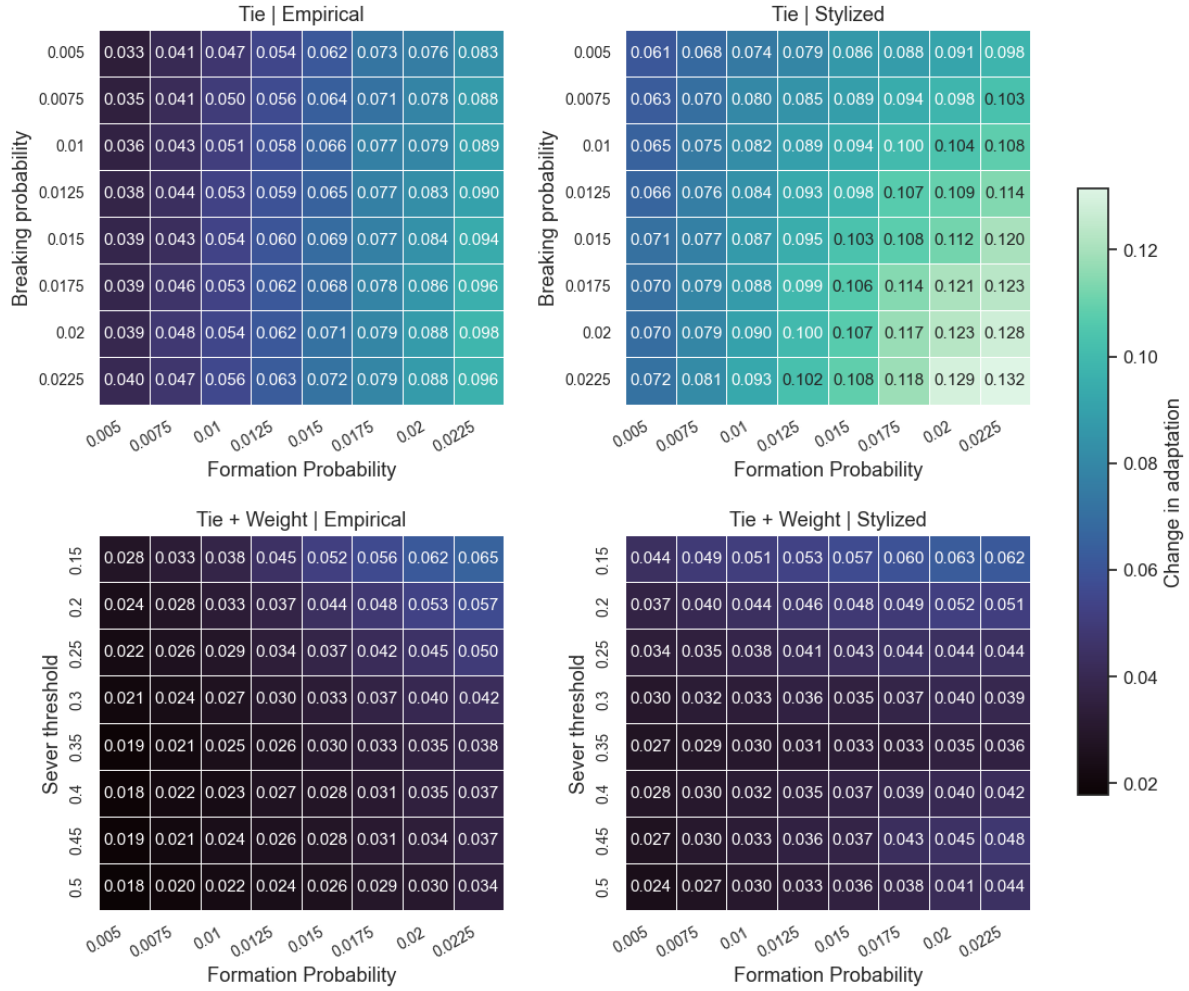


Figure B.4: Average change in adaptation under different parameter combinations and setups

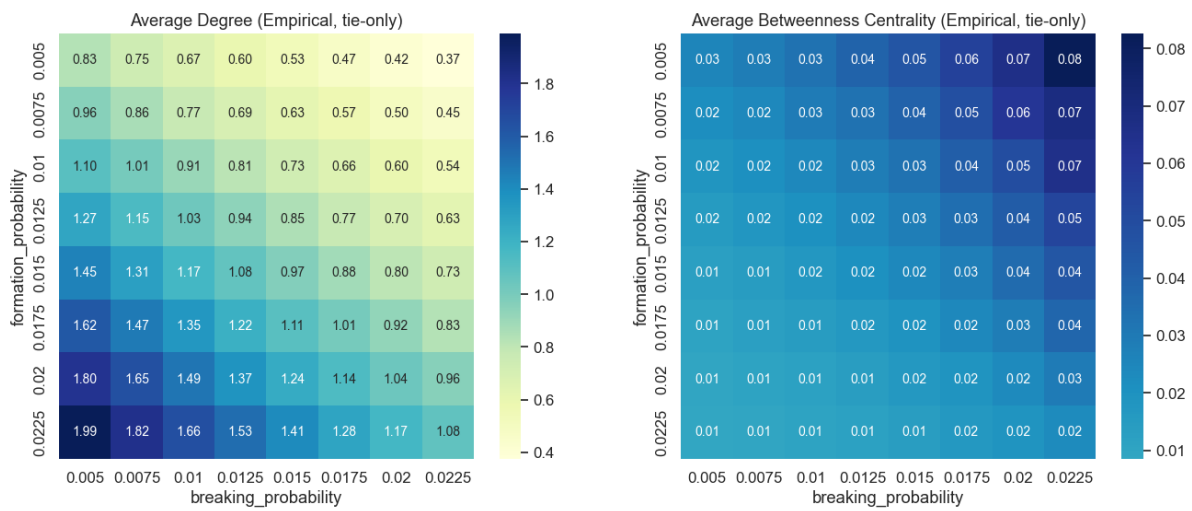


Figure B.5: Network metrics across the input parameter range (Empirical, tie-only)

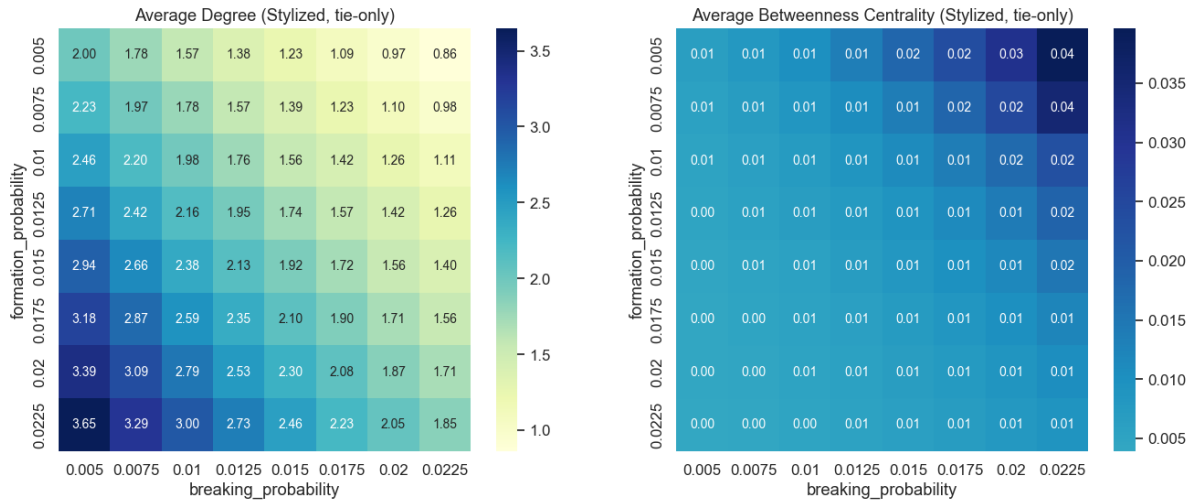


Figure B.6: Network metrics across the input parameter range (Stylized, tie-only)

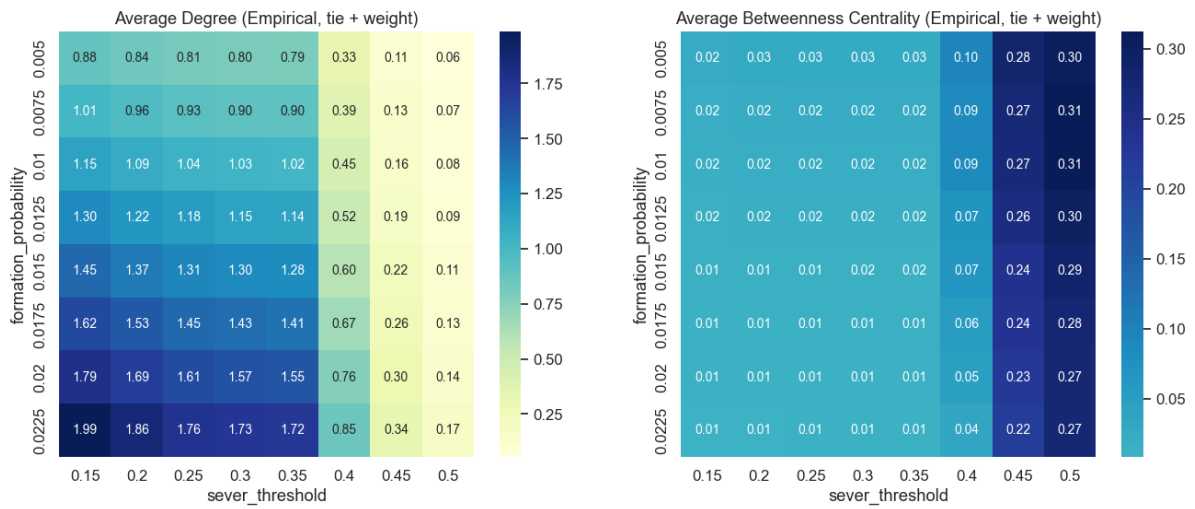


Figure B.7: Network metrics across the input parameter range (Empirical, tie + weight)

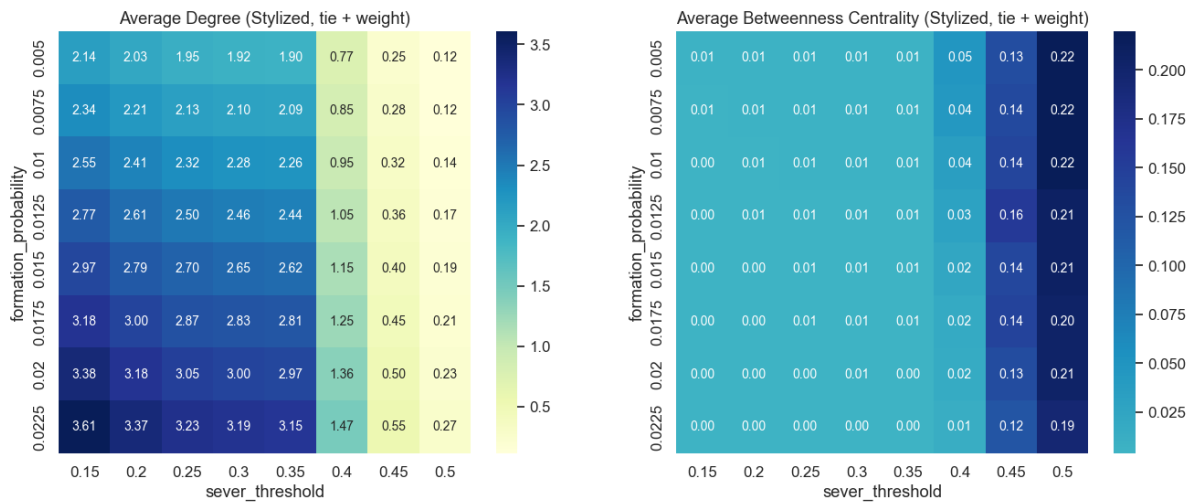


Figure B.8: Network metrics across the input parameter range (Stylized, tie + weight)

Table B.5: Appendix Table B5 — Full-context regressions

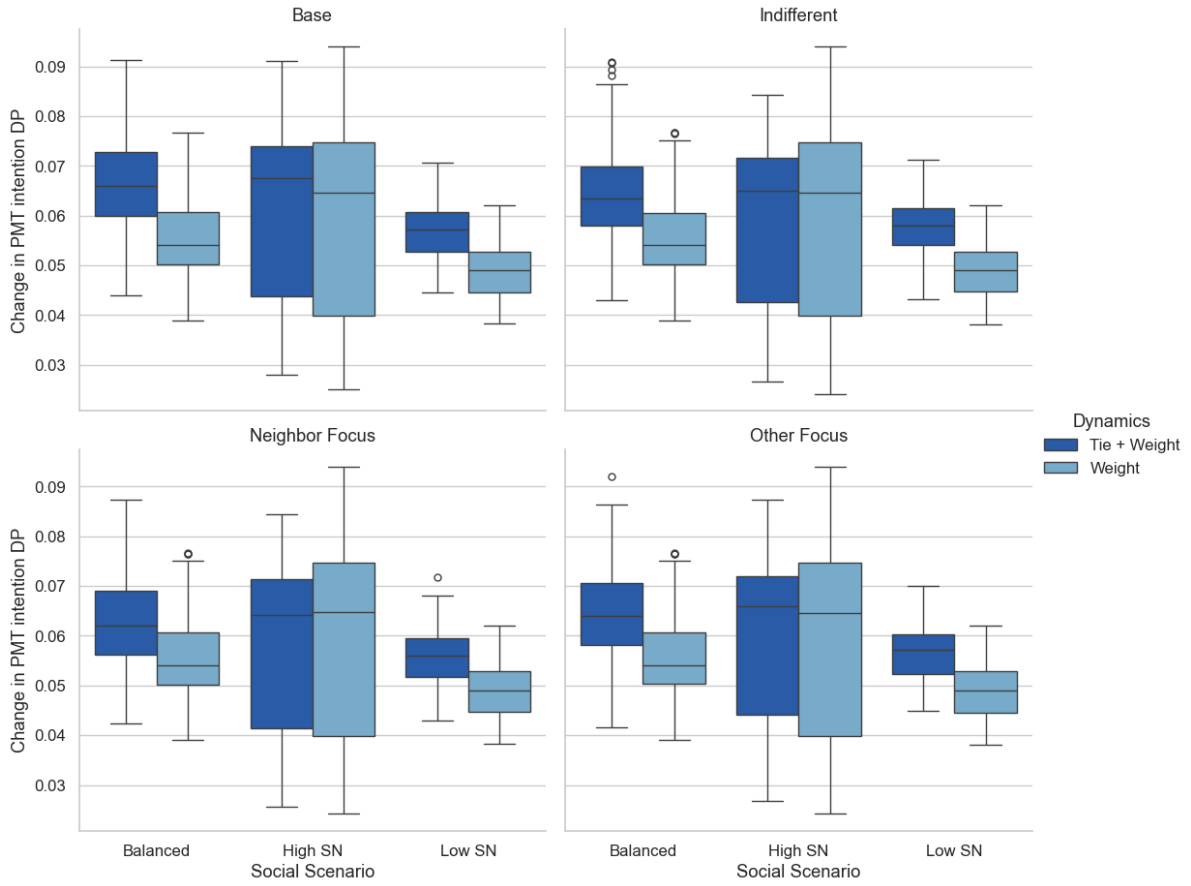
Variable	PMT-DP	PMT-WP	SN	Adaptation
Intercept	0.1196*** (0.0014)	0.1231*** (0.0004)	0.0489*** (0.0022)	0.1520*** (0.0017)
Network Type (Stylized)	0.0564*** (0.0020)	0.0131*** (0.0006)	0.1422*** (0.0032)	0.0667*** (0.0024)
Dynamics (Tie + Weight)	-0.0013 (0.0020)	-0.0005 (0.0006)	-0.0055 (0.0031)	-0.0018 (0.0024)
Tie + Weight $\times$ Stylized	-0.0072** (0.0028)	-0.0022** (0.0008)	-0.0146** (0.0045)	-0.0094** (0.0033)
Formation Probability	2.3452*** (0.0942)	0.5715*** (0.0282)	4.6252*** (0.1509)	2.8096*** (0.1129)
Disruption Parameter (y)	0.1982* (0.0942)	0.0586* (0.0282)	-0.9023*** (0.1509)	0.2213* (0.1129)
Formation $\times$ Disruption	16.7171** (6.3232)	5.5499** (1.8945)	19.3234 (10.1280)	22.0907** (7.5771)
R^2	0.8716	0.8134	0.8866	0.8739
Adj. R^2	0.8715	0.8132	0.8865	0.8737
N	12,800	12,800	12,800	12,800

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

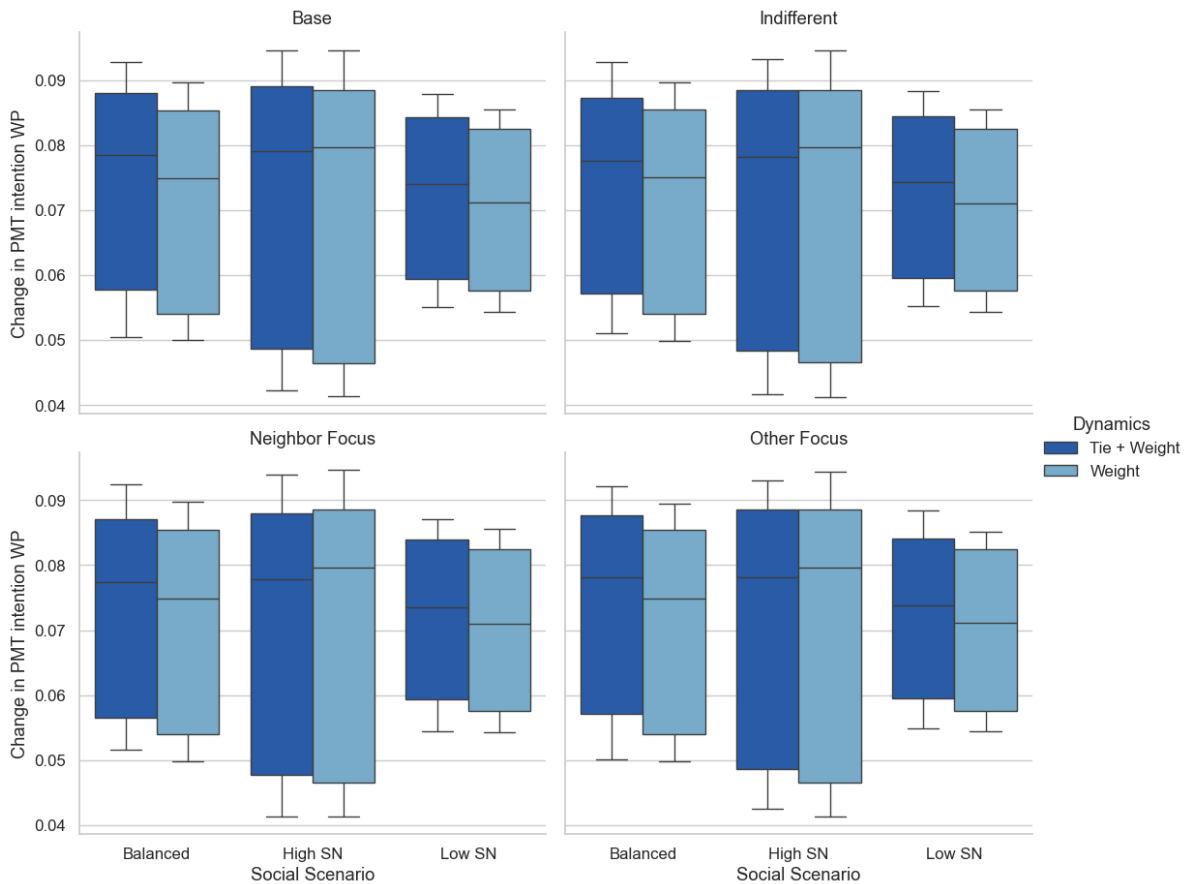
Table B.6: Appendix Table B6 — Mediation-style model

Variable	Adaptation
Intercept	0.0077*** (0.0002)
Formation Probability	0.0166*** (0.0035)
Disruption Parameter (y)	-0.0033*** (0.0001)
Avg. Intention (SN)	-0.0082*** (0.0012)
Avg. Intention (PMT-DP)	1.2096*** (0.0020)
R^2	0.9973
Adj. R^2	0.9973
N	12,800

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.



(a) PMT DP changes across weight scenarios



(b) PMT WP changes across weight scenarios

Figure B.9: Boxplots showing changes in protection-motivation intentions, for different weight and social norm scenarios. Indifferent = all relationship types valued equally. Neighbor focus = neighbor-type receive stronger connection weights. Other focus = other-type connections receive stronger connection weights. High SN = social norms are valued higher than opinions. Low SN = opinions are valued higher than social norms. Balance means base setup values are used.

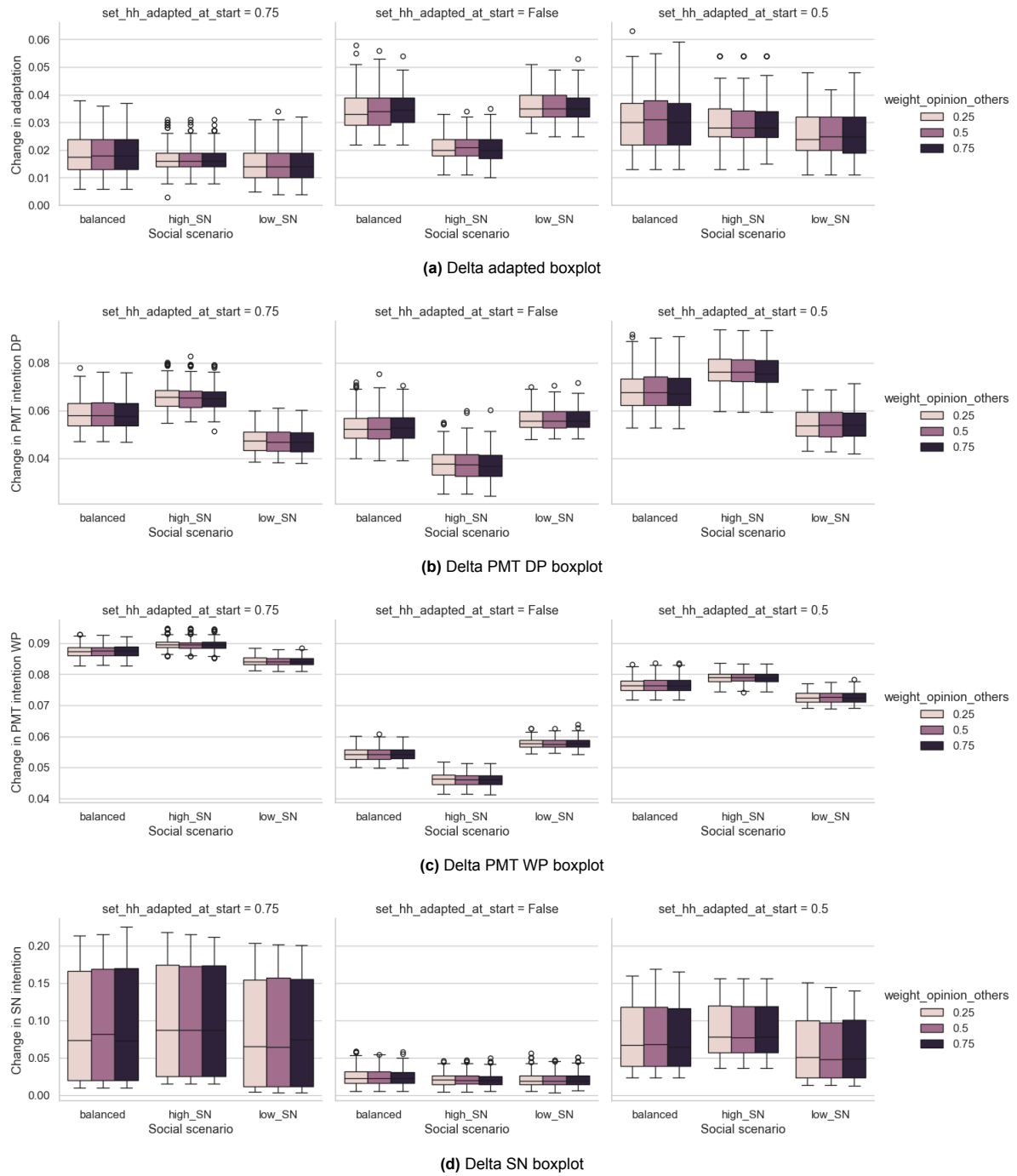


Figure B.10: Overview of boxplots of intentions and adaptation across weight scenarios: (a) Delta adapted, (b) Delta PMT DP, (c) Delta PMT WP, and (d) Delta SN. Initial adaptation level of "False" is equal to the empirical level of 0.12 or 12% of households adapted initially.

Table B.7: ANOVA Results for Experiment 3 (EXP3)

Source of Variation	Sum of Squares	df	F-statistic	p-value
Dependent Variable: Avg. Intention (SN)				
Dynamics	16.0148	1	17,718.99	< 0.001***
Relation Scenario	0.0106	3	3.92	0.0083**
Social Scenario	0.3685	2	203.83	< 0.001***
Households Adapted at Start	9.7750	2	5,407.60	< 0.001***
Residual	9.7531	10,791	—	—
Dependent Variable: Avg. Intention (PMT-DP)				
Dynamics	0.0936	1	1,103.41	< 0.001***
Relation Scenario	0.0020	3	7.84	< 0.001***
Social Scenario	0.1239	2	730.33	< 0.001***
Households Adapted at Start	0.5407	2	3,187.88	< 0.001***
Residual	0.9151	10,791	—	—
Dependent Variable: Avg. Intention (PMT-WP)				
Dynamics	0.0073	1	509.48	< 0.001***
Relation Scenario	0.0002	3	3.92	0.0083**
Social Scenario	0.0038	2	132.48	< 0.001***
Households Adapted at Start	2.2065	2	76,718.42	< 0.001***
Residual	0.1552	10,791	—	—
Dependent Variable: Fraction Adapted (Any)				
Dynamics	0.1265	1	2,988.04	< 0.001***
Relation Scenario	0.0035	3	27.32	< 0.001***
Social Scenario	0.0582	2	686.86	< 0.001***
Households Adapted at Start	0.3959	2	4,675.61	< 0.001***
Residual	0.4569	10,791	—	—

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Comma separators added to large values for readability.

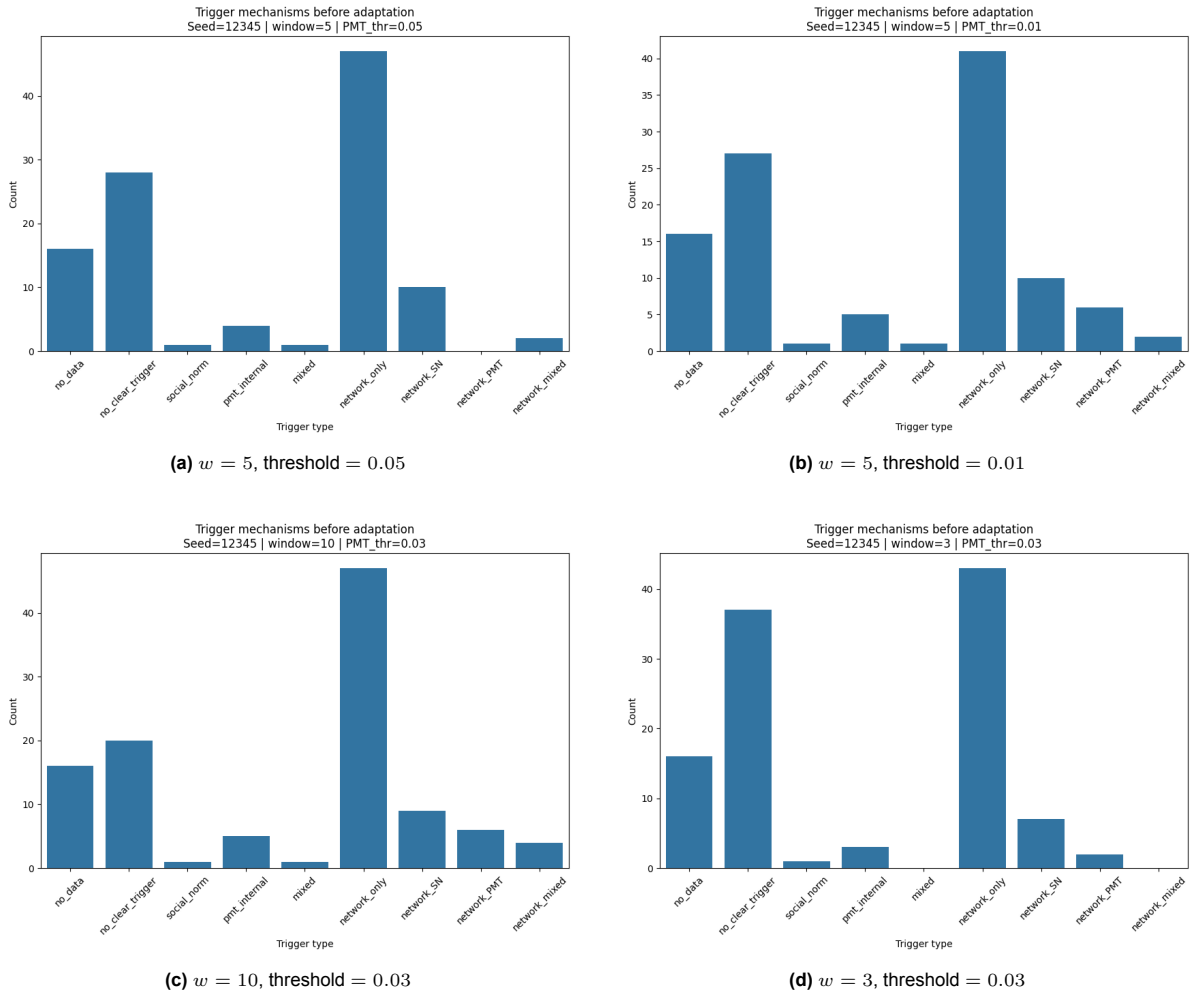


Figure B.11: Histograms showing counts of trigger types for each adaptation in a single simulation under varying window sizes (w) and activation threshold conditions.

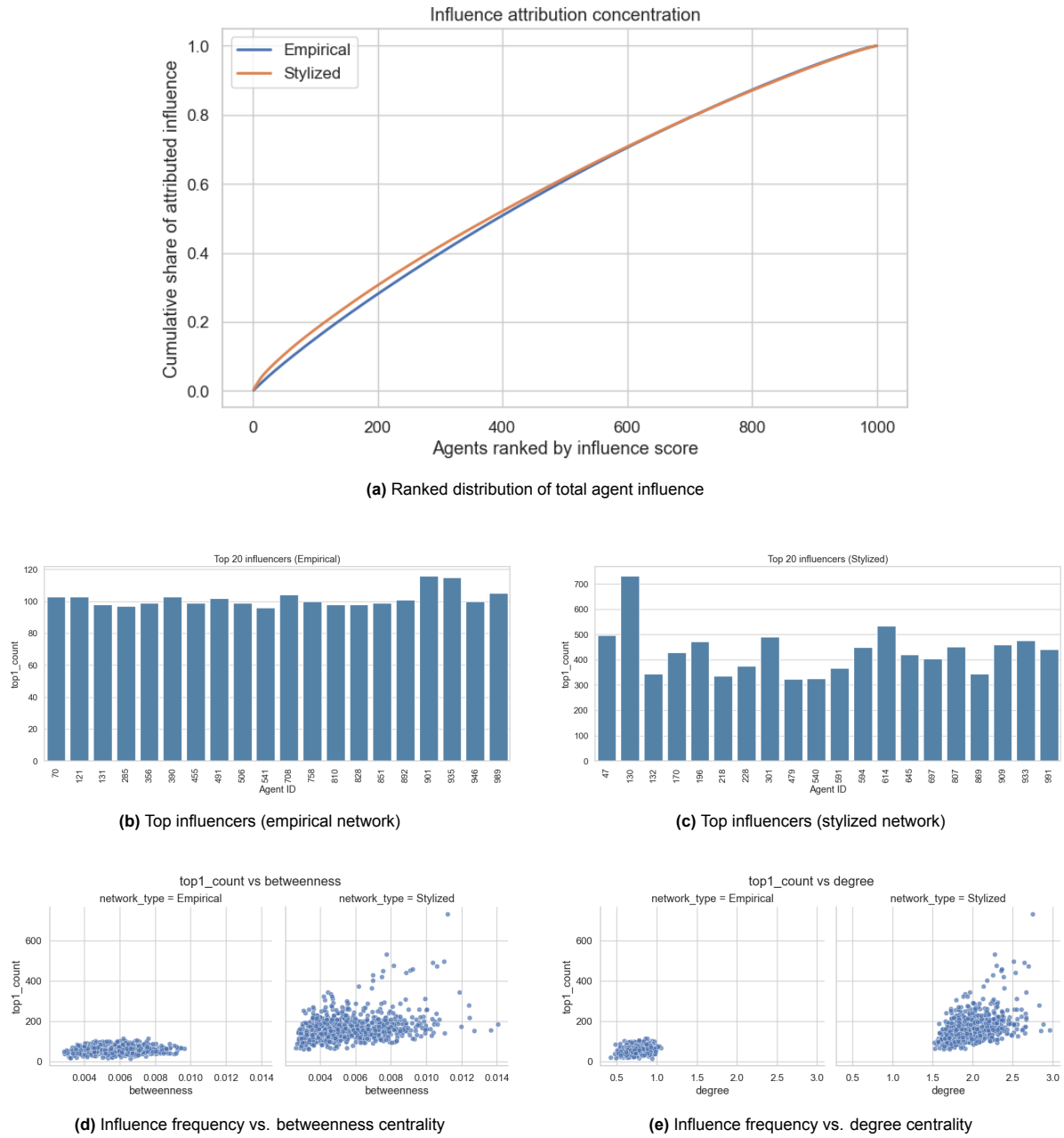


Figure B.12: Comprehensive network influence analysis, showing the macro-scale ranked distribution of agent influence (a), top influencer frequencies across empirical (b) and stylized (c) topologies, and top influencer count correlations with structural betweenness (d) and degree centralities (e).