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THE ORGANIZATIONAL EVOLUTION OF SMALL FOOD BUYING CLUBS

By

Taylor Zachary Lange

B.A. Binghamton University

M.A. Binghamton University

M.S. University of Maine

A DISSERTATION

Submitted in Partial Fulfillment of the

Requirements for the Degree of

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(in Ecology & Environmental Science)

The Graduate School

The University of Maine

May 2022

Advisory Committee:

Timothy Waring, Associate Professor of Social Ecological Systems Modeling, Advisor

Caroline Noblet, Associate Professor of Economics

Andrew Crawley, Associate Professor of Economics

Christine Beitl, Associate Professor of Anthropology

Marco Smolla, Post Doctoral Fellow, Max Plank Institute for Evolutionary Anthropology

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By Taylor Zachary Lange

Dissertation Advisor: Dr. Timothy M. Waring

An Abstract of the Dissertation Presented
In Partial Fulfillment of the Requirement for the
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Organizations are pervasive in modern society and the factors of their evolution are the subject of considerable scholarship. Most literature on organizational evolution focuses on the role of leaders and entrepreneurs, specifically their decision making interacts with market forces. However, the behavior and interactions of regular organization members, such as nonmanagerial employees or club members, is surprisingly overlooked. Specifically, examinations of social dilemmas between co-workers and the role of learning are often discounted in the current literature. This dissertation explores how the dynamics of cooperation and the learning of preferences as cultural traits become consequential in the evolution and longevity of organizations in the case of small food buying clubs. I begin by explicitly defining a model of organizational evolution that draws on the Extended Evolutionary Synthesis. I then use a novel dataset to analyze cooperation and reciprocity in a real-world setting, and examine how preferences are interdependent and socially learned. I then use the results of these investigations to test the model of organizational evolution put forth in the first chapter by estimating a survival model of food buying clubs. Results indicate that individuals within these clubs display high amounts of reciprocity, and preferences that shift and diversify over time, both of which may play a role in the survival of these clubs.

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INTRODUCTION

1. Organizations Evolve

Organizations are stitched into the fabric of society. From governmental agencies to the family-owned business, formal collections of individuals working together are integral modern civilization. Substantial research from various disciplines has revealed much about how organizations succeed in the marketplace and change over time, including economics (Coase, 1937; Foss, 1993), anthropology (Cordes et al., 2008), psychology (Van Vugt, 2017), and organizational science (Clegg & Bailey, 2008). Gleaning insights from all of these fields, evolutionary scholars have devoted substantial effort to placing the evolution of organizations and whole industries into a Darwinian framework (Hodgson & Knudsen, 2010; Wilson, 2019).

Organizations can be broadly defined as a formal groups of individuals bound together by institutions to perform a function or achieve some common goal (Hodgson, 2019). This inclusive definition reveals the diversity of organizational types and the multiple levels within them, including individual employees or members, sub groups or teams, the organizations themselves (Breslin, 2016). This multi-level structure means that research in the evolution of cooperation and cultural evolution can lend substantial insights when studying the evolution of organizations.

The front end of the organizational evolution literature hybridizes the theories of organizational ecology and strategic choice (Volberda & Lewin, 2003). Organizational ecology emerged in the 1970s using concurrent advances in population genetics to explain the evolution of industries, and it assumed that organizations were relatively inert as markets selected organizations with the best goods and services (Hannan & Freeman, 1989). Strategic choice arose thereafter, as researchers recognized that leaders and managers made decisions in response to market forces (Sminia & Nistelrooij, 2006). This theory argued that organizations weren't static entities subject to the whim of the market, but adapted to market pressure in a proactive manner as management assessed the strengths and weaknesses of products and production methods (Hrebiniak & Joyce, 1985). Eventually, scholarship landed in between these two points, acknowledging that managers made decisions, but the market changed in response. This lead to the currently prevailing theory of organizational "co-evolution," which posits a reciprocal relationship between organizations' leaderships and their social environment (Lewin & Volberda, 1999; Volberda & Lewin, 2003; Abatecola et al., 2020).

A major gap in this literature is the role that rank-and-file members play in the evolution of their organizations. While managers are rightfully credited with making strategic decisions, the interpersonal dynamics and decisions of ordinary individuals are critical to organizational functionality, and these aspects are mostly overlooked outside management-employee interactions (Van Vugt & Smith, 2019). More specifically, employees learn patterns of behavior from one another, and they often interact in social dilemmas where conflicts of interest arise (Olson, 1965; Cordes et al., 2008; Hauser et al., 2019; Atkins et al., 2019)

Social dilemmas occur when input to a common good is required by multiple individuals and benefit is spread evenly; individuals who contribute less can therefore benefit from the effort of others, which leads to the temptation to free-ride (Olson, 1965). These dilemmas can arise in many settings within organizations, such as teams or employee/employer relationships in firms (Hauser et al., 2019), and resource extraction decisions in common pool resource management regimes (Ostrom, 1990; Wilson et al., 2013). If left unchecked, social dilemmas can lead to organizational collapse as individuals neglect common goals and focus on individual gain (Cordes et al., 2021).

Cooperation is often required to overcome social dilemmas and occurs when individuals disregard the temptation to cheat and contribute to the common good anyway. Unfortunately, these individuals end up gaining less from the common good because of the effort they expended which makes cooperation a less favorable action (Axelrod & Hamilton, 1981). Despite this disadvantage, there is substantial evidence that humans have evolved to be instinctually cooperative through a process of multilevel selection, whereby groups of cooperative individuals outcompeted other groups of less cooperative individuals because of the group level fitness benefits conferred by effective coordination (Rand, 2016; Richerson et al., 2016). Additionally, multiple process such as reciprocity (Trivers, 1971; Axelrod & Hamilton, 1981; Nowak & Sigmund, 2005a; Nowak, 2006; Roberts, 2008), interaction (network) structure (Ohtsuki et al., 2006; Fehl et al., 2011; Rand et al., 2011; Rand, Nowak, et al., 2014), and institutions (Dal Bó et al., 2010; Ostrom, 2014) all serve to reinforce cooperation within groups.

Professional associates and co-workers learn behaviors from one another that can either help or hinder the organization (Cordes et al., 2008), and those that help can sometimes be integrated into organizational routines (Wilson, 2019). Understanding social learning and the transmission of behaviors to routines falls within the purview of cultural evolution, which seeks to uncover why cultural traits such as beliefs, traditions, and rules, proliferate through human populations and decipher their consequences on human genetic evolution (Mesoudi et al., 2006; Henrich & McElreath, 2007; Henrich, 2015; Waring & Wood, 2021; Smolla et al., 2021). Research over the past 50 years has revealed that the evolution of culture occurs with processes analogous to genetic evolution (Mesoudi et al., 2004), while also being subject to additional forces that influence the transmission and alteration of cultural traits (Smolla et al., 2021), such as cognitive biases (Henrich & Gil-White, 2001; McElreath, Bell, Efferson, M. Lubell, et al., 2008; Denton et al., 2020). These additional processes result in fitness consequences for the individuals who espouse the cultural traits (Henrich & Henrich, 2010) and of the traits themselves (Ramsey & De Block, 2017). Finally, cultural evolution takes place at multiple levels, wherein individuals possess cultural traits such as ideas or tools, and groups possess cultural systems such as religions and laws (Smaldino, 2014; Norenzayan et al., 2016). Incorporating these insights into the study of organizational evolution would enhance explanatory power for understanding the fitness consequences of routines, rules, and other institutions.

2. Food Buying clubs

This dissertation melds these disparate literatures in a case study of food buying clubs, which are informal organizations of individuals who purchase food and other items in bulk quantities for a variety of reasons. These clubs mostly come together to benefit from scaling, as bulk purchasing results in lower unit prices (Cotterill, 1981), though some organize to gain access to goods that aren't available to them through the traditional food system, such as purchasing from local producers or acquiring overseas specialties.

Consumer buying clubs arose with the advent of mail-order catalogues, where groups of women would order larger, and thus cheaper, quantities of common household goods (Stanger, 2008). In the 1970's and 1980's, buying clubs would form in rural communities to access fresher and more wholesome food than traditional proprietors provided, and these clubs would often transition into storefront consumer cooperative stores (Ronco, 1974; Cotterill, 1981). Though most grocery stores provide an abundance of fresh produce today, buying clubs still form to access more specialty and organic products or local produce that supermarkets may not carry (Hupper, 2019; Little et al., 2010).

Buying clubs have a simple structure consisting of a coordinator and regular members. Coordinators act as liaisons between distributers and their clubs, hold accounts with providers in their name, and oversee deliveries. Some clubs also have additional roles such as treasurer or secretary who assist with bookkeeping or collection of membership dues. Aside from these roles, all members participate in an ordering process whereby each individual picks the amount of each item they desire.

Club administration constitutes the first social dilemma of buying clubs. Coordinators often need help with club duties such as receiving deliveries and breaking them down into members' portions, though this doesn't necessarily require all members to pitch in every time. Individuals who volunteer provide a service to those that did not, and members who consistently resist volunteering can be considered free-riders (Hupper, 2017). Further, if no members volunteer to assist, coordinators are likely to burn out from all the excess labor putting the whole club in jeopardy.

The ordering procedure also constitutes a social dilemma called a threshold public good. Threshold public goods occur when a minimum amount of effort or contribution must be made for the good to be provided (Cadsby & Maynes, 1999). The order as a whole is a threshold public good because a minimum amount of goods must be purchased for the distributer to deliver them, so those who contributed would not receive their orders if too few individuals have participated. Additionally, individual bulk items often require multiple individuals to contribute in a process is called "splitting," as the item is split amongst multiple people. These items are also threshold public goods because those who start a split item will not receive it if they've ordered less than the minimum, so they rely on other members to buy shares who may not want it. It should be noted that individuals who have participated in incomplete orders and items are not charged in either circumstance, so the only loss comes from the utility that that would have been provided if the order or item was purchased, making the complete nature of the dilemmas a threshold public good with refund (Cartwright & Stepanova, 2015).

While most organizations generally measure longevity by failure or survival, buying clubs have three possible outcomes. First, buying clubs can continue to function as regular buying clubs, continuing to provide bulk orders to their members. Second, buying clubs can formalize into consumer cooperatives with a storefront that is open to non-members, as was the case with many early buying clubs (Little et al., 2010). Finally, clubs can fail and cease operations, and the factors that can lead to this option are not well understood.

2.1. Sample Characteristics

To study the evolution of these clubs, I rely on two sets of data using human subjects, both of which were approved by the University of Maine's Human Subjects Review Board. The first is a survey of food buying clubs that use one of two software companies who've generously provided access to their clubs (Hupper, 2017, 2019). Each software partner also granted access to the purchasing records of clubs that were both functioning and non-functioning, constituting the second dataset. These purchasing data consist of time-stamped information on items purchased through the software, item characteristics, and who purchasing each.

Our software partners provided information for 49 clubs, 35 of which were included in the final sample. Clubs were removed from for having too few (1-3 total) orders or too few splits, thereby rendering reciprocity difficult to detect. Of the 35 clubs included in the sample, 19 had ceased operations and 16 were still active or were store fronts as of their last purchase data observation. One software partner provided the New England subset of their clubs, and the other gave us access to all their clubs who were mainly located in New England, with several exceptions in Australia, Canada, and France, along other parts of the United States including Minnesota, Florida, and the Carolinas. Clubs were located in rural and urban areas, though we do not have full geographic data for every club beyond their state or country location.

Members in our sample can refer to individuals or families, as each household unit usually has one username that connects them to the software and the club. We do not observe which usernames are associated with multi-individual households, so all investigations are made with the assumption that it is not relevant. Our software partners describe the households within these clubs as people who are interested in acquiring their food from outside the mainstream system, i.e., grocery stores. Several clubs were formed by farmers to sell their produce and added additional distributors to their catalog, while some were formed by groups of individuals looking to connect with local farmers.

In total, the sample includes observations of 1528 individuals who purchased 10,261 splitable items over 107 club years. The average lifespan for defunct clubs is 3.16 years (2.16 SD) and 28.7 orders (21.3 SD), and the censored average lifespan for ongoing clubs is 3.24 years (1.38) and 46.9 orders (27.9 SD). The average number of members participating in an order is 7.96 for defunct clubs (6.96 SD) and 12.7 for ongoing (9.41 SD), indicating that larger clubs with more members per order tend to survive longer. Additionally, the average number of splitable items purchased in each order is 3.29 for defunct clubs (4.82 SD) and 11.2 for ongoing clubs (28.9), implying that clubs purchasing more splitable items tend to operate longer.

3. Dissertation Structure

This dissertation is woven together with a golden thread embodied by the following question: how do cooperation and preferences evolve in these clubs, and what are the consequences of each on their survival? To answer this question, the following chapters formalize a model of the evolution of organizations and use it to examine how individuals' capacity for cooperation and preference adoption contributes to their club's longevity. Each chapter is written as though it could be its own standalone article, though the final chapter draws heavily on the first three for their theoretical and empirical implications.

3.1. Chapter 1: The Multilevel Evolution of Organizations

This chapter sets organizational evolution within the context of cultural evolution and multilevel selection. Some theoretical work on organizational evolution has made reference to the insights of cultural evolution (Weeks & Galunic, 2003) and also acknowledges that organizations and markets have an inherently multilevel structure that ranges from the individuals to whole industrial sectors and markets (Breslin, 2016). The field as a whole, however, has not taken full advantage of the most recent advances in modern evolutionary theory.

I begin by reviewing the relevant literatures and follow with a verbal model that describes the different levels of selection that operate in and on organizations, and sketch what an ontogeny of organizations may look like. Current theory on organizational evolution rests on the assertion that markets and managers shape organizations through a co-evolutionary process, where the market changes and managers adapt (Abatecola et al., 2020). Insights from cultural evolutionary theory, multilevel selection theory, and niche construction theory reveal that organizational evolution is not really a co-evolutionary process, which is when two distinct individual lineages have a reciprocal pattern of adaptation (Thompson, 1989), but a process of guided cultural variation within a multilevel evolutionary system (Henrich et al., 2008; Wilson, 2019; D. Smith, 2020). This chapter is the cornerstone on which the rest of the dissertation rests because it provides a conceptual model for the remaining chapters. It is written to be published in an organizational theory journal such as *Organizational Science* or the *Journal of Leadership & Organizational Studies,* with that audience in mind.

3.2. Chapter 2: Reciprocity in Food Buying Clubs

This chapter explores how reciprocity operates in the purchasing patterns of food buying clubs. Because preferences don't always align to ensure every club member gets what they want during an order, cooperation from fellow club members is often needed to make up the difference (Hupper, 2017). Reciprocity is a key dynamic that can enable cooperative behavior to flourish within groups (Nowak, 2006), and previous experiments of reciprocal dynamics in group structured social dilemmas have found that individuals generally fit into one of three different types of behavioral patterns: reciprocators who tend to do what the rest of the group does, free riders who always contribute less than average to a common goal, and altruists who always contribute more than average (Fischbacher et al., 2001; Frey, 2017). However, these typically experimental studies do not analyze how these types emerge over time or how stable reciprocity tends to be in real world settings.

I take advantage of the structure of group purchases in small food buying clubs to analyze how reciprocity and behavioral types emerge in a non-experimental setting throughout the course our sample period. By constructing networks based on co-purchases, I can ascertain reciprocal interactions and track how individuals assist each other in completing purchases through time. This allows me to contribute to the understanding of how behavioral types in social dilemmas emerge over time and compare the results of previous experimental work with real world observations. This chapter has been revised by committee members Marco Smolla and Timothy Waring and is targeted at the journal *Nature: Human Behavior* to be submitted this summer with myself as lead author.

3.3. Chapter 3: Endogenous and interdependent preferences in food buying clubs

Small food buying clubs present a unique opportunity to study endogenous and interdependent preference formation, which occurs when individuals adopt new preferences as a result of exposure to the preferences of others, either indirectly in market settings or directly through interaction with peers (Pollak, 1976; Bowles, 1998). Most studies of endogenous and interdependent food preferences are done by observing single purchasing decisions of meals, but do not extend to habitual household consumption (Birch, 1999; Levy et al., 2021). The purchasing data provided by our software collaborators gives observations of the consumption habits of the individuals in these clubs and which provides the opportunity to fill this gap in the literature.

The chapter investigates the interdependence of preferences in these clubs by using survey data collected from club members and from the purchasing data with the intent to answer two research questions: do the purchasing habits of individuals change over time in these clubs, and do peers influence these changes? Survey responses are analyzed and inform the analysis of the purchase data. To assess changes in the purchase data, I calculated similarity scores between clubs' orders and individuals' orders by comparing the items purchased in each and estimating whether the time between the orders had a meaningful effect on their similarity. To assess peer influence, I used generalized estimating equations to estimate the effect of an individual's peers on their decision to purchase specific items. The chapter was written with the intent to submit it to a behavioral economic journal that would be interested in the dynamics of preferences such as the *Journal of Economic Behavior and Organization* or the *Journal of Behavioral and Experimental Economics*.

3.4. Chapter 4: A survival analysis of food buying clubs

The survival of organizations is a key component of their evolution, as those who survive the longest are most likely to pass on their traits to other organizations through imitation or migration of individuals (Abatecola et al., 2016). Research on organizational survival and/or collapse generally relies on models that assume collapse is precipitated by exogenous shocks or disasters (Rudolph & Repenning, 2002), while there is abundant evidence from across multiple disciplines that organizational decline is often endogenous (Cordes et al., 2021). Additionally most survival analyses of organizations assume that survival is a function of baseline investments and treat variables that may change over time as constant (Brüderl et al., 1992; Grashuis, 2020).

This chapter builds on the results of the previous two chapters and utilizes their results to build a survival model of small food buying clubs. Using a Bayesian exponential survival analysis, I estimate the effect of time-varying reciprocity as well as preference change and homogenization on the survival of these clubs. I specify an explicit causal model of the survival process that includes endogenous dynamics within the clubs. This chapter was written to be a part of a larger paper on the evolution of food buying clubs to be published with Tim Waring and my lab mates in an organizational or evolutionary science journal such as *Organizational Science* or the *Journal of Evolutionary Economics*.

4. Definition of Common Terms

The content of this dissertation draws from several interrelated literatures including economics, organizational science, evolutionary science, and psychology. To avoid any confusion that may occur from conflicting definitions in cross-disciplinary sources, I will explicitly define several key terms to unify these diverse perspectives:

- **Group –** A set of individuals who unify around a common purpose, be it survival, recreation, employment, etcetera. Examples: social groups like book clubs, community organizations, hunter gatherer bands, teams within a firm.

- **Organization –** A formalized group, namely one that has adopted specific institutions, bylaws, etc. Example: Firms such as banks and cooperatives, government at all levels, religious congregations, or unions.
- **Institution –** following Hodgson (2019) & Currie et al., (2016), a codified rule or system of rules that governs how a group functions and regulates social relationships. Examples: Currency as a means of trade, minimum wage requirements, union dues.
- **Culture –** following Mesoudi et al. (2004) & Boyd and Richerson (1985) information on beliefs, values, knowledge, & norms that are acquired through social learning and are expressed in behaviors and technology, Examples: art such as pottery and paintings, hunting patterns, stories.
- **Cooperation –** an individual acting in the best interests of another or group of others. Examples: an employee volunteering contributing their fair share to a group project, or hunters working in a group to bring down a large animal.
- **Altruism –** Using Wilson (2015), altruism is the behavioral act of accepting a cost on behalf of another or group of others, regardless of the underlying psychological motivation, e.g. expectations of later reciprocity or a feeling of utility from aiding others.
- **Social Dilemma –** A situation involving a group of individuals, whereby the interests of any specific individual conflict with the interests of other individuals or the group.
- **Reciprocity –** Repaying the action of another or a group of others with an action of comparable scale, i.e., doing unto others what has been done to you.
- **Preference –** A reason for a choice or behavior whereby an individual gains more utility or feels more positive affect from one alternative over another (Zajonc & Markus, 1982).

CHAPTER 1.

BRINGING THE EXTENDED SYNTHESIS TO ORGANIZATIONAL EVOLUTION: A MODEL OF HOW ORGANIZATIONS EVOLVE

1.1 Introduction

The application of Darwin's theory of natural selection to the study of organizations has produced a substantial amount of knowledge on how they succeed and thrive. Concurrently, the field of organizational evolution has not taken full advantage of the many advances made in the rest of evolutionary science (Hodgson, 2013). Since Darwin's (1859) *Origin of the Species*, research in the evolutionary sciences has led to an extended evolutionary synthesis of how forces aside from natural selection produce changes in populations (Laland et al., 2015; Pigliucci & Müller, 2010). Incorporating this scholarship could bring about a more complete and predictive theory about how human organizations change and endure. This chapter draws on insights from cultural evolution, multilevel selection, and cultural niche construction to advance a more complete understanding of organizational evolution.

Management and organizational science, the parent discipline of organizational evolution, draws from traditions like economics, psychology and sociology to study the impacts of society and individual decision making on organizations (Clegg & Bailey, 2008). Organizational science concerns itself with the study of firms, or organizations with the specific intent of generating profit by providing a good or service (Coase, 1937; Foss, 1993; Nelson & Winter, 1982), but its theory and methods have been used to study other types of organizations including cooperatives (Carr et al., 2008), governmental agencies (Sminia & Nistelrooij, 2006), non-profit advocacy groups (Tucker et al., 2005), and common pool resource management regimes (Ostrom & Basurto, 2011).

Organizational evolution applies Darwinian principles to study how organizations change. Firms and other entities are examined for variation, selection, and transmission of specific functions, processes, and ideas within an organization and across a whole industry (Abatecola et al., 2016; Hodgson, 2013). In an attempt to bring the agency of individuals to the forefront of this process, researchers often refer to this process as organizational "co-evolution", meaning that managers induce change by responding to industry trends (Abatecola et al., 2020; Volberda & Lewin, 2003). The role of strategic decision making and innovation in the evolution of organizations reveals that cultural evolution, specifically cultural multilevel selection and cultural niche construction, holds important insights for the study of organizational change.

Cultural evolution, multilevel selection, and niche construction are three components of the most recent framework used by many modern evolutionary scientists known as the 'extended evolutionary synthesis' (Pigliucci & Müller, 2010). This framework builds upon the combination of Darwinian natural selection and mendelian genetic inheritance known as the 'modern synthesis'. The modern synthesis posits that genes are the only mechanism of inheritance between generations of organisms, and selection upon the phenotypic representation of these genes is what drives evolution (Jablonka & Lamb, 2006). Genes are "replicators" of information and "interactors" are the organisms that responded to environmental feedback. With significant advancement in the study of other evolutionary processes such as cultural evolution (Mesoudi et al., 2006), niche construction (Day et al., 2003), epigenetics (Jablonka & Lamb, 2006), and the revival of multilevel selection (Wilson & Wilson, 2007), prominent evolutionary thinkers assembled a new synthesis that included all of these advances (Laland et al., 2015). Organizational Evolution has primarily made use of the replicator-interactor paradigm of the modern synthesis, and inclusion of cultural evolution, niche construction, and multilevel selection could inform better scholarship.

Cultural evolution examines how Darwinian processes act on human symbolic thought as it manifests in beliefs, values, artifacts, and ideas (Mesoudi et al., 2004). Due to genetic evolution favoring minds that process symbolic and behavioral social cues, humans acquired an entire system of inheritance that results in behaviors and technology that has allowed us to successfully inhabit every terrestrial biome, explore the oceans, and travel to the moon (Herrmann et al., 2007; Henrich, 2015; Muthukrishna et al., 2018). While many other species appear to have culture in the form of artifacts and learning behavior (Schaik, 2009), human culture has become a dominant inheritance mechanism for our species, and results in adaptations that are much more sophisticated and complex than those of other species (Henrich, 2015; Waring & Wood, 2021). Cultural evolution has shaped our minds and brains to allow us to persistently live in coordinated groups of kin and non-kin that are larger than those of other species (R. I. M. Dunbar, 1992), and the transmission of cultural ideas around group formation have shaped us into cooperative and group minded individuals (Boehm, 2012; Wilson, 2019). These insights about human psychology are essential to understanding how modern human groups, i.e. organizations, form and flourish (Atkins et al., 2019).

In addition to culture, the fact that humans form and maintain groups of non-related individuals makes understanding how competition between groups, and individuals within groups, essential for understanding organizational evolution. Multilevel selection theory, which conceptualizes evolution as a process that occurs at nested levels of genes, individuals, and groups, is a powerful tool in explaining how genetically unrelated people are inclined to cooperate, especially if doing so may incur a personal cost (Wilson & Wilson, 2007). In fact, humans are so inclined to cooperate with each other, that when pressed for cognitive processing time, they’re more likely to cooperate than defect when playing economic games (Rand, 2016). The premier insight of multilevel selection is that groups of cooperative individuals are more likely to outcompete groups of selfish individuals, so long as there is sufficient selection pressure between groups (Wilson & Wilson, 2007). Further, cultural mechanisms such as norms and institutions are able to suppress deviant behavior within groups (Boehm, 2012), which led to the selection of cooperative individuals in the past (Boyd & Richerson, 2009). While there have been calls for a multilevel view of organizational evolution (Breslin, 2016) and investigations of how managers can encourage cooperation in humans by capitalizing on our coalitional psychology (Price & Johnson, 2011), an explicit use of multilevel selection has not been used to explain and predict the evolution of organizations.

Organizational “co-evolution” acknowledges that there is a feedback loop between the environment and the organization, which is the process of niche construction in the extended evolutionary synthesis (Laland et al., 2015). Niche construction is broadly defined as the process whereby organisms’ actions modify their environment, thereby inducing fitness consequences on themselves and others (Odling-Smee et al., 1996). An example from human evolution is lactase persistence, where the advent of animal husbandry and agriculture led certain human populations to produce lactase after adolescence so they could consume dairy throughout their lives (O’Brien & Laland, 2012). “Co-evolution” has a very specific meaning in evolutionary theory that is being improperly used by the organizational literature, and niche construction theory can provide a more appropriate framework to model multi-level organizational evolution.

This chapter has two goals. The first is to review the current scholarship on organizational evolution, cultural evolution, multilevel selection theory, & niche construction to identify where these literatures can enhance each other. The second is to synthesize these literatures into an updated model of organizational evolution.

1.1.1 Key Definitions

Reviewing similar yet distinct literatures requires defining overlapping terms. Here are several unified definitions of key words and concepts that are common throughout these separate sub-disciplines with examples of each.

- **Group –** A set of individuals who unify around a common purpose, be it survival, recreation, employment, or others. Examples: social groups like book clubs, unions, community organizations, hunter gatherer bands, teams within a firm.
- **Organization –** A formalized group, namely one that has adopted specific institutions, bylaws, etc. Example: Firms such as banks and cooperatives, government at all levels, religious congregations.
- **Institution –** following Hodgson (2019) & Currie et al., (2016), a codified rule or system of rules that governs some way a group functions and regulates social relationships. Examples: Currency as a means of trade, minimum wage requirements, union dues.
- **Culture –** following Mesoudi et al. (2004) & Boyd and Richerson (1985) information on beliefs, values, knowledge, & norms that are acquired through social learning and are expressed in behaviors and technology, Examples: art such as pottery and paintings, hunting patterns, stories.
- **Cooperation –** an individual acting in the best interests of another or group of others. Examples: an employee volunteering contributing their fair share to a group project, or a hunters working in a group to bring down a large animal.

1.2 Organizational Evolution as it Stands

1.2.1 Evolution in the Study of Organizations

Explicitly Darwinian attempts to explain changes in organizations began with the organizational ecology framework (Hannan & Freeman, 1989). Capitalizing on contemporaneous advances in population genetics and ecology, scholars formulated a model of organizations that were akin to organisms, composed of many different practices and rules that were difficult to change due to the resource constraints (Aldrich & Pfeffer, 1976; Hannan & Freeman, 1977). The environment, i.e. markets or regulatory structures, placed pressure on these organizations to produce adequate supply, manage employee interactions, and comply with standards.

Those organizations who were able to continue function or grow despite these constraints continued operations, retaining their traits (e.g. business practices or organizational structure) and passing them on to emerging firms through mechanisms such as imitation or mentorship. Eventually, some organizations overcame some of their resource constraints and were able to settle into market niches, thus explaining the diversity of organizations in society (Hannan & Freeman, 1989).

Organizational ecology combined many assumptions found in neoclassical economics with those of population ecology. Markets were assumed to flow towards an equilibrium, and firms with competitive advantage specialized into niches (Lewin & Volberda, 1999). However, this model failed to capture the dynamics that occur within economies and firms, and the strategic and adaptive choices of managers were assumed out (Beinhocker, 1997; Lewin & Volberda, 1999; Nelson & Winter, 1982). In reality though, many of the strategic choices made by managers are the very drivers of variation that environmental conditions select, so a complete model of organizational evolution needed this facet (Hrebiniak & Joyce, 1985).

In the late 1990's and early 2000's, the study of organizations using the principles of natural selection coalesced around a new theoretical paradigm that continues to the present known as "organizational co-evolution" (Breslin, 2016; Lewin & Volberda, 1999; Volberda & Lewin, 2003). In a co-evolutionary view of organizations, managers take an active role in the evolution of their firm by observing changes in the market and proactively adjusting the firms' behavior accordingly (Beinhocker, 1997; Hrebiniak & Joyce, 1985). Additionally, firms use the innovation process to diversify their revenue streams and innovate new ways to execute and expand upon their current processes (O'Reilly & Tushman, 2008). In this respect, organizations evolve in response to their environment, and change the environment itself in so-doing (Abatecola et al., 2020), leading to a reciprocal process between organization and environment that begets the use of the term co-evolution.

Most co-evolutionary studies utilize the replicator-interactor concept in the framework of 'Generalized Darwinism' (Hodgson, 2013). This is based the modern synthesis model where evolution entails genetically coded replicators that are selected based on the resulting organism interactors. Hodgson & Knudsen (2010) propose that organizations, subgroups within them, and individual employees act as interactors, while replicators consist of personal work habits, the genes of the individuals within, and routines that institutionalize how the organization should function. This understanding is fundamentally multilevel in its approach, as what evolves in organizations is often seen as the result of selection at the individual, team/group, and organizational level (Breslin, 2016).

1.2.2 Evolution in the Study of Management

Management monitors the performance of an organization in fulfilling its purpose (Levitt & March, 1988) and facilitates the cooperation of the members of an organization (Cordes et al., 2008). Evolutionary studies of management are primarily concerned with how leadership styles evolved and the insights those processes can provide to make better management practices (Van Vugt & Ahuja, 2011). Since managers are presumed to have the most agency in organizational evolution (Sminia & Nistelrooij, 2006), understanding how leader-follower dynamics evolved and emerge explicates how strategic choice produces variation in an organization's procedure and practice.

Leaders and followers emerge from the mechanisms of dominance and prestige, which facilitate how hierarchy unfolds in human populations (Van Vugt & Smith, 2019). Dominance is commonly understood as leaders enforcing their status through coercion, where followers heed leaders' instruction for fear of retribution. Prestige flows from followers perceiving their leaders as trustworthy sources of information whose guidance will lead to better personal outcomes (Henrich & Gil-White, 2001). Both systems convey social information from leaders to followers via different mechanisms. A system based purely on dominance will result in followers being forced to copy the leader and changes in processes or information can only come from displacing or placating the current leader. Prestige systems, in contrast, allow for changes to occur without fully disrupting the hierarchy. In practice, both systems play a part and the best systems tend to find a proper balance (Van Vugt & Smith, 2019).

Followers failing to cooperate on tasks all but ensures the failure of a group, so leaders must be able to facilitate prosociality. Smaller groups who make behavior observable are adept at enforcing cooperation democratically, but this becomes much more challenging as group size increases and monitoring behavior becomes more costly (Stewart & Plotkin, 2016). In this case, leadership via hierarchy can be an effective tool of enforcing cooperation, so long as monitoring costs for the leader are sufficiently low (Hooper et al., 2010). The method of enforcement a leader employs is critical to group success however, as those who only deploy coercion increase their likelihood of expulsion and other sanctions from their followers (Price & Van Vugt, 2014). Those who lead through example and exhibit fairness and humility are much more likely to inspire prosocial behavior in their followers in the long run (Grabo & van Vugt, 2016). Signals such as charisma and prestige informed how individuals in our evolutionary past to selected their leaders, and understanding these processes and their pitfalls can help identify and train effective leadership qualities in the present.

The evolution of leadership and followership is important for understanding how evolved cognitive mechanisms lead to behavioral outcomes in an organization, but they also have important implications for how organizations continue to evolve. After all, information transfer ***is*** the transmission component of a generalized Darwinian approach, and cooperation between individuals in any social group constitutes a major internal selection pressure. Since both functions are essential to the job of managers, their performance can have major impacts on how organizations interact with their environment.

1.2.3 Key Gaps

The gold standard for evolutionary inquiry is to determine the trait that is evolving and how that evolution is taking place. In organizational evolution, there is still some debate about what exactly constitutes a "trait" (Breslin, 2016), and how these traits actually evolve (Abatecola et al., 2020). For some, the trait in question could be a set of institutions such as practices and routines that change between individuals or across teams within an organization (Abatecola et al., 2020). The mechanism for evolution is also unclear, as it could be industry selection or strategic choice that are the primary drivers of variation and differential survival. The insight provided by cultural evolution and multilevel selection is that *all* the proposed ideas are traits subject to evolutionary forces. Practices, routines, and codified institutions all vary across organizations and are transmitted between individuals, teams and other organizations, and have the potential to carry fitness consequences. Within a framework of cultural multilevel selection, researchers can evaluate the efficacy of any of these types of traits and determine whether or not they are adaptive (Kline et al., 2017).

Additionally, the term "co-evolution" is used improperly in this literature. Co-evolution occurs when two (or more) species mutually influence each other's fitness through an assortment of interactions, or when two or more traits in a species influence the evolution of each other (Janzen, 1980; Thompson, 1989). A biological example is the evolution of parasites and hosts, where host populations evolve resistances and parasite populations evolve ways around them (Thompson & Burdon, 1992). In the organizational "co-evolution", the term is used to describe the relationship between groups of organizations and their social environment, where managers make decisions in response to the fluctuations of the market (Lewin & Volberda, 1999). While there are some select cases where the term coevolution may apply, organisms altering their environment and subsequently being altered by it is niche construction (Odling-Smee et al., 1996), which is expand on in section 1.5.

1.3 Culture, the human inheritance system.

As defined above, culture is a system of symbols represented in brains and as artifacts that convey meaning and affect behavior. Cultural evolution is the process by which these symbols and artifacts change over time and impact the fitness of the humans (and other animals) that employ them (Mesoudi, 2011).

Anthropological ethnographies, psychological experimentation, and quantitative historical analyses have revealed much about how culture evolves, the impact it has on genetic evolution, and their continued coevolution (Henrich, 2015; Waring & Wood, 2021). Revelations about how culture is transmitted and selected, specifically the units and methods of inheritance, can lend substantial insight to organizational evolution.

1.3.1 Units of Cultural Evolution

As in organizational evolution, there is debate about what is transmitted between generations in the evolution of culture. Many proponents maintain that adaptations, specifically *cumulative* cultural adaptations, can only be achieved through discrete replicators that are altered through mutation akin to genes. These replicators were conceptualized as “memes” by Richard Dawkins (1976) in the final chapter of his seminal work *The Selfish Gene,* and many since have adopted this terminology in speaking about cultural replicators (Blackmore, 2000) including in organizational studies (Weeks & Galunic, 2003). Others are less convinced that culture requires discrete replicators to produce advantageous variants, and while these models are helpful, they ultimately do not tell the whole story (Henrich et al., 2008). The truth, it seems, lies somewhere in the middle.

Some examples of culture can be reduced to discrete particles that build upon each other, especially in artifactual representations. Language, and writing specifically, allows for symbolic representations of how humans ought to behave or what beliefs are of high import. Religious texts such as the Koran, the Torah, or the Christian Bible are collections of thought and tradition that dictate how their adherents should act towards each other (Hartberg & Wilson, 2016), and specific lyrical styles and musical techniques such as tritones are written down, copied, and expanded upon by musicians across many different genres and time periods (Brand et al., 2019; Nakamura & Kaneko, 2019). Technology, and how society catalogues its advances in patents also shows how discrete parts can come together and recombine to produce cumulative culture

(Bedau, 2019). For example, quantitative historical analysis of the European dye industry reveals persistent copying and innovation throughout Germany during the late 19th and early 20th century up until World War I (Murmann & Homburg, 2001). These examples show that cultural artifacts can often be decomposed into discrete parts that can be seen as a kind of cultural equivalent of genes.

At the same time, using artifacts as evidence that culture only evolves via discrete replication belies the fact that culture ultimately lives as a symbolic representations within the human mind, and these representations are certainly not discrete (Henrich et al., 2008; Wilson et al., 2014). Mathematical models developed by Henrich and Boyd (2002) demonstrate that continuous mental representations, which can (but needn't) manifest as discrete artifacts, can lead to cumulative cultural adaptation. An empirical example by Hartberg and Wilson (2016) explores this phenomenon by examining differential citations of the bible. Specifically, they examined how different pastors use bible verse citations to justify affirmation or exclusion of homosexual behavior, and the results revealed that interpretation of discrete verses exhibits wide variation characteristic of a spectrum with distinct statistical peaks. The mental reflections of the citations were encoded as sermons and writings, and though significantly different between affirmers and excluders, still saw continuous overlap.

1.3.2 Methods of Cultural Inheritance

While culture shares some similarities with genetics in terms of what is transmitted, the methods of transmission are very different (Smolla et al., 2021). Culture still spreads from parents to offspring, but it also spreads within generations. In addition, genetically evolved cognitive mechanisms skew how culture is translated to information (Tooby & Cosmides, 1992). Finally, where most genetic sources of variation are due to random mutation, cultural variation is often produced during an innovation process that can often be considered intentional and conscious.

Parents, parental cohorts, and personal cohorts are all responsible for transmitting culture. Parental transmission, also known as vertical transmission, refers to parents teaching their children (Cavalli-Sforza et al., 1982). Beginning in early childhood development and beyond, parents are often at the forefront of teaching their children ideas, beliefs, and language (Kline et al., 2018). However, humans also absorb culture from just about everyone in their personal vicinity, and have a tendency to take on the most dominant cultural traits of their surroundings (Henrich & McElreath, 2007).

There are many psychological biases that shape the outcome of social learning (Boyd & Richerson, 1985). A common observance in most animals that learn socially is payoff bias, where individuals copy the behavior of peers that appears to be doing better than them (Laland, 2004). This bias surfaces around solving specific tasks, such as copying the arrow design of a fellow hunter who lands better pray or adopting the writing schedule of a researcher who tends to publish more. People may also adopt the behavior and ideas of the majority around them in what's known as conformity bias (Andrés Guzmán et al., 2007; Henrich & McElreath, 2007). This could manifest as wearing a specific type of clothing or styling one's hair in the manner of those in their immediate surroundings. Finally, individuals tend to copy individuals who they and their peers have a high opinion of, called prestige bias (Henrich & Gil-White, 2001). This is different from copying dominant individuals in a group, as prestige is freely conferred by subordinate individuals with deference, not coerced by superiors.

Once individuals learn cultural information, they often make changes to it through innovation, thus inducing variation. This is a type of asocial learning process where individuals examine a task, evaluate their current cultural tool kit's ability to complete it, and use trial and error to make improvements if the kit is found lacking. This direct interaction with one's environment is the main source of cultural variation, and involves a number of cognitive mechanisms that operate at and below the level of conscious awareness (Fogarty et al., 2015; Wilson et al., 2014).

The fitness of a cultural variant can be decomposed into the fitness of the variant itself and the fitness of those possessing it (Ramsey & De Block, 2017). In genetic evolution, the fitness of a gene is measured by how much it is passed on relative to other variants, and the fitness of individuals are measured by how much they survive and reproduce (Jablonka & Lamb, 2006). Similarly, from the "meme's eye view", one can view the fitness of a cultural variant as how much it is passed on related to other variants (Blackmore, 2000). While this is true, if the cultural variant has sufficient adverse effects on the fitness of the individual using it, that variant's fitness can also decrease (Mesoudi, 2011).

A cultural variant that decreases the fitness of an individual can cause that individual to die or not reproduce, be changed via innovation, or be replaced with another variant (Henrich, 2015). As an example, consider the food taboos of pregnant or nursing Fijian women (Henrich & Henrich, 2010). Across all stages of pregnancy and nursing, taboos exist to prevent Fijian women from eating certain species of fish. Later analysis of some these fish species have found that they can have adverse effects on fetal and neonatal health, so the taboos have positive effects on the fitness of those women who adhere to them compared to those who do not. In this case, the taboos are a set of cultural variants that prescribed which species were acceptable to eat; those with variants with permissions to eat potentially harmful fish led to adverse outcomes, and they were replaced or changed to discourage those species in later pregnancies. The variants themselves may have spread because they were easy to understand, but their adaptiveness also lay in the outcomes they produced in the population.

1.4 Multilevel Selection

There have been several calls to consider multilevel analysis within the study of organizational evolution, specifically to consider evolution in individuals, team, and whole organization (Abatecola et al., 2020; Breslin, 2016). Multilevel selection theory provides an ideal framework to do this and is especially helpful when studying the evolution of effective team cooperation and collective action. This section will outline the major tenets of multilevel selection theory and will expand upon how it can be used to explain the evolution of cooperation and the emergence of culture.

1.4.1 What is Multilevel Selection Theory?

The core assertion of multilevel selection is that life is organized into hierarchical levels that constitute functionally adaptive units (Wilson & Wilson, 2007). From genes all the way up to societies, individual units come together and compete for scarce resources. Those that are most fit for their environment survive and reproduce, and the ultimate outcome is determined by the dominant level of selection. As an example, take the evolution of a trait such as bird calling behavior (for the full analogy see Wilson, 2002, chapter 1). Within a group, a bird may call out to alert the rest of the flock about a predator, but the call simultaneously signals the caller’s presence to the predator. The relative fitness of the individual caller is thus decreased relative to the group. However, the calling behavior may induce the whole flock to either move away or fight the predator, increasing the relative fitness of the flock when compared to those without callers. The final evolution of the trait depends on the balance between selection at the level of the individual birds and the flocks.

Selection at multiple levels means that traits can evolve at each of them, leading to two distinct processes of multilevel selection: Multilevel Selection 1 (MLS1) and Multilevel Selection 2 (MLS2) (Okasha, 2006). MLS1 refers to traits that evolve within individuals of the lower level due to dominant selection pressure above, exemplified by calling behavior in the previous paragraph. MLS2 concerns organizational characteristics of the group itself that reinforce the group’s fitness (Okasha, 2006). This could be exemplified by cellular differentiation in multicellular organisms or division of labor in humans and ultrasocial insect colonies (Gowdy & Krall, 2016). Cells performing specialized functions and bee colonies having different types of bees performing specific tasks gives the higher unit of selection (body & colony respectively) more fitness over conspecifics with less structure. In humans, MLS2 results in complex division of labor in large societies and in institutions that cultivate group identity and rules about cooperation (Smaldino, 2014).

1.4.2 Multilevel Selection and the Evolution of Cooperation

One of multilevel selection theory's largest contributions has been in explaining the evolution of cooperation and altruism (Sober & Wilson, 1999). As defined above, cooperation is generally viewed as an individual incurring a cost for the benefit of another or a group of others, and it is an evolutionary puzzle because individuals who employ selfish strategies can benefit from cooperative individuals, thus giving cooperation a relative disadvantage in fitness. Additionally, self-serving strategies have a tendency to spread to other individuals involved in collective action due to payoff bias (Fehr & Fischbacher, 2005). How then can cooperation evolve as we see it today?

A number of solutions to the stability of cooperation have been proposed including generalized reciprocity (Axelrod & Hamilton, 1981; Nowak & Sigmund, 2005a; Trivers, 1971) and kin selection (Hamilton, 1964a, 1964b; Maynard Smith, 1964), where cooperating with genetic relatives nets higher fitness for the genes in a given lineage. While these are viable solutions, they all occur in the context of groups; reciprocity requires at least 2 individuals and relatives are a special class of group. Wherever there is fierce competition between groups, those groups that function as a cohesive whole tend to fare better than those who do not. As Wilson and Wilson (2007, p. 345) so succinctly put it: "Selfishness beats altruism within groups. Altruistic groups beat selfish ones. Everything else is commentary."

Humans are among the most cooperative species on the planet, sharing similar divisions in labor and levels of cooperation to that of ultrasocial insects, and this is directly attributable to multilevel selection acting on genes and culture (Boyd & Richerson, 2009; Gowdy & Krall, 2016). At an MLS1 level, humans likely evolved cognitive mechanisms that fostered better communication and allowed for cultural innovations to overcome various environmental challenges (Boyd & Richerson, 2009). The pressure that selected for those mechanisms also selected for more docile and psychologically flexible individuals who were more likely to cooperate with each other (Henrich, 2015). This has left our species with a coalitional psychology that tends to default to cooperation, especially in time constricted circumstances (Rand, 2016).

1.4.3 Cultural Multilevel Selection

In humans, multilevel selection operates on cultural inheritance as well. At the MLS1 level, cultural traits can vary within groups and have explicit fitness consequences for the individuals that employ them, such as different tool shapes or spear throwing techniques that cause different hunters of the same band to capture more game. Further, different groups could compete with each other for common animals stocks and the groups with the highest frequency of better techniques or tools will tend to pass on those traits more often, which will contribute more to the over all proportion of those techniques in the meta population (Henrich, 2004).

Cultural multilevel selection becomes especially important when considering MLS2 traits. The resources necessary to support larger groups require institutions that divide labor and streamline food production, which are necessarily group level traits (Gowdy & Krall, 2016). This is why MLS2 traits are likely responsible for why our species cooperates so well with non-kin (Smaldino, 2014; Richerson et al., 2016). Rules, other institutions, and norms that monitor and enforce fairness have evolved across many types of human groups in order to ensure cooperation (Wilson et al., 2013), and the best of these group level traits reinforce cognitive dispositions towards maintaining a good reputation and capitalize on the human tendency towards reciprocity (Rand, Yoeli, et al., 2014).

1.5 Niche Construction

Niche construction theory originates with evolutionary biologist Richard Lewontin, whose career led him to stand up to the replicator-interactor doctrine advocated by Dawkins (1976). Throughout his career, Lewontin was a fierce opponent of viewing organisms as static interactors passively selected by their environment, and insisted that all living things actively took part in their own evolution and shaped the environment in which they evolved (Lewontin, 1985; Jablonka & Lamb, 2006). Though Lewontin never explicitly called this theory niche construction, his original position has grown into a robust body of scholarship that is a cornerstone of the extended evolutionary synthesis (Laland et al., 2015).

Understanding niche construction requires understanding niche theory. In ecology, a niche refers to the position an organism occupies within an ecosystem, including what they eat, how they interact with other organisms, and where they live (Vandermeer, 1972). Modern niche theory is a synthesis of two principles, namely what an organism needs to survive and what they do to their environment (Leibold, 1995). All living things have sets of conditions that must be met to survive. For example, fish species require certain ranges of pH or saltiness to perform proper respiration (Z. T. Wood, 2019). Furthermore, organisms perform functions within their ecosystem, such as fish species acting as predators or prey (Z. T. Wood, 2019). This formulation of niche theory explicitly posits that not only are organisms shaped by their environment, but they are active participants in the process (Kylafis & Loreau, 2011).

Environmental alterations can have far reaching impacts on ecosystems and induce fitness consequences on the altering species and their neighbors. Alterations can be caused by actions taken or leaving waste products. Beaver dams, for example, can alter the flow of streams and their construction opens new areas for young tree growth, while their abandonment can lead to the development of meadow environments that give grass species a fitness advantage (Hastings et al., 2007). Furthermore, the dams themselves have been found to have fitness consequences on beaver alleles associated with sociality and disease resistance (Naiman et al., 1988).

Regardless of how the alteration takes place, the consequences are often experienced by the next generation of individuals. Niche construction theory thus posits that the environment itself is another inheritance system, specifically one that has acquired characteristics that can either help or hinder fitness (Laland et al., 2016). Furthermore, as behaviors can be altered by environmental changes, inheritance can extend to the altering generation, where induced fitness consequences affect different behaviors (Laland et al., 2016). This observation is especially important when studying cultural niche construction in humans (Laland & O'Brien, 2011).

1.5.1 Humans and Cultural Niche Construction

Human niche construction happens primarily through cultural innovations and technology, which have had far reaching consequences on our own genes, and the genes of many other species (Laland et al., 2010; O'Brien & Laland, 2012). Though we culturally changed our environments prior to the agricultural revolution, the surplus provided by agriculture has led to the domestication of many species (O'Brien & Laland, 2012) and increasing societal complexity (Laland et al., 2014). Furthermore, social complexity gave way to social niche construction within society (Yamagishi & Hashimoto, 2016), which continues to have drastic consequences on our environment (Meneganzin et al., 2020).

Setting aside the human genome, the agricultural revolution had voluminous consequences for the fitness of many species, and cultural traits beyond agriculture continue to do so (O'Brien & Laland, 2012). Artificial selection of crops and the conversion of pasture to cropland and irrigation led to substantial changes in the geographic ranges of many species, and shaped the genetic makeup of plants and animals (O'Brien & Laland, 2012; Faris, 2014). In the present day, the expansion of human economic activity and agriculture continues to shape the fitness and extinction of many species through habitat loss, introduction of invasive species, and other factors (Czech & Krausman, 1997).

The environmental consequences of agriculture acutely shaped humanity's genes, as have other aspects of culture. The most ready example is lactase persistence (O'Brien & Laland, 2012), where domestication of cattle such as cows, goats, and sheep introduced dairy into human diets in some regions of the world. Those individuals who continually produced lactase allowed them access to a substantial source of calories, thereby inducing a fitness advantage. As such, human populations in regions that evolved dairying practices gradually became dominated by those with genes enabling lactase persistence (Laland et al., 2010). Moreover, agriculture allowed for a transition from hunting and gathering to settled populations which have gradually increased in size (Fogarty & Creanza, 2017). Larger societies introduced selection pressure for larger social brains capable of symbolic learning, thereby increasing the social complexity of the populations their cognitive ability (Henrich, 2015; Laland, 2017; Laland et al., 2010).

Increasing population size within settlements also allowed for the division of labor, as it was no longer necessary for everyone to produce food (Gowdy & Krall, 2016). This gave way to an explosion of new forms of labor and commodities such as credit and money (Czech, 2019; Peneder, 2021). As individuals performed more diverse tasks, they proceeded to construct social niches, which altered their social environment and their neighbors social niches (Yamagishi & Hashimoto, 2016). In essence, the sociality of humans added a host of new dimensions to their physical niche, and created another layer where individual niche construction could take place (Rendell et al., 2011).

The field of organizational evolution has delved into niche theory, though it has only scratched the surface. Specifically, organizational ecology posited that the environment selected for different organizations based upon the needs they fulfilled in society, and industries and organizations could thus be organized into niches (Hannan & Freeman, 1977). Similarly, entrepreneurs are rightly seen as niche constructors as they find social needs that are not being fulfilled and start businesses to meet them (Luksha, 2008). Despite these somewhat early advances, co-evolution has continued to be the common vernacular, despite not completely encompassing the process. Niche construction is a more appropriate term for the function that organizations play in shaping their own environment.

1.6 The Extended Evolutionary Synthesis of Organizations

Modern organizations are multilevel cultural systems, and a comprehensive model that integrates cultural evolution, multilevel selection, and niche construction into organizational evolution requires assessing how selection acts at all levels of an organizational hierarchy, where culture reinforces or dulls this pressure, and where these traits alter their social environment. Breslin (2016) has outlined the multiple levels that exist within organizations, and the approach outlined invokes similar language to MLS1 and MLS2, though it leaves out the social dilemmas inherent at each level. In this section, I outline the levels of selection in organizational evolution, identify the major selection pressures at each level, and present what a successful organizational ontogeny might look like.

1.6.1 Culture & Selection in the Levels of Organizational Evolution

The levels of organization that selection acts upon are individuals, groups/teams, & whole organizations, which are situated within industries and their social environment (Breslin, 2016). Individuals comprise teams and groups, and groups and teams comprise whole organizations:

1) *The Individual*

   Individuals provide the base unit of selection. Cultural information is stored in their brains, they innovate, and they perform their allotted tasks. Competition between peers constitutes the social dilemma that exists at this level.

2) *The Group/Team*

   Teams or groups of teams within organizations provide the next level of selection. They are threatened by social dilemmas internally, and competition between groups for their organization's resources constitutes a social dilemma as well. These groups can have discrete, coded cultural traits such as a work schedule, rules, and a formalized routine, or non-coded traits such as norms. Division of labor causes groups to be formed around certain task sets, and they often have a leader.

3) *The Organization*

The organization itself is the final level. It faces internal selection pressure from the social dilemmas within and between its groups, as well as external pressures from industry, society, or regulation. It contains all coded and non-coded traits of its sublevels, as well as its own discrete, coded cultural traits, such as a mission statements or company policy.

Cultural variants at all 3 levels alter their respective environments and have fitness consequences that selection can act upon, resulting in MLS1 and MLS2 outcomes. At the individual level, MLS1 cultural traits such as personal beliefs, motivations, and work methods influence how group members perform their jobs, interact with their peers and superiors, and cooperate or free ride. These cultural variants spread from peer to peer via social learning that is biased towards conformity, prestige, and payoffs (Cordes et al., 2008). At the level of the group, aggregate MLS1 traits and MLS2 group traits are selected. Groups that act more cooperative and have norms or institutions that facilitate group-oriented behavior tend to fair best. The whole organization contains the aggregate culture of its individuals, groups, and evolves MLS2 level traits of its own. At this level, groups within an organization constitute individuals in their own way, so MLS2 traits that regulate behavior within groups become MLS1 traits between groups *within* the organization. Organizations then form their own MLS2 traits that govern how the groups within them relate to each other.

Table 1.1 Culture & Selection Pressures for each Level of Organizational Evolution with Examples

Level of Selection	Cultural Forces	Selection Pressure
The Individual	Mental Representations - Understanding of Duties - Personal behaviors/artifacts	Competition Between Peers
The Group/Team	Group Level Traits - Work Schedules - Departmental Training Materials	Internal Social Dilemma External Disruptive Pressure External Structural Pressure
The Organization	Organizational Level Traits - Corporate Policies - Division into Departments	Internal social dilemma - Individuals in Groups - Between Internal Groups External Disruptive Pressure External Structural Pressure

The fitness of an organism is reflected by its ability to survive and reproduce, and the fitness of organizations is similar. Broadly speaking, an organization's fitness is determined primarily by its longevity. For a firm, this could be how long it continues to generate a profit by selling goods and services, and for non-profit organizations such as religious organizations or NGOs this could be how long they are able to stay open and serve their target communities. In some cases, organizations replicate when they open new locations, sell franchise rights, and enter new markets. For example, many food and retail chains sell franchise rights and open new store fronts, and religious institutions such as the Catholic Church continually build churches in new locations.

Three unique kinds of selection pressure act upon organizations and the groups within: internal, disruptive external, and structural external. Internal selection pressure lies in the social dilemma; conflicts of interest and free riding behavior serve an individual's fitness at a cost to the group, and this type of behavior

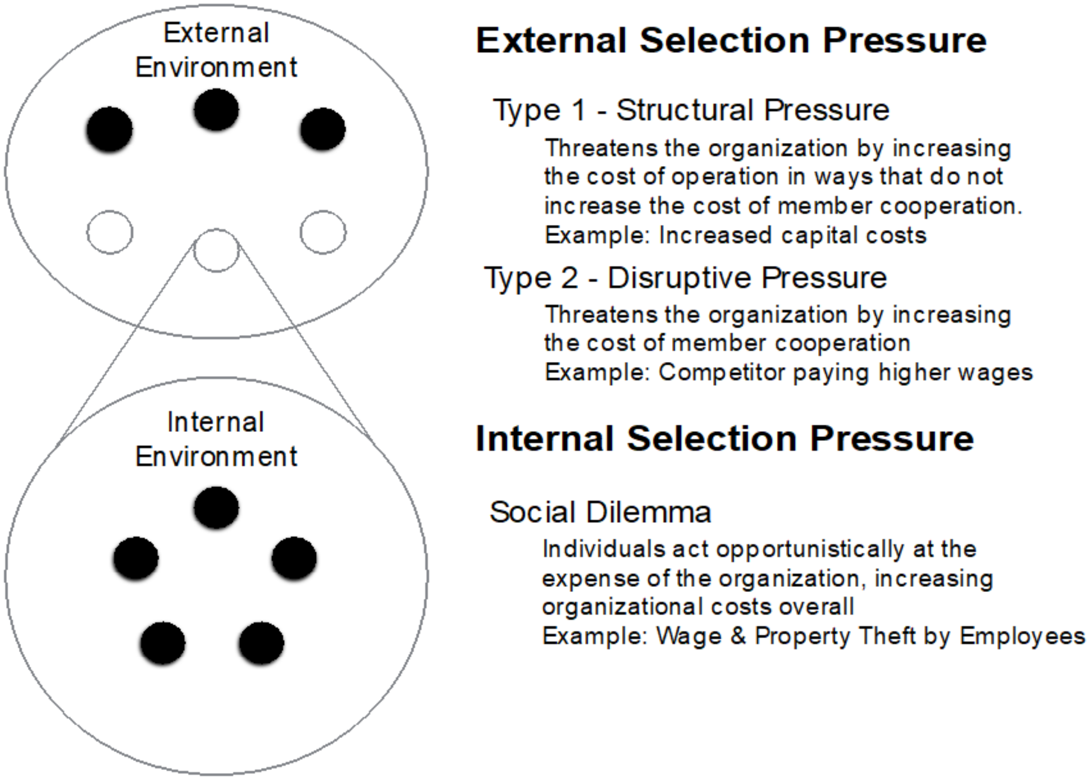

Figure 1.1 Selection pressure on groups (and organizations of groups) come from within and without. Internal selection pressure comes from the social dilemma present where individuals who act opportunistically can bring down the whole group. External selection pressure can group as a collective (Type 1 Structural Pressure), or exacerbate the social dilemma (Type 2 disruptive)

is apt to spread and bring down the organization if left unchecked. This could take the form of an employee taking excessive breaks on a work shift, a shift manager taking all the credit for the work of their subordinates, or nonconformance with a neighborhood association rule. Disruptive external selection pressure catalyzes social dilemmas by exacerbating or instigating them. An example at the group level could be a company policy that incentivizes budget surpluses by giving a portion of them to managers as a bonus, where those surpluses could go towards workplace improvements such as better office equipment or furniture. Structural external pressure is the most readily identified type when it comes to organizations, and it represents a selection for the products, ideas, and other group level traits associated with an organization.

This type of pressure could come in the form market pressures such as a rival product becoming preferable, social pressures on organizations to become more environmentally friendly, or regulatory pressures such as laws requiring safer working conditions. Figure 1 illustrates these pressures.

Actions by organizations and their internal processes can precipitate external selection pressures or alleviate them. A prominent example of this can be found in the working conditions of the meatpacking industry documented by Upton Sinclair in 1905 (Sinclair & Lee, 2003). Conditions within slaughterhouses and meat packing facilities were wholly unsanitary and resulted in human death and animal suffering. Upon this revelation, governmental inquiries by the American legislative and executive actions culminated in the Pure Food and Drug Act in 1906, which increased scrutiny on the meatpacking industry (Barkan, 1985). The actions of the meat packing industry in an environment that included journalists, like Sinclair, created structural selection pressure on their MLS2 institutional practices. A similar example is the passing of the Clean Air Act of 1970 and the Clean Water Act of 1972. Air and water pollution from powerplants and other industrial sources resulted in acid rain and adverse human health conditions, which was written about by journalists and caused a subsequent public outcry for regulation (Layzer, 2012, Chapter 2). This outcry ultimately lead congress to pass both environmental legislations and for President Nixon to sign them into law, thereby creating the environmental protection agency.

In both cases, institutional practices induced regulation and fundamentally altered the social environment in which they functioned. It could be argued that these are cases of “co-evolution” because the regulations evolved along with the industries they targeted. However, regulations induced by the Pure Food and Drug Act, the Clean Air Act, and the Clean Water Act had farther reached consequences than just the meat packing industry or the oil and gas industry, respectively. Regulations introduced by the Clean Food impacted extended to other parts of the agricultural sector such as the farms where cattle were raised (Barkan, 1985), and the Clean Air Act and Clean Water Act have had repercussions on all emerging industries that potentially cause water and air pollution (J. Currie & Walker, 2019). As niche construction posits that environmental alterations have ecological consequences beyond the species doing the alteration, the fallout from the MLS2 industry practices that resulted in these legislations are more fully characterized as cultural niche construction, rather than strictly co-evolution.

1.6.1.1 Products and services

The purpose that an organization is created around, be it a product, service, or some other function is also a product of cultural selection. After all, the original goal of studying organizations through a Darwinian lens was to gain a deeper understanding of why only some firms' products succeeded (Nelson & Winter, 1982; Hodgson & Knudsen, 2010). In the present formulation, the end products and services are organization level traits, and their methods of production are cultural traits at all three levels.

When speaking of firms, economists consider the goods and services they provide with the goal of providing profit to their shareholders, and the free exchange of these goods with consumers at the market price is what drives the economy (Bowles, 2006). Consumers mostly associate the goods provided with the firm that provides them, and not necessarily as a product of the individuals within that firm (Saad, 2007). For example, the sandwich provided by a fast-food restaurant is associated with the restaurant itself, not necessarily the sandwich maker, and the style of clothing provided by a retailer is associated with the designer and retailer, not with the worker in the textile factory. Consumers select the products they desire and provide an external structural selection pressure on organizations to change the quality of the products they create.

This principle applies to non-firm organizations as well. Non-Profit organizations such as charities or think-tanks bear the most resemblance to firms as they also put out information, provide services, and engage in advocacy that reflect the organizations as a whole (Powell & Steinberg, 2006). Other organizations, such as religious houses of worship have higher level traits that represent them as a church is represented by its sacred text, rituals, and the services it provides to its members (Wilson, 2002). All these examples can be considered organization level traits and are subject to cultural selection.

The methods for producing goods, services, and other organization level traits are created and interpreted as the result of selection at each level of the organization. Wilson (2019, pp. 201–208) citing Rother (2009) provides an account of how Toyota assembly lines are an excellent example of this process. Toyota plants are made up of many units that are overseen by managers, and workers are expected to produce inefficiencies and failures. When one of these failures occurs, workers call for help from a supervisor who makes a note of the failure and how it occurred so that the process can be improved going forward. Variation is produced by the individuals as they work and innovate on the process, and successful variations that lead to less failures are integrated into employee training, which exemplifies how an MLS1 process can result in an MLS2 group trait. Those MLS2 group traits that can affect other parts of the manufacturing process become codified in organization level manuals and training materials, which makes the MLS2 group trait an MLS2 organization trait as well. Successful innovations at the individual level become group level institutions, and the best of these group level institutions become organization level institutions.

A non-firm example of this process is the general conference of the United Methodist Church’s 2019 debate about condoning same-sex relationships in official church doctrine (Lovino, 2019). The United Methodist Church is an international religious organization with a set of governing documents that are changed by a democratic process during general conferences that include representatives from congregations all over the world. These documents are organization level traits held by all congregations, but they can be interpreted differently by every congregation, or member of each congregation, and may not be uniformly practiced. Individual beliefs and behaviors within congregations are discussed and debated, and the official policies of some individual churches adopt policies that go against organizational documents. These congregations then debate with other congregations in regional conferences, and eventually general conferences where official church policy is decided (J. R. Wood & Bloch, 1995). In this case, the official church documents constitute MLS2 organization level traits that are changed (or sustained) by the policies of congregations and regional conferences (MLS2 group level traits), which are in turn shaped by the beliefs and behaviors of their congregants (MLS1 individual level traits).

1.6.2 Organizational Ontogeny

In biology, ontogeny is the study of how organisms develop over their lifecycle. The predictions made by cultural evolution and multilevel selection allow the development of an ontogeny of organizations as well. In brief, organizations should arise when individuals join through cooperation, homogenize, or converge their goals through learning and norms, and develop institutions to reinforce prosociality.

1.6.2.1 Cooperation

Humans are exceptional at cooperating and laboratory experiments suggest that this cooperation is instinctual and substantial (Ortona, 2012; Rand, 2016). In experiments in group settings, individuals often contribute half or more of their endowments in early rounds (Fehr & Fischbacher, 2005; Rand et al., 2009; Rand, 2016). Consequently, young groups should see substantial cooperation from their founding members as well as subsequent early joiners. They will want to complete their tasks and work with others in their cohort to come up with ideas about how the group should function. In a startup business and non-profits alike, initial employees and owners should work towards the betterment of the company and will accept costs in various forms including working overtime or accepting little compensation.

This cooperation, while considerable, is ultimately unsustainable. Studies that show high initial cooperation also find that this cooperation breaks down over time without a stabilizing force (Fehr & Fischbacher, 2005; Rand et al., 2009), especially if behavior is not observable (Rand, Yoeli, et al., 2014). The observability of one’s actions invokes innate reputational concerns as well as social learning, which leads to the development of informal norms that homogenize individual goals.

1.6.2.2 Norms and Learning

Social norms often function as precursors to more formal institutions and act with a similar mechanism. Behavior adopted by the majority of group members becomes weakly enforced through mechanisms such as gossip, and this serves to keep individuals invested in group level outcomes (Bowles & Gintis, 2009). The observability of behavior is key when making social norms effective, so organizations that take advantage of this will be more likely to develop a culture centered on prosociality and group-oriented goals. These norms can be simple, such as maintaining a clean workstation in food service and offices, contributing ample effort to group goals, and showing up on time to organizational functions such as religious services or office meetings.

In addition to norms, individuals may socially learn behaviors and attitudes that can benefit the group and themselves. Smaller organizations and teams can take advantage of prestige and conformity bias to teach new and existing members how to function for the betterment of an organization, and practices will often be learned without the need for formal teaching (Cordes et al., 2008). Organizations that take care to cultivate this kind of an atmosphere of learning will be better able to belay the early effects of conflicts of interest and social dilemmas.

1.6.2.3 Formalized Institutions

When groups grow large enough, norms and learning may not be sufficient to sustain cooperation, so organizations can formalize norms and practices by making them into rules and other institutions. The advantage of institutions is that mandating behavior through more severe sanctions causes the costs of free-riding behavior to become non-zero while lowering the cost of cooperation. In addition, individuals who have a say in instituting rules cooperate much more than those who have rules imposed on them (Dal Bó et al., 2010), so democratic collective choice decisions about institutions enhance their efficacy (Wilson et al., 2013). The final stage of development for successful organizations should then see the formalization of norms and practices through institutions that govern how conflicts of interest are resolved.

1.7 Conclusion

This chapter has reinterpreted organizational evolution considering scholarship on cultural evolution, multilevel selection, and cultural niche construction. In doing so, organizations are understood as complex adaptive systems that are threatened not only by markets, regulations, and other external stressors, but by internal social dilemmas that must be overcome. The model of organizations and organizational ontogeny presents a blueprint for the next three chapters that investigate cooperation, social learning of norms and preferences, and the development of institutions in an empirical setting.

CHAPTER 2.

RECIPROCITY SUPPORTS COOPERATION IN REAL WORLD ECONOMIC INTERACTIONS

2.1 Introduction

Social organisms face a variety of social dilemmas where the interests of the group are at odds with their own (Boehm, 2012; Olson, 1965; Sober & Wilson, 1999), and these circumstances often require individual cooperation to overcome the incentive to freeride off the efforts of others (Fischbacher et al., 2001; Gintis, 2009; Fischbacher & Gächter, 2010). Studies with theoretical models, laboratory experiments, and field experiments reveal that cooperation is ephemeral without mechanisms that reduce cheating such as reciprocity (Axelrod & Hamilton, 1981; Nowak, 2006; Nowak & Sigmund, 2005a; Ohtsuki et al., 2006; Rand, Nowak, et al., 2014; Trivers, 1971). Though these findings are robust and replicate across cultural contexts (Henrich et al., 2001; Kocher et al., 2008; Apicella et al., 2012; Henrich & Muthukrishna, 2021), observations of the supporting mechanisms in non-experimental contexts is lacking, leaving current findings circumscribed (Frey, 2017, 2019). Here, we present a novel study of cooperation in organizational networks using observational data to test the validity of experimental and theoretical findings.

Cooperation is defined as giving assistance to others (Henrich & Muthukrishna, 2021), and economic and evolutionary game theory have established that reciprocity, or giving the same as what has been given to one's self, can sustain cooperative behavior across many social dilemmas (Pfeiffer et al., 2005). For example, in the case of repeated interactions between two individuals such as the iterated prisoners' dilemma, tit-for-tat direct reciprocity, i.e. doing as one's partner did in the previous round, is highly successful in sustaining cooperation (Axelrod & Hamilton, 1981; Roberts, 2008). In another version of the iterated prisoners' dilemmas where partnerships change each round, a pay-it-forward strategy of indirect reciprocity allows cooperation to persist when players can view their current partner’s previous decisions and reputational concerns emerge (Nowak & Sigmund, 2005a; Roberts, 2008).

In public goods games where individuals interact as a group, reciprocity takes a more general form of “conditional cooperation” where one gives the same as the rest of the group does on average (Fischbacher et al., 2001). However, free-riders in public goods experiments can drag the average donation down, causing conditional cooperation to decline over time (Fischbacher et al., 2001). Under such circumstances, cooperative behavior needs additional supporting mechanisms such as interpersonal reward or punishment (Fischbacher & Gächter, 2010; Rand et al., 2009). Further research on conditional cooperation suggests that individuals exhibit patterns of behavior that can be classified into three broad types: conditional cooperators (who cooperate when everyone else in the group cooperates), altruists (who always cooperate), and free-riders (who always defect) (Andreozzi et al., 2020; Fischbacher et al., 2001; Frey, 2017; Volk et al., 2012). These types are rough descriptions of individuals’ strategy profiles throughout the entire game (Fischbacher et al., 2001) and they have been robustly verified through replication in in-person (Andreozzi et al., 2020; Deversi et al., 2020; Kocher et al., 2008) and online experiments (Frey, 2017, 2019) Furthermore, individuals’ types appear to be consistent when they participate in multiple experiments across time (Andreozzi et al., 2020; Volk et al., 2012) and these types are present across cultural contexts (Frey, 2017; Kocher et al., 2008)

Despite this abundant evidence that cooperation can be sustained in experimental situations, naturalistic examples that corroborate these results are scarce. Furthermore, payoffs in real world situations are not always evident, as utility from social preferences or warm glow effects are not readily observable (Wilson, 2015). As such, questions on how human cooperation arises in everyday affairs remain unanswered. For example: How common is cooperation in structured organizational settings? How often does reciprocity support cooperation in economic interactions? Is the variation and durability of behavioral types common in cooperation experiments also perceptible in naturalistic, non-contrived settings?

The primary complication that arises when validating these results in real world settings is that testing conditions cannot be as controlled as in experimental settings (Frey, 2017, 2019), which makes differentiating between altruistic, cooperative, and selfish actions more complicated (Wilson, 2015). However, behaviors like reciprocity have discernable patterns when individual actions are observable, particularly in settings that experiments mimic. Furthermore, reciprocal strategies evolved specifically to support cooperative behavior (Roberts, 2008; Rothschild, 2009; Trivers, 1971), implying that observations of reciprocal behavior signals a simultaneous observation of cooperation to some degree. Measuring cooperation in the real world therefor entails detecting processes that sustain it and comparing them to patterns found in a laboratory or theoretical setting (Frey, 2017).

Here, we investigate whether patterns of human cooperation from theory and experiments extend to real-world contexts by examining patterns of reciprocity in networks of individual economic interactions found in consumer food clubs. A novel dataset of bulk purchasing interactions was analyzed to reveal individuals extending mutual aid to ensure that their needs are met and that the club continues to function. Patterns of reciprocity are identifiable in this data and specific club member types are derived that validate experimental findings.

2.2 Food Clubs

Consumer food clubs are small, semi-formal organizations, ranging in size from 5-100 members, that arrange food purchases from large distributers (Tremblay, 2017). Food clubs are miniature purchasing co-operatives (Little et al., 2010) as they are formed to gain access to specialty goods not available through local stores and to take advantage of wholesale bulk purchasing. Clubs place orders on a weekly or monthly basis from a common catalog containing individual items that can be purchased in any quantity, and bulk items that are generally too large for single buyers.

As co-operative organizations, food buying clubs rely on cooperation much more than a typical hierarchical organization. Co-operatives are defined by their democratic nature and member ownership scheme, and rely on cooperation and institutions to overcome conflicts of interest that may arise (Waring et al., 2021). While formal co-operative grocery stores can rely on democratically determined rules and regulations to temper social dilemmas, food buying clubs are incipient cooperatives that often lack institutions initially, making reciprocity essential for early club success (Hupper, 2019).

The core function of these clubs is to coordinate the shared purchasing of bulk food items, which represent a social dilemma. While they provide the largest price discount, it is not guaranteed that there will be sufficient demand. When there is not enough demand, members solicit help from others to ‘buy in’. This case of shared purchasing relies on cooperation between member: those who support the purchase may do so in the hope of reciprocal support in the future and not because of a preference for the item itself, an act that would constitute cooperation or altruism. This opens cooperation up to free riding, i.e. to members who frequently solicit help but do not reciprocate. Because clubs may not enforce reciprocation, assistance may ultimately constitute an altruistic donation.

The bulk purchasing dilemma resembles a threshold public good with refund (TPGR).(Cadsby & Maynes, 1999; Cartwright & Stepanova, 2015) If enough members pledge to buy a portion, the threshold is reached and the item can be purchased. If there is not enough interest, or willingness, the threshold is not reached, and no purchase is made. The payoff structure differs from the classic TPGR, where players receive a uniform payout, as only members participating in a successful bulk purchase receive a benefit of a discounted unit price, and the total savings differs depending on how much a member pledges. Additionally, TPGR interactions are dispersed across a network of purchasing interactions, so co-purchasing partners can change from item to item. As such, food clubs present an ideal environment to study how cooperation operates when individual needs and desires differ, payoffs are not clearly defined, individual outcomes depend on the actions of others, and when repeated interactions can occur with many individuals, as is the case with many organizational operations.

Research shows that food clubs are explicitly reliant on cooperation (Hupper, 2019) Research on this sample also shows that cooperation among club members is extremely high when measured with behavioral games. Within-club cooperation was measured using a dictator game (DG) and a public goods game (PGG), where club members contributed unusually large fractions of their endowment (DG: 58%, PGG: 71%) (Hupper, 2019). These contribution levels substantially exceed those reported in the literature for equivalent games. The next largest mean contributions are DG: 48% in Paciotti et al.,(2011) and PGG: 57% Apicella et al.(2012) and 58% Henrich et al. (2001). Qualitative responses of our sample reported in Hupper (2019) corroborate an abundance of cooperation among active clubs, and stress when cooperation is not sufficient. Coordinators of some clubs mentioned that "Members need to contribute more," while in other clubs, coordinators said "For the most part members carry their weight," or "Everybody steps up."

2.3 Methods

2.3.1 Dataset

Our dataset consists of a set of purchasing records from two different software platforms used by food clubs to coordinate purchases. Platform 1 provided data for 30 clubs from late 2011 to early 2017, and platform 2 provided data for 19 clubs from early 2010 to early 2019, for a total of 107 club years. For our analysis, we remove all purchases of individual items as well as clubs with no bulk purchases. The final combined dataset contained 35 clubs with 1,528 individuals across 1,341 orders for a total of 10,261 individual purchasing decisions.

The clubs in our sample hail from WEIRD (Henrich et al., 2010) countries: 2 from Australia, 1 from Canada and the rest were from the United States, mostly New England. One software provider gave us access to their whole catalog of groups, which included the 3 from outside of the United States, and the other only gave us access to their New England clubs. The sample includes defunct and still functioning clubs (as of the end of the data period), where the average lifespan of the defunct clubs was 3.16 years (2.16 SD) and 28.7 orders (21.3 SD), and the censored average lifespan for continuing clubs is 3.24 years (1.38SD) and 46.9 orders (27.9 SD). The average number of members participating in an order is 7.96 for defunct clubs (6.96 SD) and 12.7 for ongoing (9.41 SD). Additionally, the average number of co-purchased items in each order is 3.29 for defunct clubs (4.82 SD) and 11.2 for ongoing clubs (28.9), inferring that clubs that purchase more splitable items tend to operate longer (see supplementary materials table 1 for club level summary statistics).

2.3.2 Co-purchasing network construction

Networks were generated and analyzed using R (Bates et al., 2021; Csardi & Nepusz, 2018; R Core Team, 2020; Song et al., 2019; Wickham et al., 2017, 2018). To detect reciprocity in co-purchases, we construct a bipartite purchasing network for each order, connecting members to the items that they purchased (Figure 1). Subsequently, we project the bipartite network as a unipartite co-purchasing network connecting members based on co-purchases, ensuring that multiple co-purchased items result in multiple edges for a dyad. Directionality is then assigned to each edge according to the ordinal volume of a bulk purchase. Edges point to the member who purchased more and are split into two directed edges pointing at both members when equal shares are purchased. This assumes that the member who purchased more also desired or required more of the item, so individuals who purchase less stand to lose less if the bulk purchase is not completed, and thus are assisting those who purchase more. This method is corroborated by the high negative correlation between the order in which members pledge to purchase shares of a bulk purchase), and the amount they buy (Spearman's ρ = -.65, p < .001; data only available from one of the software platforms) In other words, individuals who join a bulk purchase later buy smaller shares.

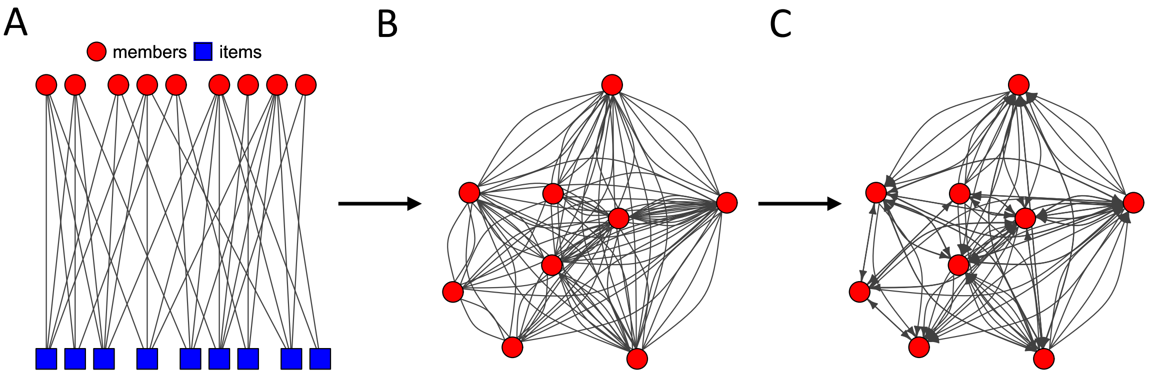

Figure 2.1 Schematic representation of creating co-purchasing networks. Our raw data contains records of bulk purchases for each order, which we use to create (a) bipartite network between members (red circles) and food items (blue squares), which can be projected as a (b) co-purchasing network between members that purchased the same product(s). We then assign directionality (c) according to each individuals' relative share of the co-purchase(s). Finally, networks can be combined across multiple orders by linking members (not shown).

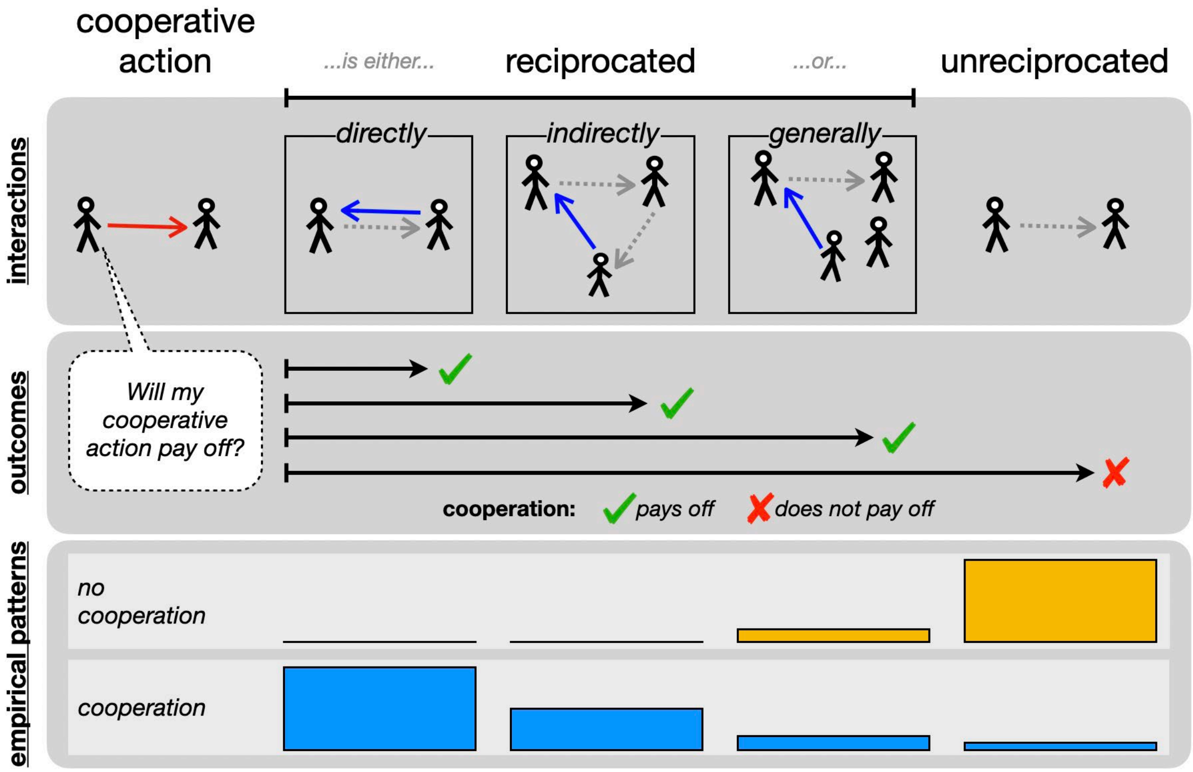

Figure 2.2 Conceptual model of cooperation in food buying clubs. Cooperative assistance in food buying clubs is beneficial to the cooperator if it is reciprocated. Assisting other members with their purchases can be reciprocated directly within dyads, indirectly in a cycle, or generally in a chain. Reciprocal patterns, especially those with abundant cycles, give the most evidence that cooperation is present.

Although cooperative by definition, co-purchasing does not constitute an altruistic action per se (Figure 2). In fact, it is often not possible to define an action as altruistic at a given moment in time, even from the perspective of the actor (Wilson, 2015). At any moment in time, t, an individual might be expecting a cooperative act to be reciprocated. Indeed, the act may never be intended as altruistic. If it is reciprocated, the individual will think of it as successful cooperation through reciprocity. If it is never reciprocated, the individual may come to consider it as an altruistic outlay. Club members often do not know how to consider a contribution to a co-purchasing effort until long afterwards. Nevertheless, the above method allows us to identify patterns of economic reciprocity as a proxy of the degree of group cooperation.

2.3.3 Identifying reciprocity

We define reciprocity as the relationship between a member's total in-degree, k_i^{in}, (number of times they were helped) and total out-degree k_i^{out} (number of times they have helped). Because of the way we analyze repeated co-purchasing situations, we expect to see some degree of reciprocity. In fact, there is evidence that members of these clubs are aware that there is reciprocity and cooperation involved in purchasing, but many members report dissatisfaction and inequality in purchasing assistance (Hupper, 2017, 2019). We therefore investigate how much reciprocity we find, and how much variation there is across clubs. Significant variation in the extent of reciprocity would suggest that these clubs are solving their social dilemma in different ways, or not at all.

We employ a network-specific approach to organize patterns of reciprocity into separate categories based upon social and temporal proximity. For each order, we denoted individuals' outgoing edges as reciprocal if they have a matching in-edge. For example, suppose two individuals, *i* and *j*, co-purchase shares of bulk purchases A and B, whereby *i* purchases a larger share of A than *j*, and j purchases a larger share of B than *i*. In this case these two co-purchases are reciprocal in terms of relative share. This method allows us to categorize edges as either reciprocated or unreciprocated.

We differentiate reciprocity as direct or indirect, and separate reciprocal behavior within the same order and between different orders. When calculating the different types of reciprocity, we assume that social and temporal closeness are salient to economic transactions and should be respected when interpreting empirical patterns. This is in line with prior research findings that direct reciprocity is more consequential in sustaining cooperation when indirect reciprocity is also present.(Roberts, 2008) We therefore count direct before indirect reciprocity and reciprocity within orders before across orders.

As the purchasing process takes place over many days, members may reciprocate within an order. *Within-order direct reciprocity* (WDR) in each order *t* is the number of mutually extended edges within each dyad. This can be found by taking the minimum dyadic out-degree between each partner *i* and *j* of a dyad. For example, if member *i* assists member *j* with 4 bulk purchases, and member j assists member i with 3 bulk purchases, then WDR = 3 for *i* and *j,* and 6 for the dyad (*i* + *j*). We then remove these matched edges from the network to prevent double counting when assessing *between-order direct reciprocity* (BDR)*,* which is calculated by matching remaining mutually extended edges across many orders for each dyad (i.e., matched edges from order t and t+1, t+2, etc.). Matched edges on each dyad are recorded and removed from the networks at each time step so that they cannot be double counted when assessing indirect reciprocity.

Once direct reciprocity is accounted for, we look, again, at individual orders to tally *within-order indirect reciprocity* (WIR). Here, we match any non-dyadic in- and out- edges per individual. For an individual *i* at time *t* this is calculated as the minimum of their in- and out-degree. As with direct reciprocity, these matched edges are removed from each order network to calculate *between-order indirect reciprocity* (BIR) by matching edges of orders at time t and t+1 with the remaining edges on each order's network. These matched edges are again removed from the network.

	Direct Reciprocity	**Indirect Reciprocity**
Within order	$DWR_{i,j,t} = min\ (k_{i,j}^{out}, k_{j,i}^{out})$	$IWR_{i,t} = min\left(k_{i,t}^{out}, k_{i,t}^{in}\right)$
Between orders	$DBR_{i,j,t} = min\left(\sum_{t}^{t+1} k_{i,j,t}^{out}, \sum_{t}^{t+1} k_{j,i,t}^{out}\right)$	$IBR_{i,t} = min\left(\sum_{t}^{t+1} k_{i,t}^{out}, \sum_{t}^{t+1} k_{i,t}^{in}\right)$

Table 2.1 Reciprocity is calculated by counting paired edges across co-purchasing networks. Social and temporal proximity is given precedence in counting paired edges, so that more proximate interactions are removed before counting more distant interactions, producing the following order: DWR, DBR, IWR, IBR. Finally, remaining unmatched co-purchasing edges are counted as unreciprocated, UR.

Edges that remain on the network after these four calculations (Table 1) are recorded as unreciprocated. However, these unreciprocated edges have the potential to become reciprocated in future orders, so these counts should be treated as simultaneously unreciprocated and potentially reciprocated.

Finally, we estimate the global average rate of reciprocity to compare with laboratory studies by regressing individuals total k_i^{out} on k_i^{in} across orders, accounting for variation across clubs using random effects:

$$\begin{aligned} k_{ic}^{out} &= \alpha + \beta k_{ic}^{in} + \epsilon_{ic} \\ \alpha &= \bar{\alpha} + \alpha_c \end{aligned} \tag{2.1}$$

In this model, α is a random intercept term which is the sum of a global mean $\bar{\alpha}$ and a club specific adjustment α_c,which allows us to account for club level variation such as unobserved socio-demographics, and ϵ_{ic} is an error term. The β parameter is interpretable as the global average percentage of in-degrees that are reciprocated across all clubs in our sample, or the average number of out-degrees extended per in-degree. As such, it is comparable to coefficients from other studies that model average public goods donations as a function average group donation (Cadsby & Maynes, 1999; Croson et al., 2005; K. M. Smith et al., 2018).

2.3.4 Altruistic effort

To improve inference regarding the prevalence of truly altruistic cooperation, we also develop a highly restrictive set of criteria to identify economic interactions that are most likely to be altruistic. The co-purchases that are most likely driven by altruism are those in which one member helps another member to purchase an item which is outside of their revealed preference set. In our dataset, we identify such cases as those in which a member *i* purchases a share of a bulk item multiple times in different orders, and member *j* never buys that item across all orders except for a single interaction in which they bought a smaller portion of the item than *i*. This pattern would suggest that *i* prefers the item, that *j* does not, even after purchasing some of it. We term this pattern *singular assistance. Singular assistance reciprocity* occurs if *i* additionally assists *j* in the same way in a later order. We repeat the model given by equation (1) to assess singular assistance reciprocity.

2.3.5 Temporal variability of reciprocity

Our accounting of each type of reciprocal edges allows us to compute their proportions over time. With this information we can look for variability in the patterns of reciprocity within groups, as well as measure their general temporal stability. We use the coefficient of variation, c_v as a simple measure of variability.

2.3.6 Shared purchase ratio and behavioral types

We use individuals' behavior across all orders to categorize them into different behavioral types. Analogous to the general behavioral types identified in laboratory circumstances (Andreozzi et al., 2020; Fehr

& Fischbacher, 2005; Frey, 2017). Within each order, we calculate a member's balance of in- and out-edges to identify how reciprocal they are in that order across all dyads. The *shared purchase ratio* (SPR) for order *t* is calculated as the log of the ratio between their out-degrees and in-degrees:

$$SPR_{it} = \ln\left(\frac{1 + k_{it}^{out}}{1 + k_{it}^{in}}\right) \tag{2.2}$$

Taking the logarithm transforms the regular ratio into an easily interpretable magnitude: A positive SPR indicates that an individual helps more than they receive, a negative SPR indicates they received more help than they gave, and a SPR of zero indicates perfect reciprocity.

To account for the fact that our measurement of ongoing reciprocity assistance is necessarily incomplete, we categorize individuals using a buffer. As individuals could give *almost* as much assistance as they received (or vice versa) and still be considered reciprocal (Molm, 2010; Trivers, 1971), a clustering approach was used to allow for a data-driven flexibility in classification. For each club, we pooled members' SPRs across a club's orders and divide similar SPRs into groups using a univariate k-means clustering algorithm. This categorizes each individual's actions per order into one of three types based on which cluster it is assigned to: helpers (a priori designated cluster centered at less than zero, i.e. $k^{out} > k^{in}$), reciprocators (a priori cluster centered at zero, i.e. $k^{out} = k^{in}$), and beneficiaries (a priori cluster above zero, i.e. $k^{out} < k^{in}$). Note that these categories are not altruists, free-riders, or conditional cooperators, but are constructed in parallel with those categories. While k-means clustering algorithms traditionally optimize all cluster centers (Steinley, 2006), we modified the algorithm by fixing the reciprocator center at zero, or perfect reciprocity (see supplemental code). In the unlikely event that an SPR fell equidistant between the reciprocator center and either of the other centers, we assigned it to either the beneficiary or helper cluster to maintain conservative estimates.

Additionally we analyze the change in behavioral type through time by calculating their transition probabilities using a Markov chain (Spedicato et al., 2021). We assign each member a most common type based on which has the largest probability in the stationary distribution of their transition matrix. We report the member type assignments for individuals in each club, as well as a global level average transition matrix, which gives us a measurement of the stability of each role across clubs and which is the predominate behavioral type (see supplemental materials Table 3 for club specific cluster centers and Table 4 for counts of member types).

2.4 Results

We find that club members are highly reciprocal in their purchasing patterns overall. The large majority (60%) of reciprocity is direct and occurs within orders (DWR). We also find that reciprocators are the most common and the most stable behavioral type.

2.4.1 Reciprocity types

Globally, members reciprocate 88% of the co-purchasing assistance they receive ($\beta = .88$, $p < 0.001$). This can be considered something of an upper bound on cooperative reciprocation. Using the more restrictive *singular assistance* measure we find that individuals reciprocate 46% of co-purchasing help they receive on average ($\beta = .46$, $p < 0.001$). As a measure of altruistic cooperation reciprocated, this is something of a lower bound estimate. See supplemental materials Table 2 for full model results. Across all edge types, we observe within-order direct reciprocity as the most frequent form with 60% of the average club's edges receiving a WDR classification (Figure 2); BDR a far second, followed by WIR and BIR (see supplemental materials Table 1 for percentages of each).

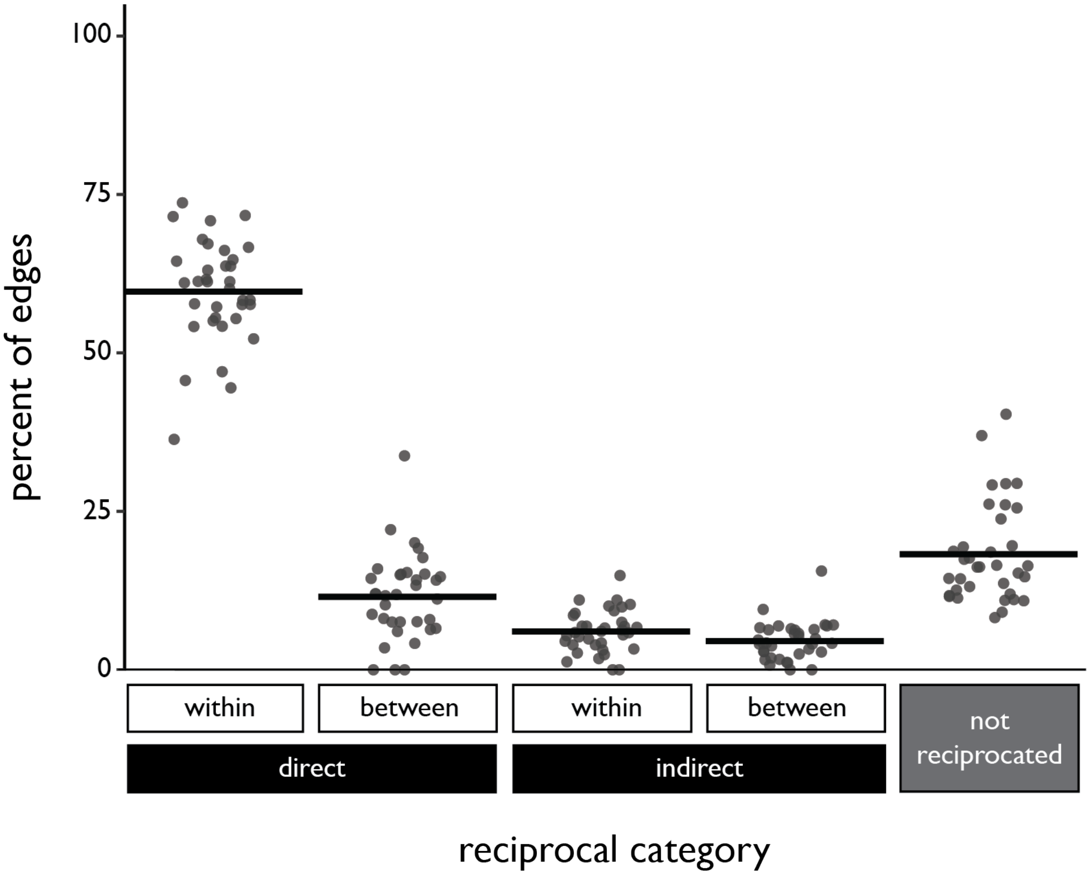

Figure 2.3 More than half of all bulk purchasing is reciprocated in other bulk items between pairs. Frequency of reciprocal co-purchasing interactions classified by edge type across 35 separate clubs reveals a consistent pattern.

2.4.2 Temporal variation

To understand how stable patterns of reciprocal economic behavior are over time, we quantify temporal variation. Since the time between orders vary within and between clubs, a traditional time-series stability analysis would produce biased estimates of stability (Scholes & Williams, 1977). Instead, we quantify stability as the temporal variation in each reciprocity category represented by its coefficient of variation (Figure 3). We find that the stability of each type of reciprocity parallels the pattern of prevalence. For example, WDR has the least temporal variation, direct reciprocity varies less over time than indirect reciprocity and within-order reciprocation is less variable than reciprocity between orders.

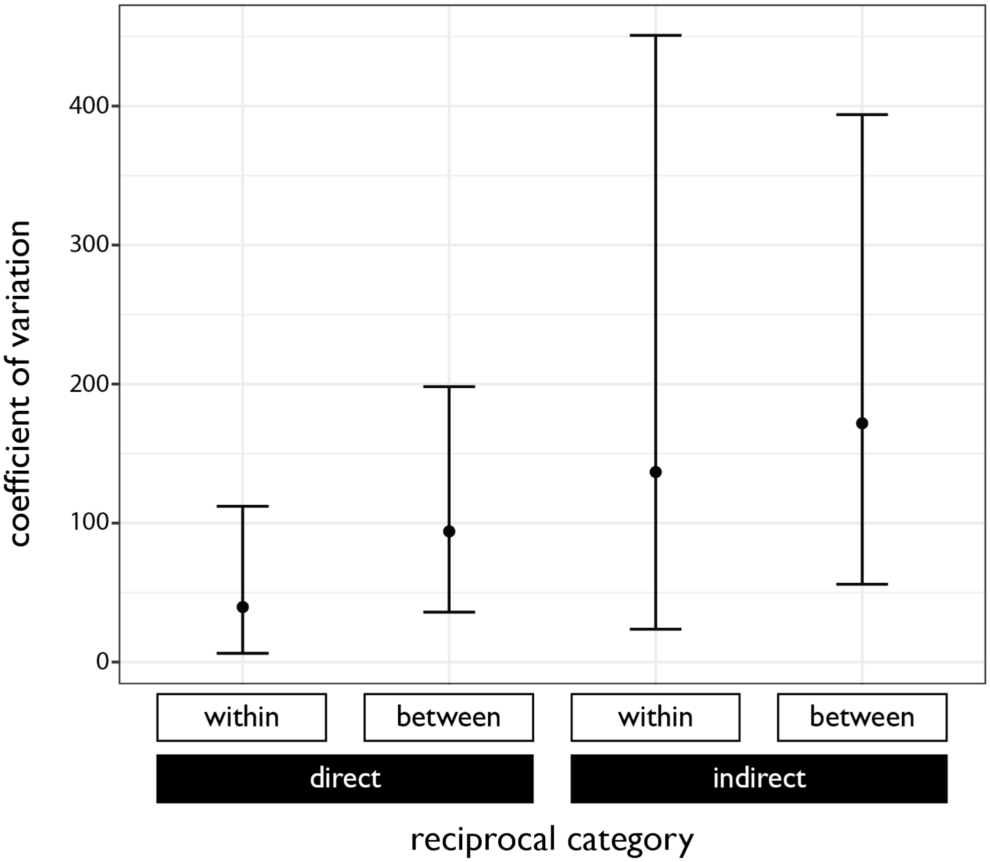

Figure 2.4 Mean and range of coefficients of variation for each reciprocal category. Points represent the average club level c_v for reciprocal category and line ends represent the minimum and maximum c_v.

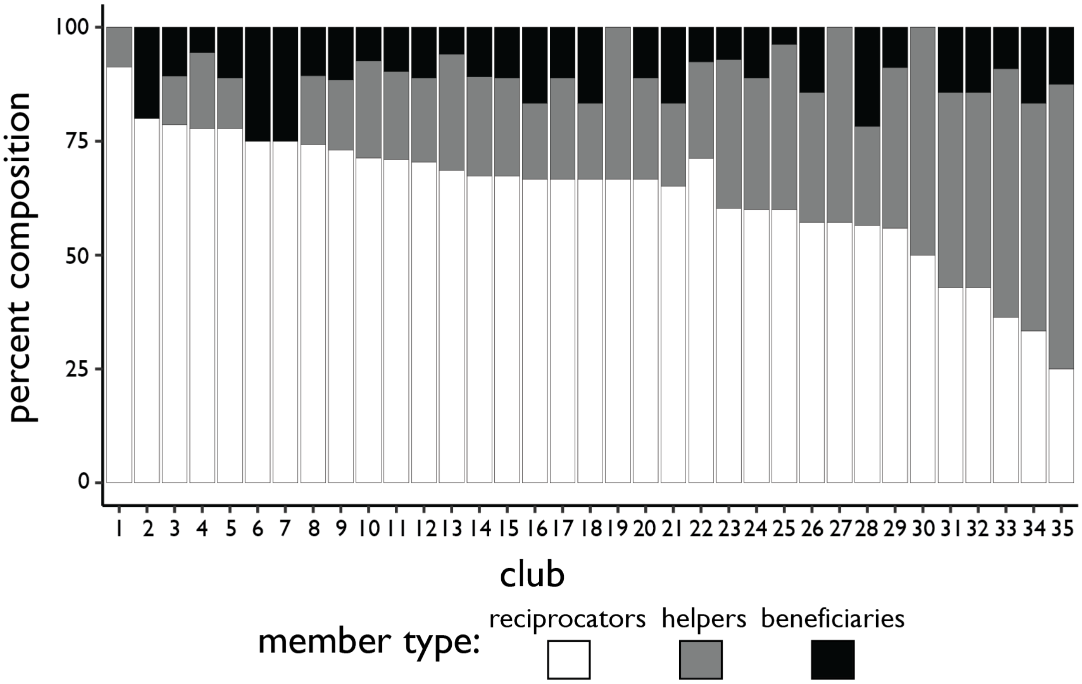

Figure 2.5 **Reciprocators are the most abundant member type.** Arranged in descending order of proportion of reciprocators, this stacked bar graph shows the proportion of each member type within each club. Reciprocators are the most abundant type, followed by helpers and beneficiaries.

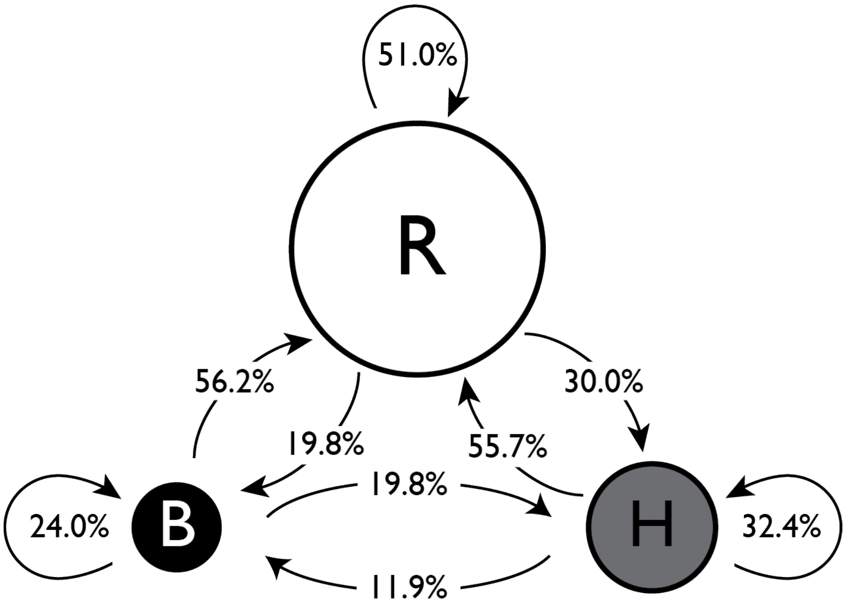

Figure 2.6 Global mean Markov transition probabilities. Reciprocator role is the average absorbing state, with a greater than 50% chance for each role to be a reciprocator in the next time stamp. Circle size is proportional to the sum of all incoming transition probabilities.

2.4.3 Behavioral types

68.5% of club members were classified as reciprocators by k-means clustering. Across all clubs, reciprocators are the most abundant member type, with an average proportion of 65.3%, followed by helpers (29.4%) and beneficiaries (12.4%) (Figure 4). Reciprocator is also the absorbing state; the global average transition probability for staying reciprocator in the next order is 51.0%, and the global average transition probability for becoming a reciprocator from helper and beneficiary is 55.7% and 56.2% respectively. Figure 5 shows the global average transition probability matrix, and Figure 3 shows the member type composition visualized on a global order network and average transition probabilities for 3 clubs, as well as the member type composition of each club in a stacked bar graph. For a full list of the average transition probabilities, SPR cluster centers, and member type network, see supplemental materials.

2.5 Discussion

Our analysis of the observed patterns of economic cooperation in small food clubs confirms multiple findings from cooperation science which have previously relied on theoretical and experimental methods. Food buying clubs generate social and economic value in part by solving a social dilemma (purchasing goods in bulk) through the maintenance of economic cooperation. We find high levels of reciprocity, which mostly consists of short-term, direct reciprocity. We also find stable behavioral types as well as significant group-level variation.

High levels of reciprocity. The degree of economic reciprocity exhibited in these clubs is, to our knowledge, unprecedented in the empirical literature, and it is supported by multiple pieces of evidence. These include a high mean level of reciprocity across clubs, the existence of multiple types of reciprocity (direct and indirect, short-term and longer-term), and the predominance of reciprocator behavioral types within clubs. Comparisons can be made with experimental studies of conditional cooperation which regress individual donations on the mean group donation with the individual excluded (Croson et al., 2005). Following this approach, we examined the global regression coefficient β, which indicate the average amount an individual reciprocates in response to a unit increase in the average ‘donation’. The in-degree of each individual can be viewed as the total donations to that individual from the entire group, and thus akin to a public goods payoff. Viewing the in-degrees in this way allows us to approximate a comparison to public good studies in which individual donation amount is statistically explained by average group donation. In public goods games with hunter-gatherers, Smith et al.,(K. M. Smith et al., 2018) found that people donated 55% of what their group donated to them. In anonymous public goods games from a WEIRD population sample, Croson et al. (2005) found that people gave an average of 40% of the group donation. Here, we find that club members reciprocated 88% of the co-purchasing assistance they receive from their clubs. This exceptionally high value of general assistance is partly explained by the fact that members are part of an organized group with clear, narrow goals that substantially overlap one another, that is, an organization. We would presume that members of these clubs are a non-random and self-selected group and may be more cooperative and reciprocal than the population. Future research is needed to determine how much cooperation differs in organizational contexts that require less cooperation.

The differences between the structure of buying clubs and experimental public goods studies are instructive. Individuals in experimental public goods games receive tangible benefits in monetary reward, as they are given a uniform payoff share plus the amount they kept during donation. In food clubs, individuals do not receive a uniform share payoff, but gain a discount on the goods they purchased in bulk and access to a greater selection of goods that may not be found in traditional market settings (i.e., the grocery store) by being in the club. This reveals that in this real-world setting, individuals act reciprocally even though the benefits of doing so are not necessarily monetary (access to the club) and are heterogeneous across individuals (as discounts are different depending on what items are bought).

However, one might argue that buying clubs act to merely *coordinate* bulk purchases without relying on economic altruism. To explore this possibility, we repeated the analysis with a maximally restrictive definition of cooperative edges, *singular assistance,* and found that club members reciprocate 46% of these edges that they received in co-purchasing, closely matching prior experimental findings (Croson et al., 2005; K. M. Smith et al., 2018). Thus, we found patterns of co-purchasing reciprocity equal to or greater than other studies, suggesting that these groups may likewise be expressing cooperation equal to or greater than other groups who are solving an experimental public good dilemma. Furthermore, the β parameter estimates for both models align with the average donations of economic games played with these groups, at least to some extent (β = .88, PGG mean donation = 71%; *singular assistance* β = .46, DG mean donation = 58%). Such alignment could imply that our singular assistant β truly measures some form of reciprocal interpersonal altruism, while our general β represents individuals cooperating *and* coordinating to support the club. This evidence of greater than expected β estimates and their alignment with experimental measures of cooperation implies that much of the reciprocity we measure is cooperative in nature, rather than just coordinative.

Predominance of rapid, direct reciprocity. Direct reciprocity is generally thought to be more effective at supporting cooperation than indirect reciprocity (Boyd & Richerson, 1989; Nowak & Sigmund, 2005b). Our findings support this assertion, as we found that most reciprocity occurred between pairs of individuals and on a short time scale (~1–4 weeks). 72% of all reciprocal interactions and 60% of all co-purchasing was attributable to within-order direct reciprocity. This highlights the importance of co-purchasing as the core function of buying clubs and the role of one-to-one reciprocity in this process. More socially and temporally distant forms of reciprocity also exist in our dataset, which itself is notable. This suggests that co-purchasing reciprocity supports cooperative and altruistic co-purchasing behavior, at least in the short term, and club members resolve that cooperation as immediately and directly as possible. If buying clubs did not require cooperation or altruism between members, we would expect less reciprocity of all types, and especially less direct reciprocity.

Our results also show how dyadic reciprocal interactions can undergird the cooperative success of larger groups. This is reminiscent of research in which experimental subjects alternated between public goods games, and dyadic prisoners dilemmas (Rand et al., 2009). The study found that cooperators who were rewarded with cooperation (and free riders who were punished via defection) in the prisoner's dilemma rounds tended to cooperate more in the public goods rounds. This same dynamic could be unfolding in the buying clubs we study, as members who aid in buying larger items that require extra individuals could be rewarded with assistance on smaller items that they initiate or could be punished for not doing so by having their items go unfulfilled. However, the current dataset does not allow for such an analysis.

Consistent behavioral types. Individuals varied significantly in their reciprocal behavior, and those differences were stable across time. 71.3% of all individuals were classified as consistent reciprocators. This measure is higher than other studies that have searched for player types in public goods experiments. For example, Frey (2017) found that 39% of individuals playing an online video game with a threshold public goods mechanism could be classified as conditional cooperators. Using the same method of positive correlations, Fischbacher et al. (2001) found a proportion of 50% of conditional cooperators in a sample of students from a WEIRD population. The similarity of our findings supports the supposition that humans may vary in their innate levels of prosociality.

Our results also reveal how our member types emerge from the roles members occupy over time. A single order in our data is an example of what laboratory experiments emulate, as it contains multiple public goods interactions; the role members take in a given order are thus akin to the behavioral type in a single experimental period (Fischbacher et al., 2001; Kocher et al., 2008). While other studies have studied the stability of behavioral types across time through experimentation (Andreozzi et al., 2020; Kocher et al., 2008), our results show that not only are all three types of members stable throughout orders, but reciprocators are the *most* stable. This suggests that reciprocity represents an evolutionarily stable strategy in these public good networks.

Group variation. Finally, we find that buying clubs vary dramatically in their reciprocal economic behavior. Clubs vary in the amount of reciprocity the exhibit on average (from 91.7% to 59.7%), and in their member behavioral type composition (16.7% to 100% reciprocators, 0%-33.3% beneficiaries, and 0%-81.3% helpers). Group level variation is a natural phenomenon in all social contexts, however, research suggests that human cultural (and organizational) evolution may be largely driven by the ability of groups to maintain effective patterns of group cooperation toward collective goals (Richerson et al., 2016). Thus, to the extent that the differences we observe in economic reciprocity are indicative of underlying patterns of cooperation, they may be consequential in the survival of these small clubs.

The wide variation we observe could be evidence of multiple means of solving these clubs' social dilemma. Clubs with a higher abundance of beneficiaries and helpers could be structured that way because helpers gain utility from the items they purchase and assisting other members of the club, i.e., they have a social preference that is fulfilled by the clubs' success. Moreover, different clubs have different rules, norms, and infrastructure. This is in line with surveys (Hupper, 2017, 2019), where some members have indicated that they enjoy completing bulk purchases that would otherwise go unfilled.

Proof of concept. The greatest implication of our research is that patterns of cooperation in real world situations are increasingly observable. Human cooperative behavior has long matched qualitative and ethnographic descriptions of human behavior (Henrich & Muthukrishna, 2021), however behavioral games that measure cooperation, such as the public goods game or the dictator game, can now be more directly calibrated to true economic cooperation. Furthermore, our results highlight that altruism, cooperation, and coordination operate within a spectrum of prosocial behavior, and reciprocity is an effective strategy at maintaining them all. As such, researchers' intent on understanding human cooperation in a naturalistic setting must further integrate real world scenarios into models of human prosociality. Our analysis shows that this is not only possible, but necessary for the study of cooperation.

Limitations. There are a few limitations in our study. First, a nuanced timeseries analysis would provide a better understanding of stability, though some of these models are infeasible when club orders occur at irregular intervals. Second, there is evidence to suggest that individuals who patronize cooperatives exhibit higher levels of cooperation in experimental games than those who patronize similar businesses that are not cooperatives (Tremblay et al., 2019). This, coupled with the highly cooperative nature of food buying clubs may indicate that these clubs are selectively biased towards cooperative individuals, which would explain the high levels of reciprocity that we have measured. Future research is necessary to understand how non-cooperative organizations compare. Finally, further information about how much cooperation and altruism occurs in these groups could help solidify the interpretation that the strong patterns of reciprocity we observe are indicative of cooperation and sometimes altruism. Our measures of altruism come close to the conditional cooperation elicited by laboratory studies. Future studies might fit dynamical models or measure individual preferences over time to determine how much of the observed reciprocity is experienced as altruistic.

Summary. We have used a novel approach to detect and describe reciprocity in the economic networks of small food buying clubs in which economic cooperation is thought to be necessary. We found substantial amounts of reciprocity in purchasing decisions. We also verify that there are 3 distinct member types based on the balances of their in- and out degrees. Our results are in line with and extend previous research. We find high levels of reciprocity compared to previous studies. We find similar fractions of behavioral types, with reciprocators or conditional altruists being most common. We find that rapid dyadic reciprocity is much more common than indirect reciprocity and that short-term reciprocity more common than longer term patterns.

The results of our study imply that a notable fraction of economic reciprocity in buying clubs is cooperative and even altruistic rather than merely coordinative because the patterns match those of experimental studies designed to elicit cooperation. Further research might use similar methods to explore the evolution of cooperation in different organizational contexts.

CHAPTER 3.

INTERDEPENDENT AND ENDOGENOUS PREFERENCES IN SMALL FOOD BUYING CLUBS

3.1 Introduction

A central axiom of neoclassical economics is that individuals make decisions that maximize their utility based upon preferences that are pre-determined and remain static throughout time. Empirical inquiry into the construction of preferences within the behavioral sciences over the last 30 years suggests this assumption may not hold (Bikhchandani et al., 1992; Bowles, 1998; Slovic, 1995; Tversky et al., 1990). Studies of social contagion in network analysis (Aral & Walker, 2012; Lewis et al., 2008, 2012) and preference interdependence in economics (Bell, 2002; Bowles, 1998; Kapteyn et al., 1980) show that individuals' preferences, as elicited by behavior, are dynamic and dependent on their peers.

Preferences are understood as reasons for behavior that flow from how a decision or action affects an individual internally (Bowles, 1998; Slovic et al., 2007). In economics, prefering something means gaining some positive utility from it (Zizzo, 2003). From the perspective of cognitive psychology, a preference indicates that an individual feels positive affect from consuming an item or making a choice (Zajonc & Markus, 1982). This affect influences the individual's decision making when choosing among alternative goods or actions.

Individuals are believed to have an extensive number of preferences for things ranging from abstract concepts to physical items. In the relatively abstract, risk preferences for decisions with uncertain outcomes (Kahneman & Tversky, 1979) and social preferences about the feelings and outcomes of peers (Charness & Rabin, 2002; Fehr & Fischbacher, 2005) have been extensively documented and tested through experimentation. Preferences for tangibles include those for food and food attributes (Birch, 1999; Brayden et al., 2018), luxury goods and wealth (Ikeda, 2006), and environmental conditions and amenities (Champ et al., 2017). The analyses in this chapter deal primarily with food and food attribute preferences of individuals in small food buying clubs.

The biological foundations of food preferences indicated that both genetics and the social environment play a role in their development (Zizzo, 2003). Evidence for the genetic component of preferences comes from twin studies, which statistically isolate the effect of genetic factors on the development of identical and fraternal twins (A. D. Smith et al., 2016), and genome wide association studies, which elicit preferences via survey or choice experiment and find statistical associations between these reports and respondents genes (Diószegi et al., 2019). A systemic review of genome association studies by Diószegi et al. (2019) revealed that many genes that code for neurological traits and taste receptors are associated with many tastes ranging from bitter to sour, and umami to sweet. Going further than taste categories, Smith et al., (2016) studied the genetic components of adolescent twins' preferences for specific food groups, e.g. fruits, vegetables, and meats, and found that genetic factors account for 32%-54% of the variation in food preferences depending on the food group. Earlier research by Falciglia & Norton, (1994) also found significant association between shared genetic factors and preferences for *specific* foods, such as cottage cheese, ground beef, and broccoli. These studies, and the ones they reference, provide substantial evidence that our genetic makeup provides a foundation upon which our likes and dislikes are constructed.

While our genes serve as the gatekeepers for what we may or may not incorporate into our dietary preferences, the environment, especially the social environment, provides the opportunity to try new things. This process is known as endogenous preference formation, or endogenous preferences for short (Bowles, 1998; Palacios-Huerta & Santos, 2004). Under theories of endogenous preferences, the process of observing goods in the marketplace over time and what other individuals purchase gives rise to our own preferences. In essence, our desires are shaped by those around us and how markets are organized to expose us to alternatives.

The subcategory of endogenous preferences that deals explicitly with the influence of others on our preferences is known as interdependent preferences, which can also come in several forms (Gaertner, 1974; Pollak, 1976; Zizzo, 2003). At its most basic level, interdependence is a function of exposure, i.e. individuals have a higher probability of trying a good and acquiring a preference for it so long as they experience others purchasing it (Bell, 2002). In this case, interdependent preferences and endogenous preferences are equivalent, as the market structure exposes individuals to others engaging in a transaction and is causing the preference to be acquired. However, interdependent preferences can also include the social dynamic of conformity, which simply means that individuals acquire preferences because doing so endows additional utility from being similar to the majority of those around them (Bernheim, 1994) , leading to increased homogeneity of the social group. In this case, interdependent preferences serve as a special case of endogenous preferences, as the social environment is operating on a level not inherent to the market.

As noted early on by Bowles (1998), endogenous and interdependent preferences involve the social learning of cultural traits. The preference for a good, in this case a kind of food, is one variant in a population of potential preferences which are subject to several biases in social learning. Conformity as described by Bernheim (1994) is one such bias that heavily influences whether or not a trait preference is adopted, which can act in tandem with preferentially learning from prestigious, dominant, or successful individuals (Henrich & McElreath, 2007). Further, preference traits can be learned vertically from parents and horizontally from anyone else (Cavalli-Sforza et al., 1982; Bisin & Verdier, 2001; Jablonka & Lamb, 2006; Henrich & McElreath, 2007).

Food, and the preparation thereof, is innately cultural as recipes develop over time and taboos form around which foods are acceptable. While the physical ingredients themselves aren’t technically cultural traits, cooking techniques, consumption patterns, and agricultural production methods have been shown to change in line with cultural evolutionary theory (Henrich, 2015; Hanes & Waring, 2018; Waring & Acheson,

2018) and observed social influence on meal choices for food and food attributes suggest that food preferences confirm a social learning component (Cruwys et al., 2015; Levy et al., 2021). While social learning has long been understood to be a crucial component of the development in food preferences in children (Birch, 1999), a recent systemic review by Cruwys et al., (2015) found that this process continues through adulthood.

The interdependence and endogeneity of food preferences in children and adults has been clearly demonstrated for purchasing and consumption decisions in individual meals or snacks. However, whether this pattern extends beyond meetings where peers are present and into habitual, in-home consumption patterns is less clear. This study makes use of a novel dataset of small food buying clubs, introduced in chapter 2, that contains longitudinal observations of individual food purchasing behavior in a social setting. These food buying clubs allow us to observe the potential establishment of endogenously formed preferences that are inherently interdependent because they often require more than one club member to complete the transaction.

3.1.1 Small Food Buying Clubs

Small food buying clubs, introduced in chapter 2, are semi-formal groups of individuals who purchase bulk quantities of food together. These groups are often formed to procure specialty foods or local goods not readily available in the traditional food system, as well as to take advantage of economies of scale achieved through bulk purchasing. As bulk food often requires more than one member to complete the purchase in a "split", these clubs present a distinct opportunity to study how interdependent and endogenous preferences extend beyond face-to-face peer interactions and into day-to-day consumption decisions.

When members log into online software providers, they can view which splits are available join, which could act as a signal of what others like and what is available for purchase. Further, members often encounter split partners and others when they are picking up food from the appointed delivery location, which would also expose them to new types of items. Lastly, as many of these clubs are made by friend groups or at least acquaintances, members could also observe each other's preferences outside of club specific interactions. Though we can't explicitly detect this, interview results suggest that this is not an unreasonable mechanism for preference interdependence (Hupper, 2019).

The "single assistance" reciprocity analysis from chapter 2 provides further evidence that these clubs are uniquely suited for studying interdependent and endogenous preferences. These edges, which occur when an individual aids other on a particular item once across all orders, indicates that members of these clubs at least *try* new food by assisting others. It thus stands to reason that there are also instances where assistance that was intended to be singular turned into a sustained preference.

Preferences in these groups can either diversify or homogenize overtime at the group and individual level. Diversifying preferences means that the set of items purchased changes in composition over time to include more variety, while homogenization means that the variety remains relatively constant. At the individual level, diversity means that the set of items that an individual purchases changes in variety, while homogenization would indicate the opposite. Diversity at the group level can indicate two possible scenarios: 1) the group is purchasing the same items over time, but smaller groups are purchasing specific subsets of the items, which are different from each other, and 2) the set of items the group buys each week changes over time. These two definitions are not mutually exclusive, but they are distinct. Similarly, homogenization at the group level means that group purchases are relatively invariable in composition across orders, or that group members are all buying the same things without subgroups.

It should be noted that homogenization and diversification can be observed together. For example, a time-invariant set of items that is spread across multiple subsets would indicate that while a club's set of items is homogeneous, the sets of individuals within the club that buy them is diverse. Additionally, preferences could homogenize or diversify within these subsets, meaning that the subgroups that buy them are variant or invariant.

3.1.2 Research Questions

I address two specific research questions in this study:

R1. Do preferences, as elicited through purchasing behavior, change over time on the individual or club level?

R2. Can observed changes in preferences be attributed to exposure to the preferences of fellow club members.

3.2 Methodology

There are two prevailing methodologies for eliciting preferences in economics: revealed preferences (Samuelson, 1948; Richter, 1966; Nishimura et al., 2017) and stated preferences (Loureiro et al., 2003; Engström & Forsell, 2018). Revealed preference methods use the axioms of utility theory that A) individual's act to maximize their utility, and B) their utility is determined by their preferences. Researchers use this logic to estimate the preferences of individuals and their monetary valuations by studying their behavior and choices (Nishimura et al., 2017). Stated preference methods rely on survey and interview methods, asking individuals explicitly where their preferences lie and how much they are willing to pay for something (Kroes & Sheldon, 1988). While these methods were developed in environmental economics and nonmarket valuation (Champ et al., 2017), they have been used to study preferences for food and food attributes (Resano-Ezcaray et al., 2010; Gracia & de-Magistris, 2016; Brayden et al., 2018). I use stated and revealed preference methods to investigate my research questions.

Table 3.1 Survey Questions on preference change posed to clubs

Question	Question Text	Answer Type
1	A) Have your preferences changed since being in your buying club?	Binary (yes/ no) - Count of each answer reported
	B) If so, how?	Written response - Code of common themes and count of answers containing them reported
2	The needs and wants of my group influence my own	Agreement with statement (0-100) 0 = Strongly Disagree 50 = Neither Agree/Disagree 100 = Strongly Agree Mean & SD reported

3.2.1 Data Description

3.2.1.1 Survey

The stated preference aspect of the analysis utilizes survey data gathered from members of 14 clubs who use the software of our two collaborators, hereon A and B. 164 individuals responded to our survey which covered a wide arrangement of topics pertaining to the operation of buying clubs (Hupper, 2017, 2019). Data collection occurred between November of 2016 and March of 2017 for clubs from software A and from July through September of 2018 for software B. Clubs were primarily located in the New England region of the United States.

Individuals were asked directly whether they believe their preferences have changed since being in the club, and if so how. Additionally, we ask the extent to which individuals believe the needs and wants of club members influence their own needs and wants. Table 1 contains question text, data returned, and method of report.

3.2.1.2 Purchase Data

The revealed preference analysis uses the purchase data and networks introduced in chapter 2. To reiterate, orders from 35 clubs were arranged into bipartite networks that connected members to the split items that they purchased a portion of. These bipartite networks were then projected into unipartite co-purchasing networks that connect individuals based on their shared purchases (co-purchasing network). Edge directionality was then denoted according to relative amounts of each item purchased.

In this analysis, the co-purchasing networks were aggregated to the quarter level to account for several factors in the data. First, individuals do not always participate in every order, so estimating the transmission of preferences between orders would not be feasible at this timescale. Second, the bulk nature of the items means that many of them will not be bought in every order, so purchasing differences between individual orders would inflate preference change estimates. Aggregating orders' networks to the quarter level allows us to analyze overarching trends in purchasing and account for the strength of dyadic interactions, while eliminating extraneous noise introduced by differences from order to order.

To determine what individuals purchased during each quarter, I referred to item connections in the bipartite networks. Similar items are often uniquely labeled which can cause false positives when identifying changes in behavior, so items were harmonized into "types" from different brands and labels using a system developed by the European Food Safety Authority (2011) . These type classifications yielded comparable food items trackable through time to identify individuals' preferences and buying habits. After type classification, item labels were also assigned attributes found in the literature on common food labels (Gracia & de-Magistris, 2016; Brayden et al., 2018). Of the many potential labels identified, only labels indicating "Organic" were found abundantly in all clubs' purchases, so items were assessed for only this label.

Once classified, I selected item types that were purchased in a club during 3 or more quarters for analysis, as this number produced enough variation in purchasing to estimate influence. For each type, I extracted the quarter-aggregated co-purchasing networks they were purchased in and constructed panels of relationship data. Each dyad yielded two observations from the point of view of each partner, and included in each observation was the purchase decision of each partner in the current quarter *t*, their previous purchase decision in quarter *t-1*, and network characteristics of each partner and the dyad itself at *t*. Finally, the panels were filtered so that only pairs of observations where both partners were present in *t* and *t-1* were kept, as exposure should only happen if they are both participating in each order.

This process was repeated for items with the label organic. Across all quarters, I constructed a panel of relationships recording the total number of items and number of organic items purchased by each dyadic partner along with network position and dyadic characteristics.

3.2.2 Evaluating Change

To measure the presence of change in purchasing patterns over time, I used a combination of techniques used in time series trend measurements and changes in species concentrations in ecology (Billheimer et al., 2001). If the data had a continuous distribution, a trend or change could be estimated using time series techniques that explicitly estimate trends or stationarity and stability. This purchase data, however, is compositional, meaning that each club and individual's orders are composed of different combinations of items. To evaluate if the composition of the purchases made in each quarter changes fundamentally over time, I measure the similarity of each quarter to all the quarters for every individual and compare it to the amount of time (in quarters) that has passed between them.

I calculated the similarity of purchases using the Jaccard similarity index (Jaccard, 1912), which was originally formulated to compare the species composition of ecosystems. the purchases of club *c* are treated as a set *O* that is indexed by quarters such that O_t^c contains all the items purchased by club *c* in quarter *t.* The Jaccard similarity J between quarters *t* and *m* for club *c* is then calculated as the count *C(.)* of distinct items contained in the intersection of sets O_t^c and O_m^c divided by the count of distinct items contained in the union of O_t^c and O_m^c:

$$J_{tm}^{c} = \frac{C(O_t^c \cap O_m^c)}{C(O_t^c \cup O_m^c)} \quad t \neq m \tag{3.1}$$

This identity is equal to the proportion of all items purchased in *t* and *m*.

Similarity is also calculated at the individual level, where the Jaccard similarity between quarters *t* and *m* for individual *i* is calculated as the count of distinct items contained in the intersection of sets O_t^i and O_m^i divided by the count of distinct items contained in the union of O_t^i and O_m^i:2

$$J_{tm}^{c} = \frac{C\left(O_t^i \cap O_m^i\right)}{C(O_t^i \cup O_m^i)} \quad t \neq m \tag{3.2}$$

Once the similarity between all quarters has been calculated, assessing change over time is done using a Ordinary least squares. In this regression, J_{tm}^i is assumed to be a normally distributed variable with a conditional mean of μ_{tm}^i and variance of σ^2:

$$\begin{aligned} J_{tm}^i &\sim \mathrm{Normal}\left(\mu_{tm}^i, \sigma^2\right) \\ \mu_{tm}^i &= \alpha^i + \beta D_{tm} + \gamma S_{tm} \end{aligned} \tag{3.3}$$

μ_{tm}^i is then assumed to be a linear combination of a fixed individual intercept α^i, the time difference between *t* and *m* D_{tm}, and a seasonal indicator dummy S_{tm} that takes on a value of 1 when *t* and *m* take place in the same quarter of different years. The β parameter is interpretable as the sample average change in the similarity between two quarters as a result of increasing the number of quarters between *t* and *m* by one. This is an approximate measure of the strength of autocorrelation between purchases. The γ parameter on the seasonal dummy variable measures any changes in similarity resulting from the seasonal availability of items due to factors such as harvest timing for local produce.

3.2.3 Evaluating Influence

Analyzing longitudinal network data requires a model that can account for correlated outcomes. While estimates from traditional linear models will be consistent, dyadic observations can lead to correlated errors rendering estimates inefficient (Levy et al., 2021). Generalized estimating equations (GEEs), which estimate population mean parameters using a pre-specified correlation matrix for observations, were first introduced by Liang & Zeger (1986) for use in longitudinal epidemiological models where correlation could occur within observations of a single patient (Ballinger, 2004). Recently, GEEs have been used to analyze network data where observations are correlated across dyads, and provide good estimates of behavioral influence (Sauser Zachrison et al., 2016; Levy et al., 2021). All GEEs and data manipulation was done using R (Højsgaard et al., 2005; Viechtbauer, 2010; Wickham & RStudio, 2017; R Core Team, 2020; Csardi & Nepusz, 2018). In order to estimate GEE's for item types and organic purchases, I use similar formulas and specify an exchangeable correlation matrix. Exchangeable correlation matrices assume that each dyad has the same correlation, i.e. the correlation of outcomes between individuals in dyad A is the same as that of dyad B and so on, and the correlation coefficient is estimated simultaneously with the model parameters.

3.2.3.1 Food Types

To measure influence and preference adoption, I specify a model where the probability of an individual, here on referred to as ego, purchasing an item in time *t* is modeled as a normally distributed variable with a conditional mean $\bar{p}_t^{ego}$ and variance σ^2, i.e. a linear probability model (Gomila, 2021):

$$\begin{gathered}\Pr(\mathrm{Ego_t\ Purchase} = 1) \sim \mathrm{Normal}\left(\bar{p}_t^{ego}, \sigma^2\right) \\ \bar{p}_t^{ego} = \alpha + \beta_1(Alter_t) + \beta_2(Ego_{t-1}) + \beta_3(Alter_{t-1}) \\ +\gamma_1\left(k_t^{dyad}\right) + \gamma_2\left(DC_t^{ego}\right) + \gamma_3\left(DC_t^{alter}\right)\end{gathered} \tag{3.4}$$

The conditional probability is modeled as a function of an intercept α, 3 β terms describing various levels of influence, and 3 γ network control terms. β_1 describes the influence of the average alter's adoption in time t, $Alter_t$, on ego. β_2 is the parameter that estimates ego's propensity to change their preference and addresses R1 by estimating the probability of continuing to purchase an item in time *t* if they already purchased it in time *t-1*; a positive β_2 would indicate that the average ego has an preference for the item and vice versa. β_3 represents the influence of alter's purchase decision in the previous quarter *t-1* on ego's current purchase and addresses R2. β_3 is interpretable as the overall tendency of alter's previous decisions to influence ego.

The γ control terms account for the extent of the relationship between ego & alter as well as their respective centrality within the network. γ_1 measures the impact of relationship strength, measured as the dyad degree k_t^{dyad} or total number of edges extended to between the ego and alter, impacts the probability of purchase. γ_2 and γ_3 represent the effect of ego and alter's network prominence on their probability to purchase, as measured by their *degree centrality* (*DC*), which is the sum of their total in-degrees and out-degrees:

$$DC_t = k_t^{in} + k_t^{out}. \tag{3.5}$$

These additional terms account for the social dynamics of prestige and relationship strength that can affect alter's influence on ego.

3.2.3.2 Accounting for multiple types

Because a unique GEE is estimated for every item type purchased in a club in 3 or more quarters, I summarize the results of all equations for each club using the methods common to random effects meta-analysis which estimate the average parameter value across all types (Viechtbauer, 2010; Gurevitch et al., 2018). Meta-analysis methods combine effect estimates from different experiments and studies to determine the current state of scientific inquiry on a given phenomenon. Here, the same method is employed to estimate the expected impact of the explanatory variables on the probability of purchasing an item. In a random effects meta-analysis, the true value of a given parameter in equation (1), here on θ, is normally distributed with a mean $\bar{\theta}$ and a variance of τ^2:

$$\begin{gathered} \theta \sim \text{Normal}(\overline{\theta}, \tau^2) \\ \bar{\theta} = \frac{\sum_{i=1} w_i\left(\hat{\theta}_i\right)}{I} \end{gathered} \tag{3.6}$$

$\bar{\theta}$ is assumed to be a weighted average of the estimated effects $\hat{\theta}_i$ for item types $i \in k$, where k is the total number of items in a club and w_i is a weight equal to the inverse of the estimated variance of $\hat{\theta}_i$ (Higgins & Thompson, 2002). As each GEE included in the estimation of $\bar{\theta}$ is the same (the regression terms are all the same), no additional adjustments need to be made (Cochran, 1954; Gurevitch et al., 2018).

Random-effects meta-analysis was chosen over fixed-effects based on the assumption that there are true differences in estimates due to characteristics of each type not attributable to measurement error (Gurevitch et al., 2018). This assumption is tested in addition to estimating the average parameter estimate using several other statistics common to meta analysis: T^2, Q, & I^2.

The T^2 statistic tests the null hypothesis that $\hat{\theta}_1 = \hat{\theta}_2 \ldots = \hat{\theta}_k = 0$ against the alternative that at least 1 $\widehat{\theta_\iota} \neq 0$ (Snijders & Baerveldt, 2003) and takes the form of:

$$T^2 = \sum_i \frac{\widehat{\theta_\iota}}{\text{SE}\left(\widehat{\theta_\iota}\right)} \tag{3.7}$$

It is χ^2 distributed with degrees of freedom equal to $k - 1$. In essence, this statistic estimates the probability that there is a true $\widehat{\theta_\iota}$ for 1 or more of the items, even if the meta level average effect is not significant.

Q & I^2 explicitly estimate and quantify heterogeneity. The Q statistic tests a null hypotheses of homogeneity by estimating a fixed effects meta-analysis and calculating Q as:

$$Q = \sum_i w_i \left(\widehat{\theta_i} - \bar{\theta}_{FE}\right)^2 \tag{3.8}$$

where w_i is the inverse-variance weight from (3) and $\bar{\theta}_{FE}$ is the fixed-effect estimated meta average effect for $\bar{\theta}$. Q is also χ^2 distributed with degrees of freedom equal to $k-1$. If the null hypothesis is rejected, there is heterogeneity between the estimates for $\bar{\theta}$ and a random effects estimator will yield higher precision (Higgins & Thompson, 2002). I^2 is interpretable as the proportion of the variance in θ_i that is attributable to heterogeneity, and is calculated as:

$$I^2 = \frac{\left(\frac{Q}{k-1}\right) - 1}{\frac{Q}{k-1}} \tag{3.9}$$

For a full derivation of these statistics see Higgins & Thompson (2002).

A final step is taken to quantify the direction of heterogeneity, i.e. whether most $\widehat{\theta_i}$ are negative or positive. This is done by taking the log of the ratio of positive $\widehat{\theta_i}$ estimates to negative $\widehat{\theta_i}$. If the ratio is greater than 1, more items have a positive estimate for a given parameter, while a ratio less than 1 but greater than 0 indicates more items have a negative estimate. Taking the logarithm of this ratio transforms the ratio to a continuous scale on the number line where negative values indicate more negative $\widehat{\theta_i}$ estimates and positive values indicate more positive $\widehat{\theta_i}$ estimates.

3.2.3.3 Organic Items

The linear element of the estimating equation for determining preference change and influence on the amount of organic items purchased at time *t* is the same as that used for food types. However, the dependent variable is specified differently:

$$\begin{gathered}\text{Ego \# Organic Items} \sim \text{Binomial}(Items^{ego}, p_t^{ego}) \\ \text{Probit}\left(p_t^{ego}\right) = \alpha + \beta_1(Alter_t) + \beta_2(Ego_{t-1}) + \beta_3(Alter_{t-1}) + \\ \gamma_1\left(k_t^{dyad}\right) + \gamma_2\left(DC_t^{ego}\right) + \gamma_3(DC_t^{alter})\end{gathered} \tag{3.10}$$

The count of organic items is binomially distributed where *items* is the number of items, and p_t^{ego} is the probability that each one is organic. Additionally, a probit link function is used to transforms the linear model into probabilities on the interval [0,1]. Finally, as only one attribute is assessed for influence, one GEE is estimated per club and meta-analysis is not required to summarize the results.

3.3 Results

Evidence from stated and revealed preference analyses indicates that members of small food buying clubs change their preferences over time and that this change is often due to influence from their peers.

3.3.1 Stated Preference Survey

Survey results indicate that club members believe their preferences are changing. A little over half of respondents stated that their preferences have changed since joining their respective clubs, and the average strength of agreement with the statement “the needs and wants of fellow club members influence their own needs and wants” was 63.5%; put another way, the average person believes their preferences have changed and slightly agrees that it’s due to influence from fellow club members. Of the responses to Question 1b, individuals mostly pointed out that the attributes of their foods were changing, with a particular emphasis on increases in organic, “less-processed”, and locally grown. Additionally, some individuals pointed out that the specific brands they were purchasing changed and that they were trying new types of food.

Some individuals also pointed out that other members’ preferences influenced their purchasing decisions and preferences. Some members said that this was because of curiosity, similarity to other items they had previously purchased, or simply to help fellow club members fulfill their needs:

"I've certainly tried foods I wouldn't have otherwise. Sometimes I'll help others fill a split and end up with something I wouldn't have purchased otherwise."

"Yes, healthier. Less processed. Incorporating new types of food into daily life."

"I buy more based on what other orders need filled"

"If I notice someone buying a different brand or kind of food that piques my curiosity, I'm likely to give it a try."

Table 3.2 Preference Related Survey Results

Software	Question 1a			Question 1b			Question 2
	N	Yes	Percent Yes	Brand *Δ*	Type *Δ*	Organic *Δ*	Mean % Agreement
A	81	41	51%	2	7	6	63%
B	83	49	59%	0	11	22	64%
Total	164	90	55%	2	18	28	63.5%

3.3.2 Revealed Preference Models

Group and individual Jaccard similarity indexes were calculated for all 35 clubs. Of those, 18 had item types that were purchased in three or more quarters. Of those, 14 had more than one analyzable type and required aggregation with meta-analysis methods. Additionally, 29 clubs had enough longitudinal dyads to allow the Organic GEE to converge. 23 of these clubs yielded interpretable results, as the remaining 6 clubs equations calculated predicted probabilities of exclusively 1 or 0 See supplemental materials for a summary of these results.

3.3.2.1 Preference Change

Figure 3.1 shows club level similarity scores, averaged according to the number of quarters between *t* and *m*. The distribution of similarities skews towards zero for all lengths of time, and the median average similarity falls below 0.1 for all time lengths. This indicates that most the preferences of clubs are diversifying over time, as they are continuously purchasing new items. There are several clubs with average similarities

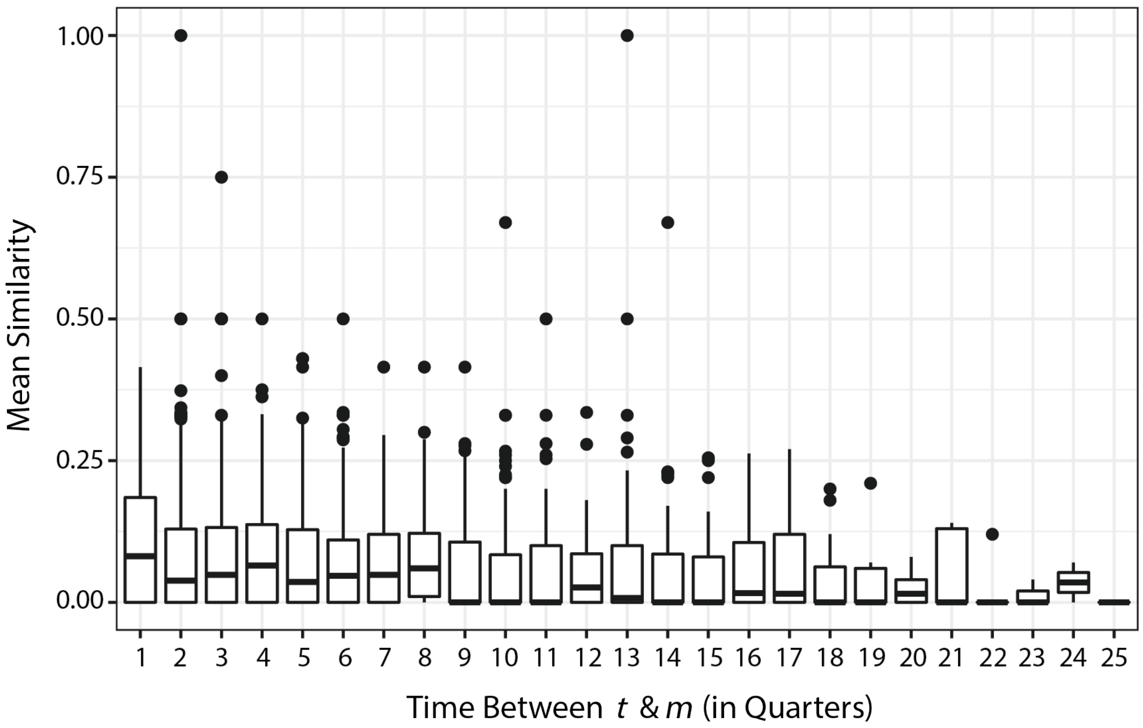

Figure 3.1 Club level similarity scores. Club level similarity scores calculate the similarity of sets of items bought in each quarter. Similarity scores are averaged according to how far apart the sets are in time. The box plots show the distribution of these averages. Most clubs have very low similarity between sets of items bought in each quarter, indicating that the types of items bought in these clubs are diversifying.

around 50, so there is variety in the amount of diversification that occurs across clubs.

The group level diversification holds at the individual level as well, as individuals' similarity scores between quarters reveal that purchasing compositions are subject to considerable change, even at short time scales. Figure 3.1 displays the distribution of club-mean of individuals' similarities between quarters organized by the time (in number of quarters) between them. Though there is variation across clubs, the global mean similarity for individuals falls between 0 and 0.1 for all temporal differences, and the distribution is skewed towards 0. This means that, for the average individual in any club, we would expect to observe 10% or less of the same items when comparing purchases from different quarters, regardless of the time difference.

This already low similarity also tends to decrease over time. Results from the regression analysis show that the β effect of increasing the time difference between two quarters by 1 (Figure 3.2) significantly decreases the Jaccard similarity of items purchased within them for 11 clubs, but significantly *increases it* in 1 club. Overall, 25 clubs had trends that were slightly negative regardless of statistical significance, while 5 clubs had zero trends and 5 had positive trends. Further investigation into the 5 clubs with positive trends revealed that these clubs had relatively few members and only existed for between 1 and 5 quarters. Each of these clubs also had members who purchased many of the same items in each order regardless of seasonal considerations, and these individuals heavily influenced the trend line.

3.3.2.2 Food Types

Clubs showed considerable variation in the direction and magnitude of preferences influence estimates. $Alter$'s influence parameters for time t and t-1 (β_1& β_3, respectively) were mostly negative for most clubs indicating that they decrease the probability of Ego purchasing the average item type (Figure 3.3). Additionally, while the number of negatively and positively estimated influence parameters vary per club in magnitude and direction of influence, most estimates tend to be negative, especially for $\mathrm{Alter}_{\mathrm{t}-1}$. However, not all the parameter estimates are negative, indicating that Alter's past purchases do increase the probability of Ego's purchase for certain item types with frequency varying by club. Ego's own influence on themselves, β_2, also varies across clubs in estimates of meta-average effect and the ratio of negative to positive estimates, showing that only some item types tend to establish themselves as preferences for the average Ego (supplemental materials Figure A2.1). Heterogeneity estimates reinforce this result as most I^2 estimates are greater than 75%, meaning that more than three quarters of the variance in these parameter estimates is due to item level differences (Figure 3.5).

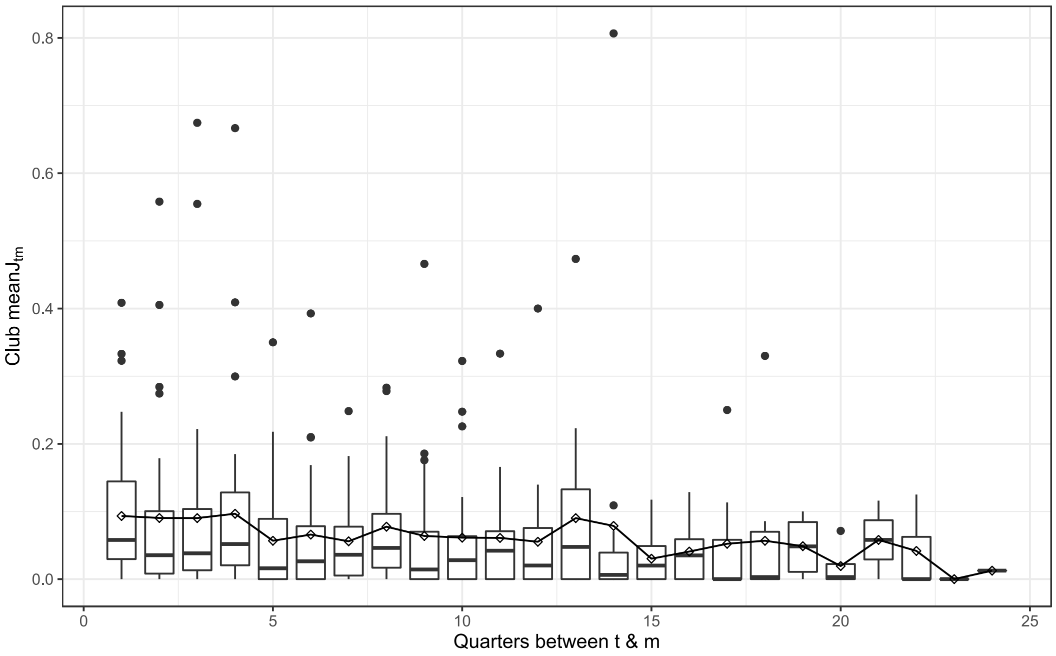

Figure 3.2 Distribution of club mean J^{i}_{tm} over time. Mean J^{i}_{tm} is taken for each club at each quarter distance, and these are organized into a global distribution of means. Most similarities fall below 0.2 for all time distances, indicating that orders change considerably in composition between quarters. The line connected diamonds signify the global mean for each quarter distance.

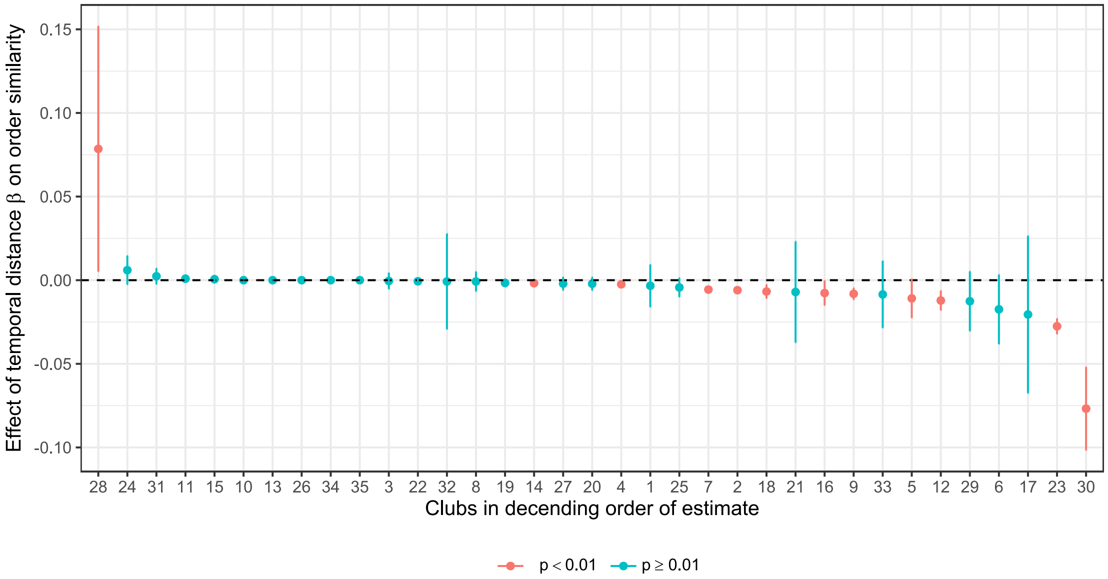

Figure 3.3 Jaccard's similarity regression results for the effect of temporal distance. Results of each club's similarity equation with null hypothesis testing results with an α level of .01. Points indicate the estimates for β with a 99% confidence interval of heteroscedasticity consistent standard errors surrounding them. The dashed line indicates zero.

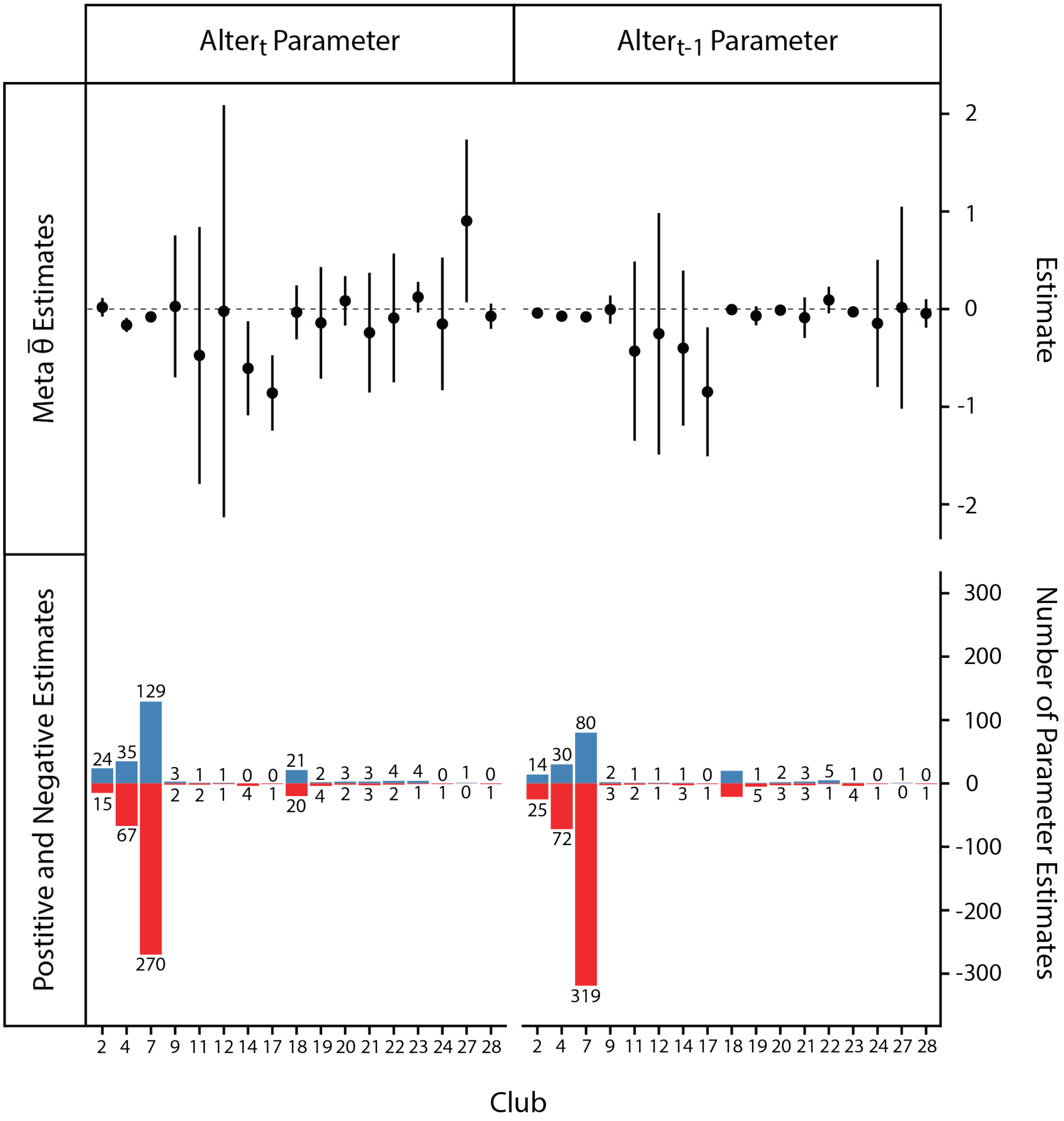

Figure 3.4 Summary of meta-analytic $\overline{\theta}$ estimates and count of positive and negative θ estimates. The log transformation helps visualize if there are more negative estimates or more positive estimates; those ratios that line up with either the red or blue solid lines indicate only negative (red) or positive (blue) estimates. Clubs with only 1 analyzable item do not have corresponding log-ratio values. Log ratio values have no associated null hypothesis tests associated with them, so their points are denoted by diamonds to avoid confusion.

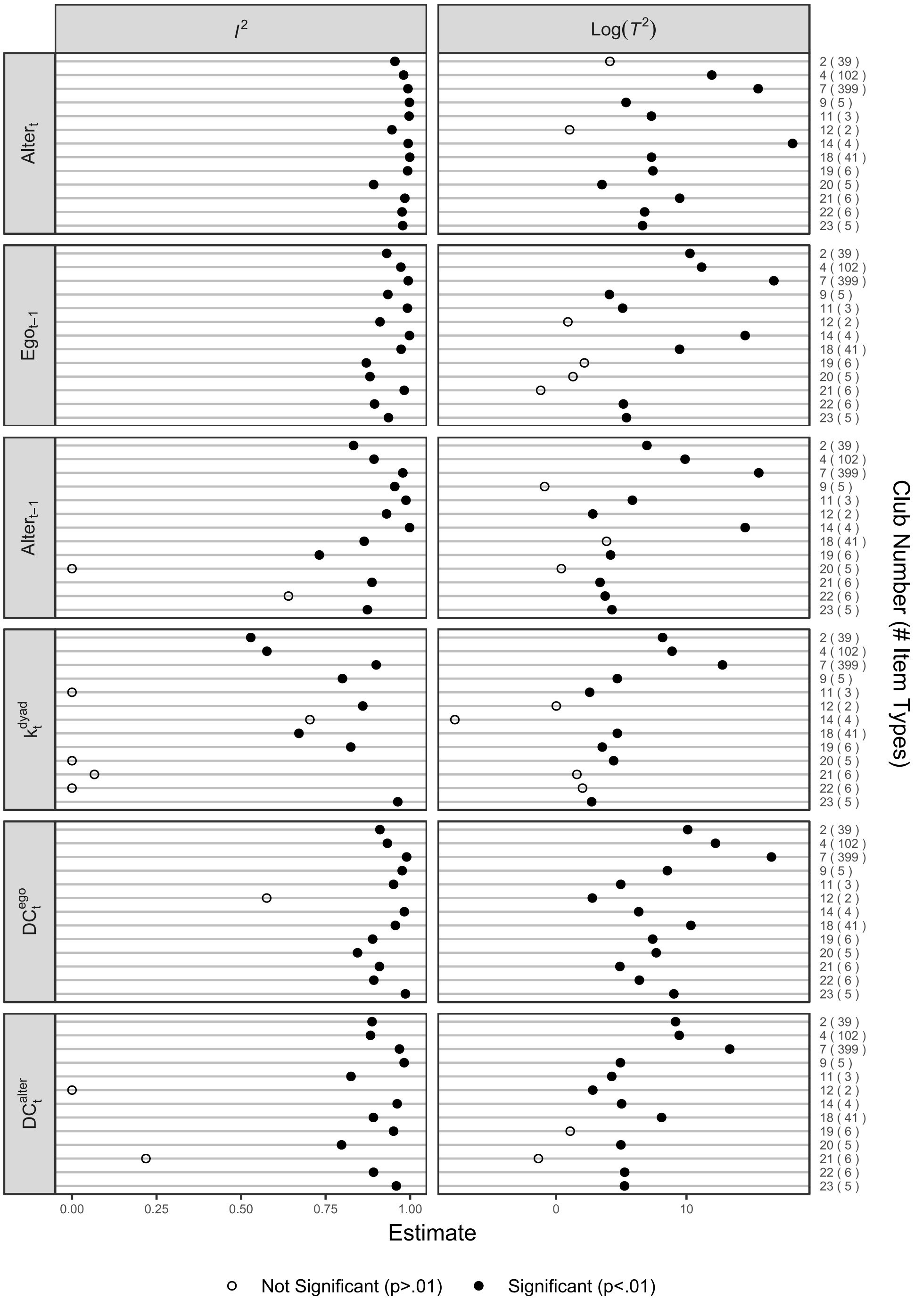

Figure 3.5 Summary of meta-analytic heterogeneity estimates. I^2 statistical significance is based on the hypothesis test performed using the Q statistic. The T^2 statistic has been logarithmically transformed to aid in visual comparisons, as the estimates from some clubs are orders of magnitude greater than others. Clubs with only 1 analyzable item are not included here as meta-analysis was not required.

The relationship and degree-centrality parameters have small average marginal effects on the probability of adoption (Supplemental materials figure A2.1), which is likely due to the saturation of degrees on the network. Since most individuals have large degree centralities and are highly connected to each other, the effect of adding one additional connection is likely to have a small effect.

3.3.2.1 Organic Preferences

GEE estimates for average influence in organic purchases is like the meta-analysis results of types with a few distinctions. To begin, increasing Alter's organic purchases in time *t* increased the number of Ego's organic purchases for all clubs except for 1, which is a significant departure from the item type analysis. Second, the more organic items that Ego purchased in time *t-1* also increased the probability of buying more organic items in *t* for *most* clubs, validating stated preference evidence. Finally, Alter's organic purchases in time *t-1* had average positive effects on Ego's purchases for more clubs than the Item level analysis, suggesting that many clubs experience conformity around item attributes than around specific items. Network and relationship level controls were similar as those in the item type analysis.

3.4 Discussion & Conclusion

3.4.1 Research Questions

Stated and revealed preference methods suggest that preferences for different foods and food attributes are endogenous and interdependent in food buying clubs, and tend to diversify at the club and individual level.

3.4.1.1 Preference Change

Greater than half of individuals in the survey indicated that their preferences changed, and the most abundant kind of change is in item attributes. Most notably, many individuals reference purchasing more organic items, and GEE estimates for $\mathrm{Ego}_{\mathrm{t-1}}$ in organic items confirm this to be the case for most clubs.

Jaccard similarity analyses also reveal that purchasing decisions made during each quarter are variable and are often increasingly dissimilar as time progresses. As there is still some similarity, it could be that individuals do purchase some staples through the club, but mainly use them to explore new items.

3.4.1.2 Social Influence

Results from both investigations reveal that social influence likely plays a role in preference change. Respondent members slightly agree (63.5%) on average that the needs and wants of their fellow club members influence their own, which means that members perceive that influence occurs, and their behavior as represented in their purchasing decisions appears to match this perception. In total, this study suggests that social influence of food choices extends beyond social gatherings like in Levy et al. (2021), to sustained behavior within households. Food clubs may accelerate the transmission of preferences between households, thereby indicating preference interdependence. Further, the presence of positive and negative influence parameters suggests that two kinds of influence may be at play in these clubs: homogenization and diversification.

3.4.2 Homogenization & Diversification

Homogenization is when a group of individuals become more similar over time while diversification occurs when individuals increase in their differences. There are several social learning biases that could account for either processes, namely conformity, anti-conformity, and payoff bias (McElreath & Boyd, 2007). Conformity refers to *positive* frequency-dependent learning, where individuals are more likely to adapt a practice or idea if a greater proportion of individuals have it, while anti-conformity describes when the opposite is true. In the presence of different groups, conformity often decreases trait variation within groups while increasing it between groups. Anti-conformity, on the other hand, increases the variation of traits within groups and can decrease it between groups (Henrich & Boyd, 1998). Pay-off bias is when individuals preferentially learn based on cues of success exhibited by their peers (McElreath, Bell, Efferson, Lubell, et al., 2008). In this sample, diversification appears to function most at the group level, and homogenization and diversification appear to be a factor in preference change at the individual level in most clubs.

Preferences appear to change throughout time at the group and individual level. Club level similarity estimates between sets bought in different quarters skew low, and they increase in dissimilarity as the time between them increases. Furthermore, this pattern is observable at the individual level. Changes in purchasing habits could be attributable to club turnover, where new individuals enter the club and others exit, thereby altering the underlying preference set of the group and the splits that are initiated. Additionally, individuals could be using the club to explore new types of food to expand their preferences, which is one of the reasons given for the formation of these clubs (Hupper, 2019).

While the influence parameters only measure the population average effect of one peer on the purchase choice of alter, it provides at least indirect evidence of conformity and/or anti-conformity. Additionally, cues of success such as greater discounts on items or satisfaction with an item could constitute a form of pay-off bias leading to homogenization. Analyses for most clubs indicate that influence from Alter was positive for t and t-1, for at least 1 item type, indicating that homogenization likely operates in these clubs. However, most clubs had negative $\bar{\theta}$ estimates and a majority negative estimates for individual items on the parameters for $\mathrm{Alter}_{\mathrm{t}}$ & $\mathrm{Alter}_{\mathrm{t}-1}$. This indicates that diversification is the dominant trend for preference interdependence, rather than homogenization.

A possible explanation for this is the second type of group level diversification, where preference clusters form with high influence within. Most group members are connected via some common item types that appear to homogenize, such as staple foods like flour or milk. However, it is possible that some members' preferences are more interdependent due to similar niche preferences, such as foreign or artisanal food. In this case, these individuals would be more tightly connected to each other are than with the rest of the group. If this is the case, our group mean estimates suffer from Simpson's paradox (Simpson, 1951; Pearl, 2022), where the average effect is negative and inter-cluster effects are positive.

These mechanisms of diversification and homogenization highlight the endogeneity and interdependence of preferences within these clubs as measured by their purchasing habits. As highlighted previously, the online purchasing environment allows for individuals to explore new items, which is an endogenous mechanism for diversification. Additionally, most clubs have items with positive influence parameters, which indicates that members' preferences depend on each other to some degree. Further, though I do not measure any clustering in this analysis, a multilevel analysis that accounts for network clustering could confirm clustered social influence. Further, including item specific characteristics in a future analysis, such as what food group it belongs to, could determine whether an item is more likely to be adopted by the whole group or just a subset of members.

3.4.3 Limitations & Future Work

This study of clubs' preferences through time has several limitations. To begin, as Jaccard's similarity values are bound on the interval [0,1], they are not technically normally distributed. A more robust investigation of change in similarity over time would be more appropriately modeled using techniques specifically formulated for analyzing interval data, such as zero-one-inflated beta mixture regression (Ospina & Ferrari, 2012). However, for the purposes of detecting trends, the OLS with heteroskedastic consistent standard errors was deemed to be sufficient.

Second, the GEE model specification assumes that preference change is a Markov process, where orders in each quarter *t* are only a function of events that take place within that quarter and in the preceding quarter. Survey results from some clubs indicate that one of their primary functions as a club is to support local farms and businesses, which can exhibit seasonality in what is available. While an ideal model would have included a seasonal component, e.g. Alter's purchase decisions at t-4 ago, many clubs did not have enough quarters that would have produced enough variation to properly model. Additionally influence from Alter's decisions in other past time stamps (e.g. *t-2* or *t-3)* may have a compounding effect on Ego's decision in time *t*, which is not modeled in a Markov process.

Second, GEE's are excellent models for detecting social influence on networks, but there are specific tradeoffs to consider when they are used. GEE's were specifically formulated to estimate average population level effects in a computationally efficient manner when correlated outcomes are likely within identifiable clusters (Højsgaard et al., 2005). They perform less well at detecting homophily, where individuals cluster *because* of similarity (Sauser Zachrison et al., 2016), and do not specialize in estimating individual level fixed or random effects (Carlin et al., 2001). It is not unreasonable to believe that some of the influence estimated in these models may be due to homophily and that influence may be asymmetric across individuals (Aral & Walker, 2012).

The evidence of diversification presented by these results suggest that future work utilizing a Bayesian hierarchical approach, such as those found in social relation models (Koster et al., 2015), would be useful in fully explaining the process more completely. Additionally, reanalyzing the co-purchasing networks using a more advanced network clustering technique would aid in determining if there truly is a latent multilevel structure that can add explanatory power to the model. Finally, literature describing social influence on other types of preferences (ie.movies, books), is often dependent on the item's similarity to orthers that are already preferred (i.e. same genre) (Lewis et al., 2012). Considering whether new food types have common attributes, flavors, or textures with club members' previous purchases may also add explanatory power on how new preferences come to be adopted.

3.4.4 Conclusion

Multiple lines of evidence derive from surveys and analysis of complete purchase data suggest the presence of endogenous and interdependent preferences in food buying clubs. Substantial heterogeneity in influence between types of items within most clubs, along with heterogeneity in network control estimates also suggest that interdependence may be dependent on more than just exposure to a new food. In addition to traditional models of conformity in these clubs, results also suggest that smaller clusters likely form within these clubs due to anti-conformity, and consideration of these clusters may lead to more thorough explanation.

CHAPTER 4.

RECIPROCITY AND PREFERENCE INTERDEPENDENCE AS FACTORS OF SURVIVAL IN SMALL FOOD BUYING CLUBS

4.1 Introduction

Longevity is a key dimension of organizational evolution. While performance measures such as growth are informative, the ability of organizations to overcome challenges and continue operating is paramount when determining their fitness. Recent theoretical work on the collapse of organizations suggests that the neglecting to properly reinforce interpersonal cooperation can cause conflicts of interest to overcome collective action and lead to organizational failure (Cordes et al., 2021). The present study analyzes the interconnected role of reciprocity and preference interdependence for the long-term survival of small informal food buying clubs.

Most work on organizational survival, or collapse and failure, has been done with the goal of understanding the process of business survival (Habersang et al., 2019; Kücher & Feldbauer-Durstmüller, 2019), though advancements in the field have been beneficial in understanding non-firm entities such as police departments (King, 2014) and public healthcare organizations (Hendy & Tucker, 2021). The most often cited work that specifically focuses on the process of organizational failure can be divided into two broad categories: Organization Ecology/Industrial organization, and strategic choice (Kücher & Feldbauer-Durstmüller, 2019). As discussed in chapter one, organizational ecology generally views organizations as relatively inert and slow to change, and those that survive are determined by external factors such as market forces or regulations (Hannan & Freeman, 1977). As a result, those organizations that build up routines and products within a special niche of the market are generally the most fit. The strategic choice perspective takes a different approach, arguing that firms where managers and entrepreneurs are able to make changes to organizational routines and products in response to external forces are most likely to succeed (Volberda & Lewin, 2003). As such, the interplay between exterior conditions and managerial agency is what leads to the diversity of firms and products and is explained as a process of co-evolution (Abatecola et al., 2020).

While exterior conditions and managerial choice are undoubtedly important, the neglect to consider interpersonal interactions disregards the majority of individuals within organizations, except where explicit evolutionary theory is used (Cordes et al., 2008; Hodgson & Knudsen, 2010; Wilson et al., 2013). While interpersonal dynamics are sometimes considered in strategic choice settings, the extent of theory lies with managers' ability to keep employees working efficiently towards a common goal without considering the *how* they do so. Furthermore, businesses rely on the cooperation of their employees in-so-far as they expect adequate effort when direct oversight is not constant (Cordes et al., 2008). Disregarding employee level dynamics has been a crucial misstep in the organizational failure literature, as managing cooperation to overcome conflicts of interest can often make all the difference in the success of an organization (Olson, 1965).

Most of the research on organizational success that does consider the decisions of all individuals involved comes primarily from the literature on non-firm entities that manage natural resources or engage in some form of collective action like labor unions (Olson, 1965; Ostrom, 2005; M. Cox et al., 2010). Resource management regimes, especially those in charge of common pool resources, are particularly vulnerable to conflicts of interest wherein individuals have a personal incentive to take as much of the resource as possible even though everyone acting on this incentive would lead to the collapse of the resource and collective (Hardin, 1968). Cooperation, wherein individuals put aside personal incentives for the good of sustaining the resource, can overcome this dilemma, but such behavior is ephemeral without a stabilizing force (Nowak, 2006). To this end, the most successful common pool resource management organizations harness the power of institutions and social learning to limit the costs or increase the benefits of cooperation (Ostrom, 1990, 2014)

Chapter one described a life cycle model of successful organizations that makes specific predictions about how organizations might overcome their internal social dilemmas thereby staving off endogenous failure. To reiterate in brief, organizations should rely on cooperation initially and develop norms, institutions, and homogeneous goals to sustain this cooperation in the long term. Using empirical evidence discovered during chapters two and three, this chapter tests this theory of organizational ontogeny by investigating the causal effects of reciprocity and preference interdependence the survival of these buying clubs.

4.1.1 Small Food Buying Clubs

Food buying clubs are small, often informal organizations that are formed to order food in bulk from distributers. In addition to the scaling benefits provided by bulk purchasing on everyday items, these clubs also extend their purchasing power to local producers as well as specialized and foreign goods (Hupper, 2019). Groups typically have widely varying memberships numbering anywhere from between 3 to 100 and place orders at intervals ranging from weekly to bi-monthly. Groups also generally have designated coordinators who hold software accounts and oversee administrative duties for the club as well as participate in orders. As they do not produce services to anyone other than their members and internal social dilemmas pay a large part in their functionality (as seen in chapter two), these clubs are closer as organizations to common pool resource and collective action organizations than they are to firms (Little et al., 2010).

Cooperation can take many forms in food buying clubs, from members assisting coordinators with club jobs to the ordering process itself. Many clubs rely on volunteer labor to perform tasks related to club maintenance such as assisting with deliveries to collection of member dues, and volunteers can be considered cooperative in this because non-volunteers are benefiting from this labor (Hupper, 2017). Additionally, ordering the food itself can involve cooperation, as chapter two and prior survey evidence reveal (Hupper, 2017). Bulk orders often require co-purchasing larger items that require multiple club members to contribute, and these co-purchases can be considered threshold public goods (Cartwright & Stepanova, 2015). Cooperation occurs in these co-purchases when individuals assist with items that they don't have a prior preference for because they are accepting the risk of gaining no utility from the item on behalf of those who will.

Aside from the goal of keeping the buying club going, the goals that would need to be unified in buying clubs have to do with the preferences of members. Preferences ultimately determine what is purchased and from where. If some individuals prefer purchasing from local producers, some desire specialty or foreign goods, and others desire to simply purchase staples, the resulting heterogeneity could result in some individuals deriving more utility from the club than others. If a compromise is not reached or goals do not homogenize over time, club failure may result. The preference interdependence investigation from chapter three helps to capture this dynamic to some degree, as it tracks the homogenization of preferences over time. As such, preference related goal harmonization is observable in these clubs, at least to an extent.

Member retention and club size are critical components of buying clubs (Hupper, 2019) that likely to play a prominent role in club survival by mediating the effects of cooperation and preference sharing. When members leave the club or do not participate in many orders, it can interfere with clubs' ability to fulfil order minimums or raise enough in membership dues to pay for software subscriptions. Additionally, the less members available to participate in each order, the less likely there are to be individuals who will cooperate or share a preference. Furthermore, member retention may be impacted by cooperation (or the lack thereof) and how many preferences are shared in the club; uncooperative members may make it harder for others to complete their co-purchases, which can impact member satisfaction (Hupper, 2019) and cause more members to leave. This would result in a positive feedback loop between decreasing member satisfaction, decreasing club size and probability of club failure.

Using this background information on buying clubs, the rest of this chapter formulates a causal model of buying club failure based on the blueprint given in chapter one and quantifies the model using a Bayesian survival analysis. The remainder of the chapter is ordered as follows: section two describes the causal model using a directed causal graph and describes the statistical models that flow from it. Section three describes the posterior distributions of the parameters on the models estimated, and section four discusses the implications of the results and the limitations of these methods.

4.2 Materials & Methods

4.2.1 Causal Model

Figure 1 gives a causal model of buying club survival using a directed causal graph (Pearl, 1995; Spirtes, 1995), and adapts the general model of organizational evolution from chapter one. Member turnover and club size should have direct causal effects, δ_0 & γ_0, on survival, as the less members there are, the less likely a club may be to meet their minimum order requirements, delivery costs per person may increase beyond members' willingness to pay, and less members means less individuals help with the logistics of running the club. Cooperation is reported as essential for buying clubs (Little et al., 2010; Hupper, 2017; Tremblay, 2017), and has a direct causal effect, α_0, on club survival. Preference sharing has a causal effect β_0 on survival, as the more members who share preferences, the more they will be able to purchase through the club and the more likely they will be able to meet minimum purchase amounts.

The direct effects of α_0, β_0, & γ_0 are only interpretable as partial causalities because the total effects of cooperation, preference sharing, and institutions have backdoor paths to survival (Westreich & Greenland, 2013). Cooperation should have an effect α_1 on member turnover, as members who receive less assistance report less satisfaction (Hupper, 2017). Results from chapters two and three also indicate that cooperation should influence the interdependence of preferences indicated by α_2, because cooperative

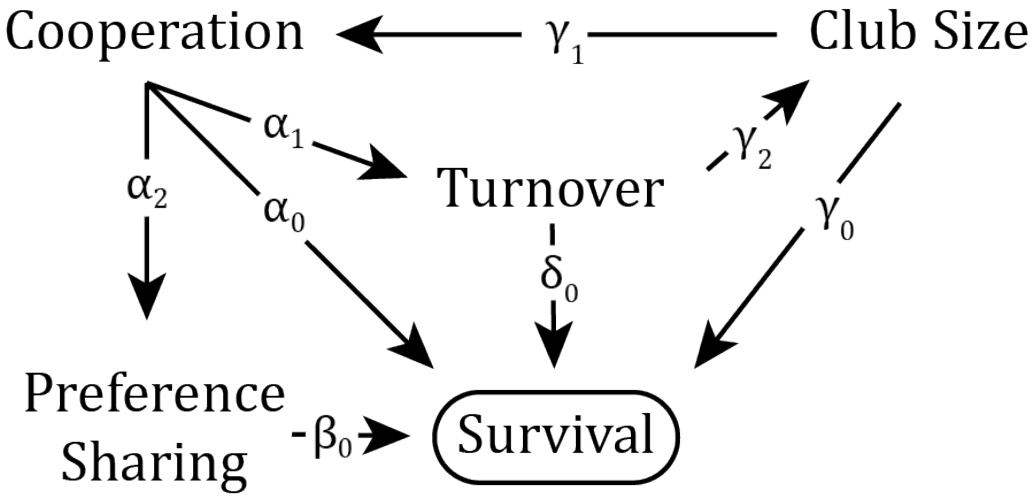

Figure 4.1 Directed Graph of Buying Club Survival

individuals who assist with non-preferred items could acquire the preference thereafter. Preference sharing should also have a causal effect on member turnover, because the more members who share one's preferences means they will be more likely to complete their co-purchases, which contributes to their satisfaction and probability of staying active in the club (Hupper, 2019). Finally, member turnover should have a causal effect on club size, as the more individuals who leave the club, the smaller it will be. As a result of these backdoor effects, the direct causal effects of cooperation, preference sharing, and institutions on club survival are only interpretable as partial causalities.

4.2.2 Survival models

The class of models used to analyze the graph in Figure 1 are known as hazard models, or time-to-event models, which estimate the impact of covariates on the probability of an event, in this case a club ceasing operations, occurring within an observed time frame (Allison, 2014). The model deals with 3 important but distinct probabilities: the hazard rate, which is the probability that an event occurs at a given time t; the cumulative hazard, which is the cumulative probability of an event occurring across a given interval $t_0 \rightarrow t_1$;

the survival probability, which is the cumulative probability that an individual will continue activity after the cumulative hazard interval (Brilleman et al., 2020).

Hazard models are estimated by comparing the observation periods for individuals where the event has occurred (i.e. the individual or the club died) and where it did not. The latter individuals are known as "censored" because the event does not occur during the observation period, but it is assumed that it will eventually. This is the essence of the hazard rate: what is the probability that an event will be censored or observed for a specific individual at a given duration *t.* In the case of food buying clubs, clubs that have ceased operations and those that are still active at the end of the period are observed, making hazard models an appropriate modeling strategy.

The basic formulation of this class of models seeks to estimate the hazard rate of individual *i*, hereon club, at time *t* as:

$$h_i(t) = h_0(t) * \exp\left(\theta x_i\right) \tag{4.1}$$

where $h_0(t)$ is the baseline hazard when all covariates are equal to 0, and θx_i is a linear combination of the explanatory covariate vector x_i and parameter vector θ. The θ parameters are interpretable as hazard ratios, which indicate the change in the probability of failure due to a one unit increase in the explanatory covariate (Oakes, 2000).

In most survival models, explanatory covariates are assumed to be time invariant descriptors of *i* that have some causal effect on their survival. For example, many survival models used to investigate the efficacy of vaccines or other short term drug therapies often include age, gender, and treatment group as time invariant covariates (Singh & Mukhopadhyay, 2011). In an organizational context, researchers may include founders' years of schooling or initial capital investments as time invariant covariates (Brüderl et al., 1992; Grashuis, 2020). In many cases, however, covariates such as age in clinical trials or capital investments may change over the course of the study, which could impact the survival probability after the change occurs (Zhang et al., 2018). As such, time *t* becomes an index and the hazard rate is evaluated at each indexed *t* through the observation period *T*.

Several classes of distributions have been used to model the baseline hazard function, which is necessary to interpret parameter estimates. Several classic distributions that describe durations such as the Exponential, Weibull, and Gompertz distributions have all been used to formulate survival models (Allison, 2014). Additionally, Cox (1972) derived a proportional hazards model that was interpretable without needing an exact distribution, and this is the primary method for analyzing survival models (Allison, 2014).

4.2.3 Data

The data used to estimate the survival models implied by Figure 1 is the purchase data introduced in chapters two and three. After being transformed into networks, the co-purchasing records yielded information about member purchasing interactions over time. The results from each chapter are used as explanatory variables in this analysis, and several new variables concerning turnover and institutions are constructed as well. Models are estimated using data from clubs with complete data on reciprocity and preferences, thus the final data set comprised 16 clubs with varying observation lengths for a total of 220 distinct observations.

Member turnover – This variable quantifies the reverse of member retention. It is time-varying by quarter and is calculated using a modified formula for employee turnover in the management literature, which is the number of employees who have left divided by the average number of employees (Glebbeek & Bax, 2004). In the case of buying clubs, the member turnover for club *i* in quarter *t* is equal to the number of members whose final order occurred in quarter *t* divided by the total number of members who participated in an order during quarter *t* (multiplied by 100 to make it a percentage):

$$Turnover_{it} = \frac{(Members\ who\ have\ left)_{it}}{(Total\ Members\ who\ Participated\ in\ an\ Order)_{it}} * 100 \qquad (4.2)$$

A higher turnover value corresponds to more members having left, thus the effect of this variable on the hazard rate should be positive, i.e., greater turnover in quarter *t* should increase the probability of club expiration in *t+1*.

This calculation was altered slightly for the final quarter, as all remaining members would have had their final order in this quarter resulting in a turnover value of 1 for all clubs. To amend this, members who did not participate in the final 3 orders of the final quarter were considered to have left. This represents a conservative estimate of turnover for the final period, as 3 orders is the longest hiatus that most members in the sample took from ordering during the observation period.

Club Size – this variable measures the number of members a club has throughout the quarter that actively participate in orders. This variable often changes from order to order, so we quantify it as the average number of members per order during quarter *t*.

Reciprocity –As reciprocity stabilizes cooperation, it can act as an adequate proxy for cooperation in the purchasing process. This variable is time varying by quarter and is calculated using the count of reciprocal edges from chapter two divided by the total number of edges aggregated to the quarter level. Reciprocity is equal to the sum of all edges from club *i* that are reciprocated directly and indirectly, and within and between orders during quarter *t*, divided by the total number of edges in quarter *t* (multiplied by 100 to make it a percentage:

$$Reciprocity_{it} = \frac{WDR_{it} + WIR_{it} + BDR_{it} + BIR_{it}}{Total\ Edges_{it}} * 100 \qquad (4.3)$$

A higher reciprocity value indicates that more edges were reciprocated during the quarter, thus the predicted effect on the hazard rate should be negative, i.e., more reciprocity in quarter *t* should decrease the probability of club expiration in *t+1.*

Preference Sharing – The number of preferences shared is measured using the pseudo-meta-analysis results from chapter three. Specifically, the random effects average parameter estimates for *Alter's* purchase in *t-1* may indicate evidence of the club's tendency to have diversifying or homogenizing preferences, and thus may act as a proxy for the degree to which preferences are shared in each club. As the average parameter values measure the tendency for preferences to be adopted over the observation period, this will be a time-invariant covariate. Preference homogenization is predicted to aid survival, so the effect of this variable should be negative.

4.2.4 Statistical Model Specification

In this investigation, I use an exponential hazard model (Glasser, 1967; Rodríguez, 2007) which assumes that the baseline hazard is constant over time. Let T_i be the survival time of club *i* in quarters, which is an exponentially distributed variable with a rate parameter λ_{it}. The rate parameter is assumed to be equal to the exponential of a linear combination of the explanatory covariates which can vary over time:

$$\begin{gathered} T_i \sim \text{Exponential}(\lambda_{it}) \\ \lambda_{it} = \exp\left(\beta x_{it}\right) \end{gathered} \tag{4.4}$$

In this formulation, $h_i(t)$ is equivalent to the rate parameter (Brilleman et al., 2020).

4.2.4.1 Base Model

The first model analyzed is a base model where λ_{it} is equal to the exponential of an intercept term ι, member turnover, and club size:

$$\lambda_{it} = \exp\left(\iota + \delta_0(Turnover_{it}) + \gamma_0(Size_{it})\right) \tag{4.5}$$

This basic model serves as a standard by which the rest of the models can be compared.

4.2.4.2 Reciprocity Model

The second model estimates the effects of cooperation throughout time as proxied by the proportion of edges that are reciprocated in each quarter. As such the rate parameter is modeled as a linear combination of a time invariant intercept ι, member turnover, and a time-varying covariate $Reciprocity_{it}$ with the direct effect parameter α_0:

$$\lambda_{it} = \exp\,(\iota + \delta_0(Turnover_{it}) + \gamma_0(Size_{it}) + \alpha_0(Reciprocity_{it})) \tag{4.6}$$

4.2.4.3 Preference Model

The next model estimates how preference sharing influences club survival in addition to the reciprocity model. This controls for the potential mediating effect of purchase sharing on cooperation and member turnover.

$$\begin{aligned}\lambda_{it} = \exp\big(\iota + \delta_0(Turnover_{it}) + \gamma_0(Size_{it})\big) + \\ \alpha_0(Reciprocity_{it}) + \beta_0(Preference\ Sharing)\end{aligned} \tag{4.7}$$

4.2.5 Prior Selection and Stan Settings

All models were estimated using the ‘rstanarm’ and ‘rethinking’ packages for the R statistical software (Brilleman et al., 2020; Csardi & Nepusz, 2018; Gabry et al., 2020; Guo et al., 2020; McElreath, 2013/2021; R Core Team, 2020; Wickham & RStudio, 2017). These models are estimated using a Bayesian framework, which assumes that parameters are unobserved variables with their own distinct distributions (McElreath, 2020). The process of Bayesian inference requires that a researcher first specify a prior distribution that they think a parameter of interest may have, ideally using careful theoretical consideration of the data generating process or historical estimates gleaned from previous research (Gelman, 2009; Li et al., 2016). These priors are then updated into posterior distributions using multiple methods, but most commonly by artificially sampling from the posterior using a Markov Chain Monte Carlo (MCMC) procedure (McElreath, 2020). Due to the software constraints of rstanarm, parameters can only be specified as having Cauchy, normal, or students t prior distributions (Brilleman et al., 2020), which restricts the ability to build priors based on theory. As such, I specified weakly informative priors as advocated by Gelman (2009), which allows MCMC procedures to efficiently explore the posterior distribution while not spending time exploring values that are theoretically unlikely. To do this I specify a distinct prior for the ι intercept and standard normal priors with variances scaled by the ratio of the standard deviations of the explanatory variables to that of the dependent variable, which is an automated procedure in rstanarm (Gabry et al., 2020). This resulted in the following priors:

$$\begin{aligned} \iota &\sim \text{Normal } (0,2.5) \\ \delta_0 &\sim \text{Normal } (0, 0.08) \\ \gamma_0 &\sim \text{Normal } (0, .12) \\ \alpha_0 &\sim \text{Normal } (0,0.12) \\ \beta_0 &\sim \text{Normal } (0,5.32) \end{aligned} \tag{4.8}$$

These priors fulfill two functions. First, specifying standard normal distributions allows for the possibility that any of these effects can either increase or decrease the hazard, regardless of the predicted effect. Second, scaling the priors by the ratio of the standard deviations allows for a weakly informative prior that spreads probability more evenly than a Cauchy or Student's t distribution at the same location, which helps the Markov chains mix when sampling the posterior (Brilleman et al., 2020).

Rstanarm uses the Stan program to run a Hamiltonian MCMC procedure using the RStan interface (Gabry et al., 2020; Guo et al., 2020). For each model, I use 4 Markov chains with a length of 10000 and draw my posterior estimates from an even mix of all 4 chains. For full Markov Chain diagnostics, see Appendix 3. Inference is done on the posterior distribution by taking 20,000 sample parameter values from the estimated posterior. Point estimates include posterior means and medians, and range estimates are given using an 89%

highest probability density interval (HPDI), which is the region of the posterior that contains the highest 89% probability density (McElreath, 2020). HPDI's are similar to confidence intervals but are not equivalent because they are not based on standard errors.

4.3 Results

The posterior distributions resulting from analysis indicate that higher values of member turnover, preference homogenization, and reciprocity, and smaller club sizes are associated with an average increase in hazard. However, HPDI's for all values contain an effect of 0, indicating that there is uncertainty in the direction of effect. Robustness checks that remove preferences and increase the sample size remove the uncertainty of the effect of turnover and increases it for reciprocity.

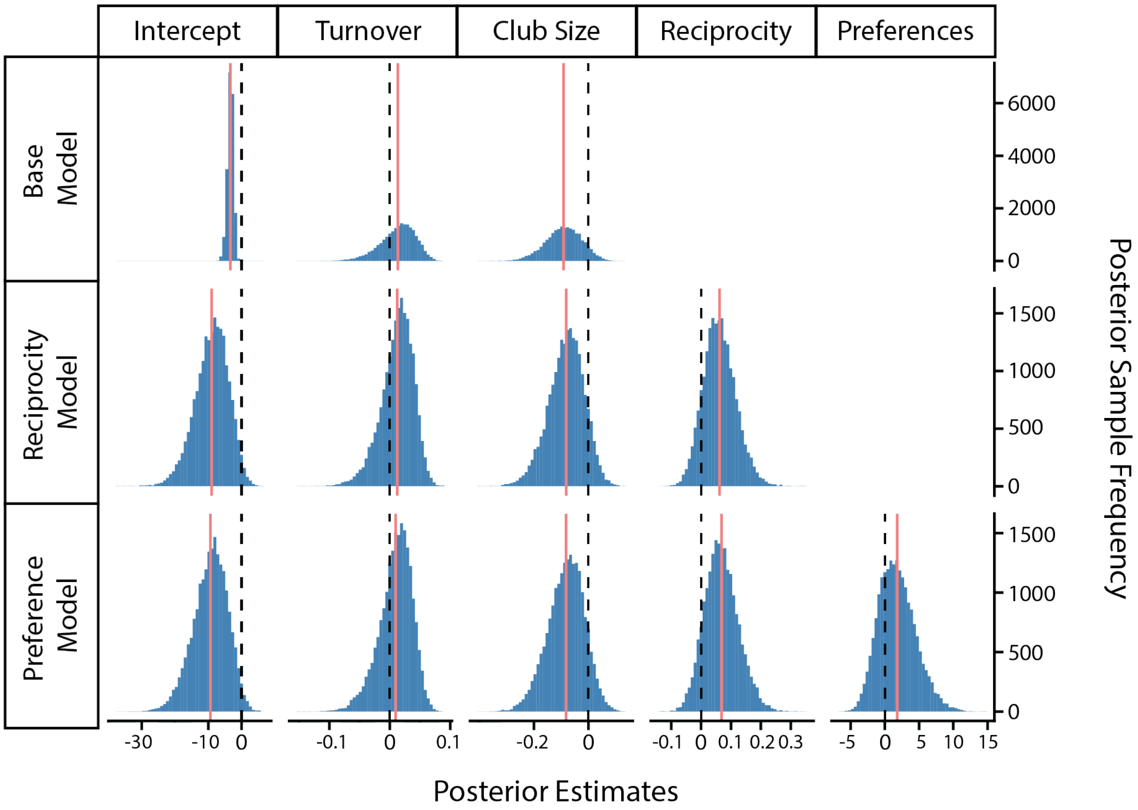

Figure 4.2 Approximate parameter posterior distributions of each model based on a sample draw of 20000. Each histogram contains 50 bins, and posterior means are given in light red.

Figure 2 gives histograms of the samples drawn from the posterior distributions of each model. As predicted, the posterior distribution for member turnover indicates a weak positive, though uncertain, effect (mean = 0.01, median = 0.01, HPDI = [-0.03,0.05], Preference Model). Furthermore, smaller clubs tend to be at a higher risk of termination with some uncertainty (posterior mean = -0.08, median = -0.08, HPDI = [-0.19,0.03]). Counter to predictions, higher proportions of reciprocity are associated with increases in the hazard rate (posterior mean = 0.07, median = 0.07, Preference Model), as do increases in preference homogenization (posterior mean = 1.80, median = 1.60, Preference Model), though these effects are relatively uncertain (reciprocity HPDI = [-0.02,0.16], preference HPDI [-2.56,5.96]).

These results are reflected in cumulative survival probability curves shown in Figure 3. Each survival curve is calculated by holding all effects constant except for the target variable and extrapolating forward in time with the same values. Survival probability curves for all variables are mutually contained within each other's HPDI ribbons, indicating that these variables are not sufficient in predicting the failure of these clubs.

4.3.1 Robustness Check

Complete data on reciprocity and preferences were only available for 16 clubs and preference homogenization was the limiting variable. If preference homogenization was left out of the model, complete data would be available for 34 clubs for a new *n* of 376. I re-estimated the base and reciprocity models using this expanded dataset.

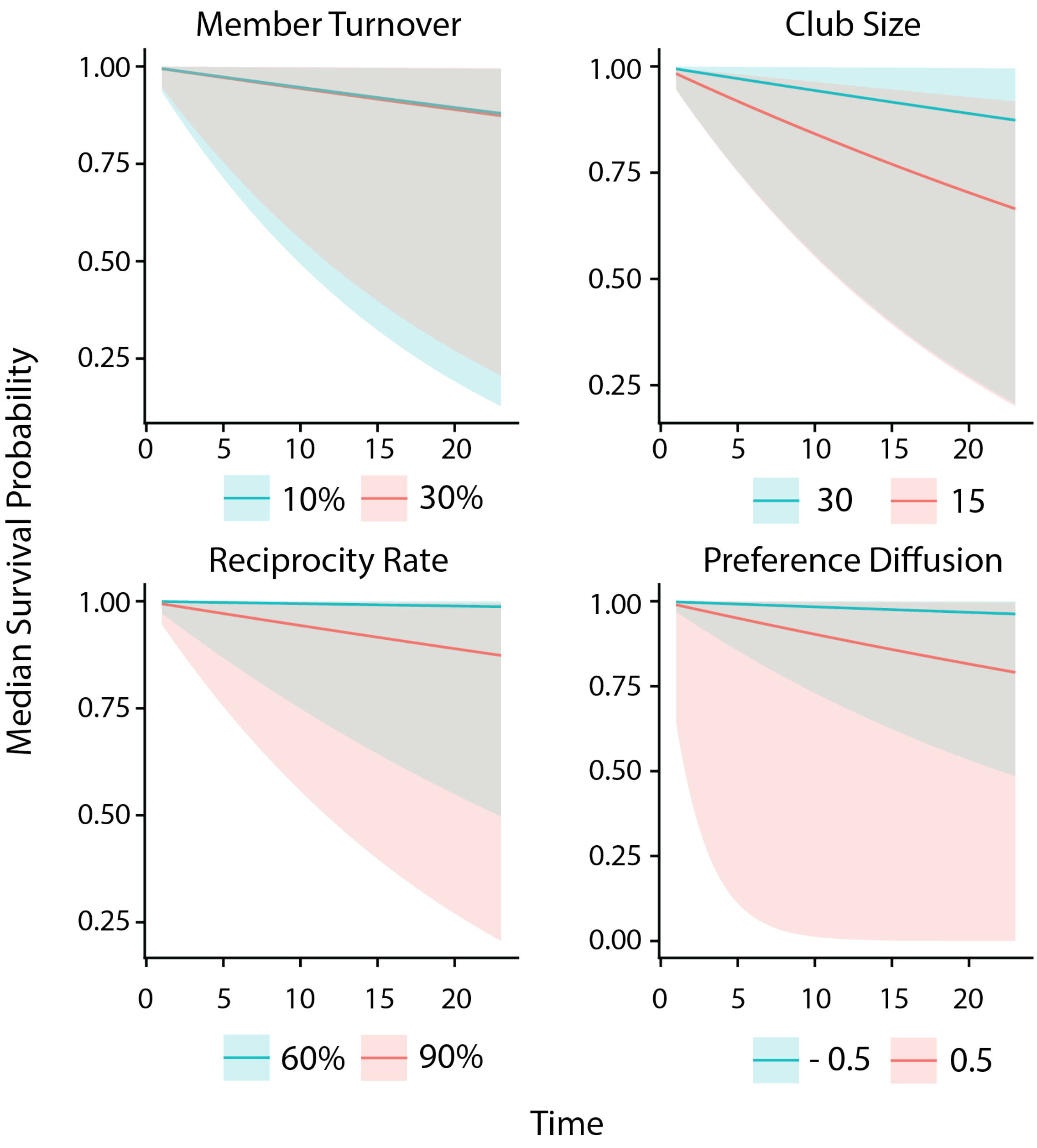

Figure 4.3 Predicted cumulative survival probability consequences of for changes in each variable of the full institution model. Each survival curve changes the specified variable and holds all other variables constant. Ribbons indicate 95% HPDIs.

The increased sample size also changed the scaling of the priors:

$$
\begin{aligned}
\iota &\sim \text{Normal}\,(0,5)\\
\delta_0 &\sim \text{Normal}\,(0, 0.07)\\
\gamma_0 &\sim \text{Normal}(0,0.12)\\
\alpha_0 &\sim \text{Normal}\,(0,0.06)
\end{aligned}
\tag{4.9}
$$

The main result of the estimation of these revised models is that the turnover parameter δ_0 has lost most of the uncertainty concerning its positive sign (mean = 0.03, median = 0.03, HPDI = [0.01,0.05], Reciprocity Model), indicating that it is very likely that more turnover in time *t* increases the probability of club failure in *t+1*. Surprisingly, the increased sample size and omission of the preference variable dampened the effects of the club size and reciprocity variables, and did not eliminate any of their

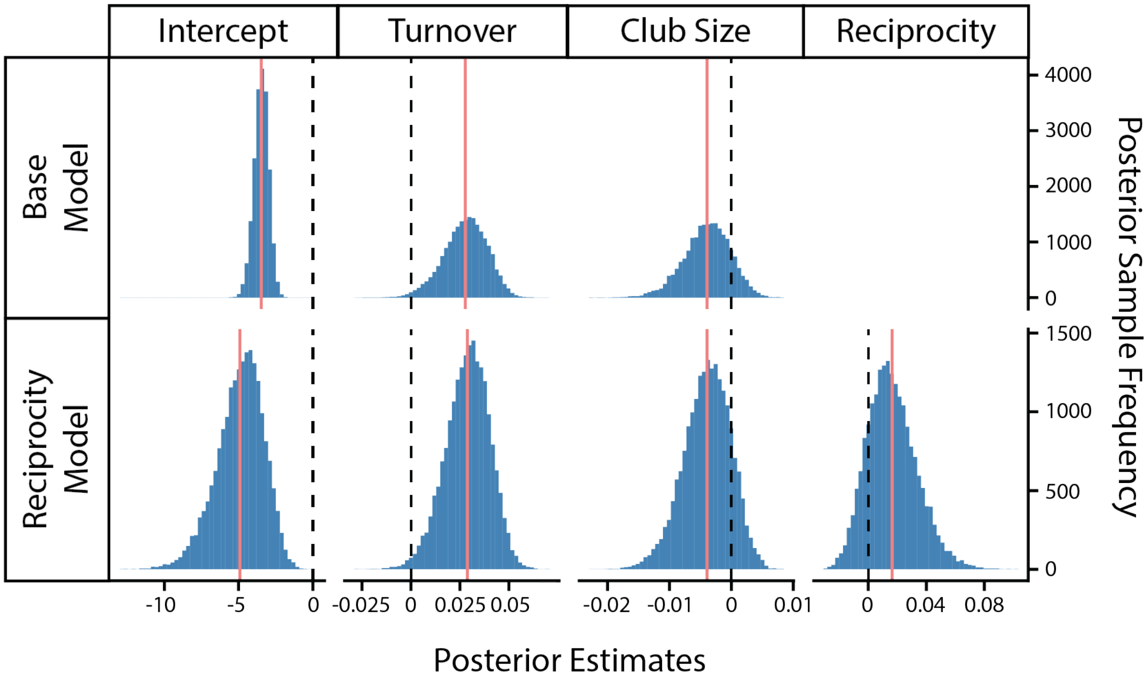

Figure 4.4 Approximate parameter posterior distributions of each model with larger sample that does not include a preference homogenization term. Each histogram contains 50 mins and distributions are based on a sample draw of 20000, and posterior means are given in light red.

uncertainty (club size posterior mean = 0.04, median = 0.04, HPDI = [-0.10,0.02] Reciprocity Model; reciprocity posterior mean = 0.02, median = 0.02, HPDI = [-0.01,0.05], Reciprocity Model). This could indicate that neither reciprocity nor club size have a substantial effect on club survival.

4.4 Discussion & Conclusion

Food buying clubs primarily serve to connect their members with food sources that may be otherwise inaccessible in the traditional food system. In doing so, they provide a service to their members and function as an organization that should thrive in the presence of collective action (Little et al., 2010). Considering this hypothesis, the following insights have been garnered from this analysis: 1) member retention likely plays a key role the continued operation of food buying clubs, 2) preference diversity appears to be associated with greater club longevity and homogenization may decrease it, 3) higher amounts of reciprocity may be associated with earlier club failure, and 4) smaller clubs may be more susceptible to failure than larger clubs.

The models estimated in the robustness check indicated that member turnover is very likely to have negative impact on club survival as the hazard ratio is positive. In firms, employee turnover can be detrimental to the organization as a whole because of the cost of training a replacement and the lower performance usually observed in new employees when compared to seasoned staff (Glebbeek & Bax, 2004). Buying clubs could suffer from a similar phenomenon in that newer members may not share the preferences of many existing members and integrating them could be costly to the group. Further, members that aren’t replaced leave less individuals to fill co-purchases and less member dues, which could lead to the feedback loop referred to earlier.

The preference dynamics of the clubs that survive the longest appear to favor preference diversity over homogenization. Preference homogenization was originally meant to proxy the homogenization of goals, though this may not be an accurate analogy. The primary goal of the buying club is to make sure everyone can order what they want or need, which could be achieved though homogenization; if most members have the same preferences, then this goal can be achieved quite easily. Diversification may also be an adequate means of making sure everyone gets what they want, as more options to choose from leads to an increased probability of people being able to purchase what they prefer. Diversification may also mediate the adverse costs of new members joining the club, for the same reason. As such, the preference diversification variable may not be measuring the homogenization of goals so much as it is measuring one of the ways that the primary goal is achieved.

Perhaps the most surprising results are the positive, albeit uncertain, estimate for reciprocity. The literatures of evolutionary game theory and social network analysis clearly indicate that reciprocity is a sufficient condition to sustain cooperation (Nowak, 2006), and that the presence of reinforcing institutions should bolster it as well (Ostrom, 2014). However, variables that include these factors appear to increase the likelihood of club death or have relatively null effect, and there are a couple of reasons why this may be the case. As chapter two suggested, reciprocity appears to reinforce cooperative behavior in these clubs, but it could be that cooperation extracts a higher price than previously considered. This cost could manifest as a reciprocal member accumulating large amounts of items that their family does not want or need, and the cost of storing those items or giving them away starts to outweigh the benefits of receiving the items they prefer. It also could be that a more sustainable club set up contains more acts of unreciprocated assistance, i.e., has more helpers and beneficiaries than reciprocators as found in chapter one.

4.4.1 Institutions

Institutions likely have causal effects on cooperation and preference sharing as well. Institutions such as common funds to complete co-purchases can lessen the necessity of direct cooperation as the members pay a common cost for the fund which fills co-purchases automatically. Additionally, the need for direct cooperation can dull the effect of preference sharing, as members may not try new goods if co-purchases are fulfilled without requiring their direct input.

Most institutions such as membership dues or pickup schedules are not observable within the purchase data, and are only observable through interviews or surveys, which are unavailable for most clubs in our sample (Hupper, 2019). However, some features of the softwares that provided the data allows clubs to create a surplus account, which fills most co-purchases that would otherwise require cooperation on the part of other members (J. Bloom & A. Fairbank, personal communication, 2018). These accounts are often funded through increases in membership dues or voluntary contributions and can be considered institutions, as they relieve members of the burden of making the choice to cooperate on a case-by-case basis, and instead building it into the cost of being a part of the club.

The use of a surplus account is observable in the purchase data, but it was only observed in 2 clubs for several quarters. As such, there was insufficient variation to make meaningful inferences on how the account affected cooperation or club survival and was not included in the model. A possible explanation for the lack of surplus accounts could be that the sample is unbalanced and including clubs that use other software may alleviate this. Alternatively, it is possible that clubs don’t use surplus accounts as often as originally thought because it may add additional stress for the coordinator or have a general lack of interest in its implementation.

4.4.2 Limitations

The largest empirical limitation of this analysis is the exponential specification of the model. As stated previously, exponential survival models assume that the baseline hazard is a constant through time and that changes in hazard in different time periods are due to covariates. It is possible that buying clubs face different baseline hazards at different times or that it continually increases as time progresses. A method such as a Weibull or Gompertz model would take into account the possibility that baseline hazards increase over time, while an M- or B- spline method could account for stochastic changes (Brilleman et al., 2020). An additional model limitation is that parameters were specified as constant over time, when it is possible that the effects of certain variables are actually time varying (Scheike, 2003). For example, it could be that high amounts of reciprocity can decrease the probability of early club failure, while the relationship inverts as the club grows older. It could also be that the effect of a surplus account is relatively inert in the beginning of a club but becomes more important as the club grows older. Inclusion of time varying effects or a different model specification could shed more light on the.

There are three data related limitations of this analysis. The first is that there are no readily observable institutions for the whole dataset outside of the surplus account. Previous research with a subset of this sample has found that clubs benefit from clearly defined institutions that govern club management because it can help alleviate the burnout of coordinators (Hupper, 2017), but this kind of data was not available for many clubs that had already failed. Concurrently, we had no information on clubs' logistical functionality aside from that proxied by club size and member turnover. Because of this, we are only able to partially model survival as a function of the purchasing process, rather than the combined purchasing and logistical processes. Finally, the variable used to proxy preference homogenization was unavailable for all clubs which substantially truncated the dataset. A more thorough investigation of preference diversification than chapter three may reveal a better measure that is available for more clubs, which would help to decrease the uncertainty of the parameter estimates.

A final limitation of this analysis was how survival was determined. The success censoring in these clubs was coded as either failure or continuance, meaning that clubs could ceased operations or continue functioning. Continuation could be broken down further into continuation as buying club and continuation as a storefront consumer cooperative, as some buying clubs are formed with that explicit intention and succeed in doing so (Jeremy Bloom, Personal Communication, 2016). The decision to pool these two types of success was made primarily because only two of the sampled clubs had transitioned to storefronts and there would not have been enough variation between outcome types to feasibly garner inference from a multi-outcome analysis. If more data is gathered on these clubs, and complete information on their transition status at the end of the observation period could be collected, a multi-outcome analysis would lead to superior insights into the evolution of these clubs.

4.4.3 Conclusion

This final chapter analyzed how reciprocity and preference homogenization impact the survival of small food buying clubs. Data were gathered primarily using the results from previous chapters and was supplemented by previous work that analyzed this sample (Hupper, 2017; Tremblay, 2017; Hupper, 2019). Results suggest that higher levels of reciprocity tend to be associated with club failure and the diversity of preferences tends to increase longevity. Additionally, member retention has a very probable positive effect on extending club success and institutions which help to mediate ordering and decrease the cost of cooperation appear to have very little impact if any at all. Finally, further study using different specifications and an expanded data set would improve these inferences.

CONCLUSION

This dissertation explored several facets of interpersonal behavior and organizational evolution, by seeking to answer a three-part question: what can the behavior of individuals in small food buying clubs reveal about how cooperation functions in real world situations, how preferences evolve in groups of individuals, and what are their consequences for the survival of informal organizations? The investigations have uncovered much about interpersonal dynamics in these clubs, and they have implications beyond the organizational science literature. On a theoretical level, I have demonstrated that the extended evolutionary synthesis is an ideal framework to study interpersonal dynamics and their consequences for organizational survival. Furthermore, this dissertation has measured individual behavior in an empirical situation that reveals how cooperation and reciprocity can unfold in the real world, that preference interdependence extends to prolonged food buying habits, and that interpersonal dynamics have observable consequences on the longevity of organizations.

Cooperation is observable in real world situations. As stated in chapter 2, most studies of cooperation occur within a contrived setting, where researchers can control payoffs and manufacture a social dilemma. Besides Frey (2017, 2019) who used videogame data to elicit cooperative actions and reciprocity, this is among first example of quantifiable reciprocity and cooperation in a real world setting to my knowledge.

Detecting this cooperation and reciprocity required several steps. The first involved identifying a social dilemma where behavior was not only observable, but measurable. Creating networks out of the co-purchases allowed me to track who was interacting with whom, and how much assistance was moving between individuals. The next step required looking for evidence of structures that support cooperation. As Wilson (2015) points out, altruism and prosocial motivations are nearly impossible to parse out, but altruistic *behavior* is readily observable regardless of motivations, and action is ultimately of consequence when determining organism or cultural fitness. Assigning directionality based on share ordinality and creating the single assistance definition allowed us to see when assistance occurred, thus revealing prosocial behavior. From there, we were able to count the overall amount of reciprocity in the groups, which turned out to be higher than expected.

Direct reciprocity in organizations. Direct reciprocity was expected to be abundant in these clubs, as it has been found to increase general prosociality in public goods dilemmas (Rand et al., 2009), and plays a more integral part in sustaining cooperation than indirect reciprocity when both are present (Roberts, 2008). It was found that members reciprocate at an average 88% rate, and that over 70% of all edges could be classified as direct reciprocity, which are far above the average rate of reciprocity in public goods dilemmas. Furthermore, our singular assistance reciprocity rate fell within the range of traditional public goods measurements, indicating that these co-purchase decisions may have a degree of altruism.

These clubs are not representative of all organizations, and selection bias is at play at the level of the individual members and the type of organization. However, these food clubs are fundamentally cooperative organizations with a social dilemma at the core of their function. It is possible that buying clubs represent a good case study of other cooperative organizations, such as cooperatives or neighborhood associations, where individuals need to work together to maintain their organization (or neighborhood) in the absence of a hierarchical order. As such, research on these types of organizations should pay close attention to interpersonal reciprocity, as the results of this dissertation indicate that it will be abundant in sustaining prosocial behavior.

Reciprocity is not enough for group survival. A surprising result from chapter 4 was the negative average parameter estimate for the reciprocity term. Though there was some uncertainty surrounding the effect, additional reciprocity was associated with an increased chance of club failure in the next time stamp. This may act as additional evidence of the necessity of institutions for the long-term sustainability of cooperation.

While reciprocity is good at sustaining cooperation, it is vulnerable to changing population structure (Fehr & Fischbacher, 2005). Should the ratio of free-riders to cooperators change through the attrition of cooperators or addition of free-riders, the free-riders could potentially bring down moral. In the case of these clubs, if too many beneficiaries enter and there are not enough helpers or reciprocators to meet their assistance needs, the club may break down. Institutions can act as buffers against free-rider behavior by internalizing the cost of cooperation and spreading it across group members. Additionally, they can mandate sanctions against free riding behavior, thereby raising its cost. In future examinations with this or larger samples of food clubs, a greater survey or interview effort of defunct clubs could shed additional light on the role that institutions play in maintaining cooperation.

Preferences are interdependent and they diversify in these clubs. The results of the similarity score analysis and generalized estimating equations in chapter 3 reveal substantial evidence that preferences change over time and that at least some of these changes are caused by social influence. At the individual and group level, the comparative item composition of orders is dissimilar at short time scales and increases in dissimilarity as the time between them progresses. Furthermore, there is evidence that preference homogenization takes place for some item types in most clubs, though the tendency is for diversification. A more network focused approach that could locate embedded clusters would shed more light on whether homogenization occurs at a more localized scale.

The more preferences diversify, the longer clubs continue operation. Clubs with increasing diversification, as measured by the generalized estimating equation influence parameter estimates, tend to operate longer than those with more homogenization. This could be because diverse preferences correspond with a higher probability of preference matching between individuals. Additionally, it could be that many members use these clubs to explore new preferences, and diversifying orders would be evidence of this taking place. Going forward, research with these groups should examine how preference diversity corresponds to member attrition, which appears to be a key factor in club survival.

Turnover is a determinant of club survival. The literature on group turnover tends to focus on employee turnover in businesses (Ongori, 2007), and the results of chapter 4 indicate that the effects observed in this literature may extend to non-business organizations. There are several reasons to explain why increases in turnover can cause issues for clubs. For one, members leaving means that there are fewer individuals to fill orders and splits, thereby causing failure in both threshold public good scenarios. The failure of splits can be further broken down to a matter of preference overlap or cooperation; fewer preference sets lead to less probability of corresponding preferences, and fewer individuals means that there may be less helpers or reciprocators in the club to act prosocially. Finally, fewer members means that there are fewer dues coming into the club treasury, which increases the costs for the remaining members to meet software subscription and delivery costs. Follow up surveys with members who have left could help to understand this phenomenon more clearly for research purposes and to help the clubs.

Concluding Remarks. The results of this dissertation have implications for buying clubs and their supporters who are looking to improve their functionality. First and foremost, clubs should identify the causes of member attrition in their own club, as turnover is detrimental to their continued functionality. Second, members should be open minded about trying new things and welcoming new preferences into the club. A diversity of preferences increases the survival of clubs and gaining diversity in one's preferences makes them an asset to their club. Furthermore, an abundance of members with wide preference sets increases the probability that new members will be able to find desired splits and gain more utility from the club. Finally, though reciprocity is abundant in these clubs, there is evidence that it may decrease their survival probability. Surveys indicates that many folks don't believe they are being helped enough (Hupper, 2017), so it may be in clubs' best interest to supplement voluntary cooperation and reciprocity with institutions that spread the cost of help around.

The three empirical chapters of this dissertation represent a preliminary investigation of small food buying clubs, and the role of interpersonal dynamics in their survival. While this investigation has been extensive, it is by no means exhaustive. There are many other questions on cooperation and preference evolution in these clubs that have emerged from the results, including an examination of the role of preference diversity and reciprocity in member turn over, uncovering the coevolution of co-purchasing network structure and reciprocity, and determining the role of logistical institutions on club survival. My results indicate that the rate of reciprocity in cooperative organizations may be higher than experimental evidence suggests, and that interdependent preferences, as revealed through behavior, extend to consistent purchasing habits. Additionally, I have demonstrated that neglecting the part that rank-and-file individuals play in organizational evolution is a tragic misstep in the literature. In all, small food buying clubs have presented a revealing case study in the evolution of cooperative organizations that explored the key role that individuals play in the evolution of their organizations.

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APPENDIX 1
SUPPLEMENT TO CHAPTER 2

Table A1.1 Reciprocal Edge Classifications and Coefficients of Variation

			Percent of Total Edges				Coefficient of Variation			
Club	Orders	Members	DWR	DBR	IWR	IBR	DWR	DBR	IWR	IBR
1	59	23	0.71	0.12	0.03	0.03	28.77	78.05	120.88	147.78
2	11	10	0.65	0	0.06	0	73.43		331.66	
3	22	28	0.67	0.08	0.06	0.05	19.21	91.81	87.29	112.77
4	27	18	0.62	0.08	0.07	0.06	68.37	154.02	137.39	172.58
5	69	9	0.57	0.15	0.03	0.06	63.31	147.32	281.49	242.32
6	15	4	0.63	0.14	0.05	0.06	81.21	146.99	273.94	230.75
7	93	8	0.64	0.16	0.02	0.07	79.24	150.72	450.82	271.84
8	64	66	0.54	0.15	0.1	0.04	43.17	109.03	93.08	172.86
9	48	26	0.46	0.12	0.1	0.07	59.34	152.03	132.13	216.36
10	91	122	0.58	0.12	0.1	0.04	13.53	40.11	39.79	86.51
11	67	31	0.58	0.12	0.07	0.04	43.81	91.61	109.77	135.8
12	10	27	0.72	0.11	0.07	0.02	9.65	37.65	28.08	56.07
13	69	51	0.58	0.15	0.07	0.05	27.74	55.13	56.51	96.41
14	80	46	0.55	0.18	0.07	0.05	33.05	75.29	102.94	103.74
15	80	144	0.52	0.1	0.11	0.07	24.58	51.12	52.48	58.61
16	76	78	0.58	0.13	0.09	0.04	22.3	49.65	58.45	92.28
17	30	9	0.55	0.22	0.04	0.04	41.59	59.62	160.4	175.02
18	46	6	0.56	0.06	0.02	0.06	62.84	173.14	368.19	227.58
19	20	3	0.68	0.15	0	0.06	83.63	183.9		324.63
20	14	9	0.58	0.2	0.03	0.03	21.63	49.64	136.29	138.62
21	52	66	0.61	0.15	0.07	0.03	12.2	35.95	48.67	63.86
22	95	66	0.66	0.14	0.05	0.01	23.07	51.71	55.79	393.82
23	100	141	0.74	0.08	0.06	0.02	22.59	52.21	72.25	296.7
24	34	45	0.64	0.08	0.09	0.02	6.35	37.19	23.71	75.64
25	30	80	0.64	0.06	0.09	0.02	8.67	37.68	24.51	88.82
26	5	7	0.54	0.04	0.06	0.06	40.61	142.88	100.33	189.81
27	34	7	0.72	0.08	0.01	0.07	52.25	198.15	329.63	245.41
28	17	23	0.61	0.14	0.06	0.07	20.82	54.33	99.73	98.16
29	67	34	0.61	0.19	0.05	0.04	19.04	49.68	77.84	94.82
30	17	4	0.67	0	0	0.1	55.08			209.44
31	44	7	0.36	0.34	0.05	0.16	112.18	102.91	277.17	158.48
32	37	7	0.6	0.07	0.04	0.03	70.79	168.9	215.3	270.34
33	5	11	0.47	0	0.15	0.01	7.86		25.75	124.32
34	6	6	0.61	0.09	0.04	0	16.16	89.78	78.31	
35	62	16	0.44	0.03	0.11	0.01	19.25	90.96	61.45	296.87
Totals:	1596	1238	0.6	0.12	0.06	0.05	39.64	94.04	136.73	171.79

Table 2: Mixed Effects Model

	Dependent variable: Out Degree	
	All Edges	Singular Assistance Edges
	(1)	(2)
Global Mean Intercept	25.936***	4.006***
	(9.869)	(1.199)
In Degree	0.882***	0.457***
	(0.009)	(0.011)
Random Effects:		
Clubs	35	13
Standard Deviation	36.36	6.71
Observations	1530	702
REML	21098.26	8248.94
AIC	21106.26	8256.94

Table A1.3: SPR Cluster Centers

Club	Beneficiary	Reciprocator	Helper
1	-0.880	0	0.836
2	-0.742	0	0.783
3	-0.977	0	0.868
4	-1.160	0	0.905
5	-1.033	0	0.706
6	-0.805	0	0.766
7	-0.730	0	0.864
8	-1.033	0	1.037
9	-1.053	0	0.956
10	-1.403	0	0.816
11	-1.059	0	0.948
12	-1.707	0	0.467
13	-1.125	0	0.904
14	-1.062	0	0.873
15	-1.180	0	0.904
16	-1.083	0	0.871
17	-0.888	0	0.878
18	-0.904	0	0.761
19	-0.573	0	0.678
20	-0.970	0	0.707
21	-1.063	0	0.695
22	-0.885	0	0.745
23	-1.527	0	0.537
24	-0.999	0	0.688
25	-1.633	0	0.586
26	-0.981	0	0.798
27	-0.621	0	0.733
28	-0.922	0	0.731
29	-0.952	0	0.864
30	-1.134	0	0.505
31	-0.952	0	0.747
32	-0.920	0	0.709
33	-1.969	0	0.663
34	-0.761	0	0.847
35	-1.527	0	1.007

Table A1.4: Count of Member Types

Club	Beneficiaries	Reciprocators	Helpers	Unclassified*
1	0	21	2	4
2	2	8	0	2
3	3	22	3	7
4	1	14	3	9
5	1	7	1	1
6	1	3	0	10
7	2	6	0	4
8	7	49	10	11
9	3	19	4	6
10	9	87	26	25
11	3	22	6	6
12	3	19	5	3
13	3	35	13	13
14	5	31	10	10
15	16	97	31	46
16	13	52	13	11
17	1	6	2	3
18	1	4	1	11
19	0	2	1	5
20	1	6	2	1
21	11	43	12	2
22	5	47	14	6
23	10	85	46	41
24	5	27	13	6
25	3	48	29	16
26	1	4	2	3
27	0	4	3	2
28	5	13	5	6
29	3	19	12	5
30	0	2	2	1
31	1	3	3	1
32	1	3	3	3
33	1	4	6	8
34	1	2	3	2
35	2	4	10	2
Totals				
	124	818	296	292

Note:

* Members who only participate in one order do not have a Markov matrix and thus remain unclassified

APPENDIX 2
SUPPLEMENT TO CHAPTER 3

Table A2.1 Summary of Which Clubs yielded Results

Club Number	Item GEE	Meta Analysis	Organic GEE
1	-	-	✓
2	✓	✓	✓
3	-	-	✓
4	✓	✓	✓
5	-	-	✓
6	-	-	✓
7	✓	✓	✓
8	-	-	✓
9	✓	✓	✓
10	-	-	-
11	✓	✓	✓
12	✓	✓	-
13	-	-	✓
14	✓	✓	✓
15	✓	✓	✓
16	-	-	✓
17	✓	-	✓
18	✓	✓	✓
19	✓	✓	✓
20	✓	✓	✓
21	✓	✓	✓
22	✓	✓	✓
23	✓	✓	✓
24	✓	-	✓
25	-	-	✓
26	-	-	-
27	✓	-	✓
28	✓	-	-
29	-	-	✓
30	-	-	✓
31	-	-	✓
32	-	-	✓
33	-	-	✓
34	-	-	-
35	-	-	-

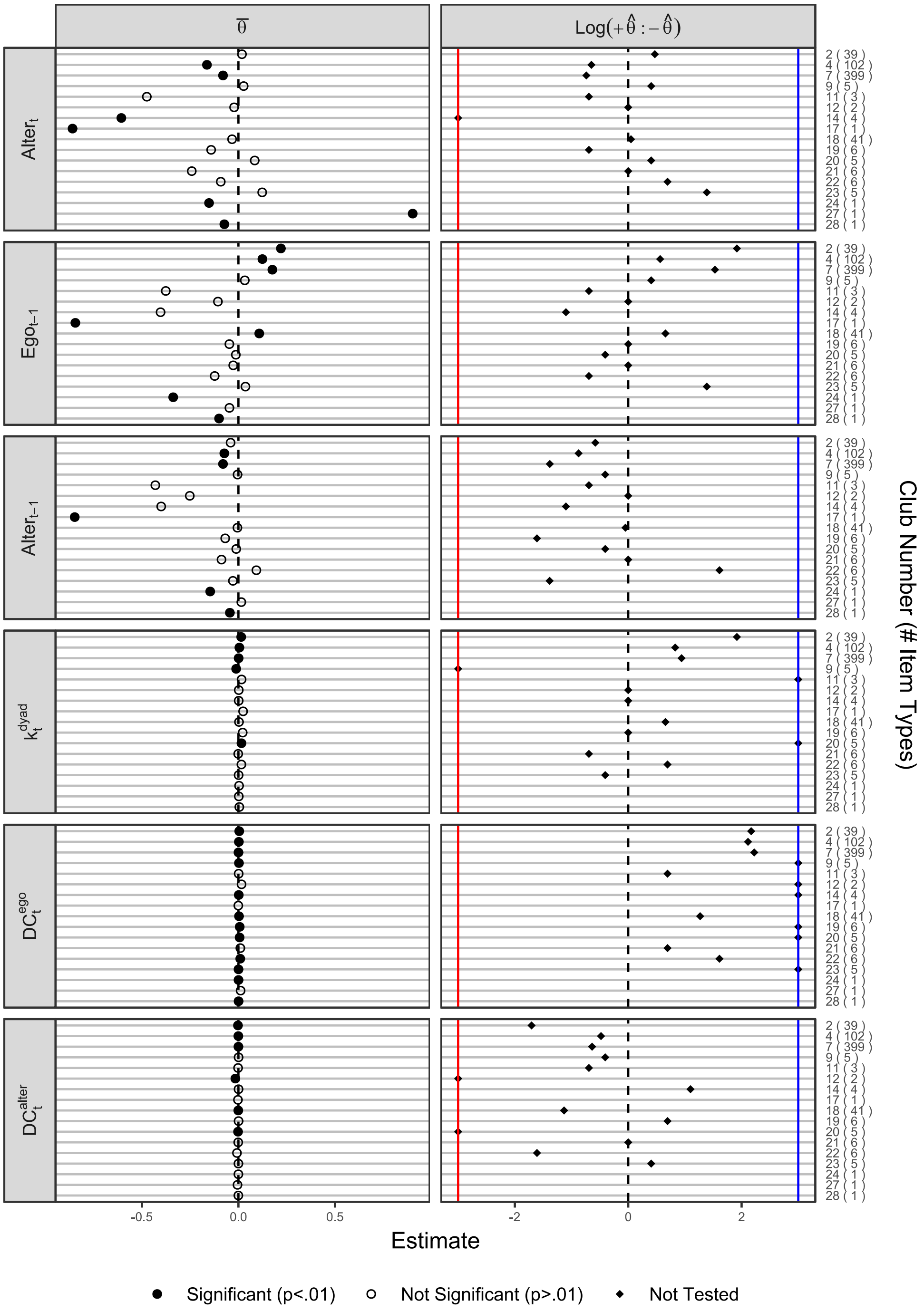
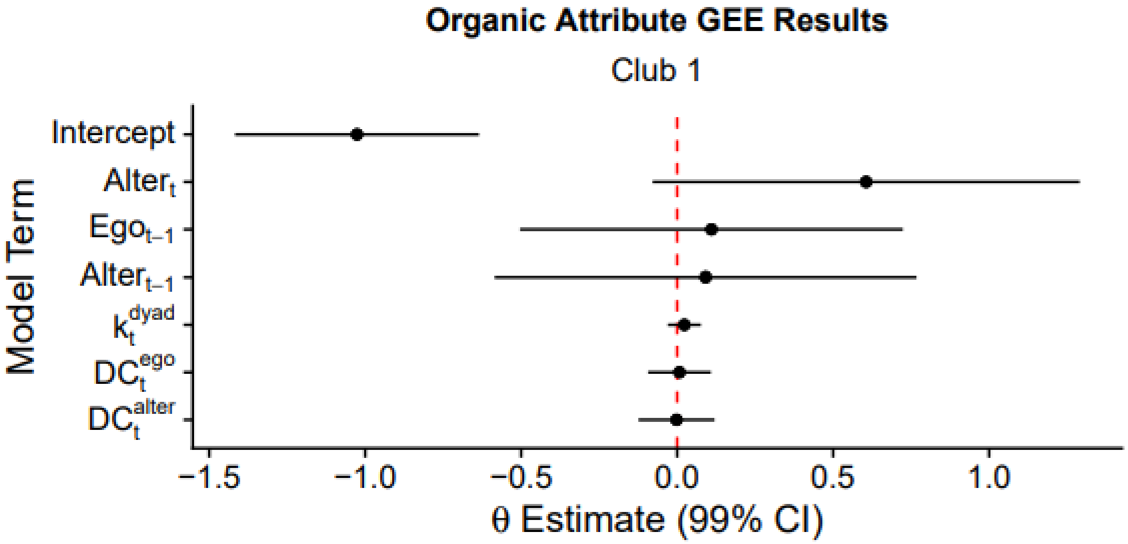


Figure A2.1 Summary of meta-analytic $\overline{\theta}$ estimates and the log-ratio of positive $\widehat{\theta_\iota}$ to negative $\widehat{\theta_\iota}$ per club. The log transformation helps visualize if there are more negative estimates or more positive estimates; those ratios that line up with either the red or blue solid lines indicate only negative (red) or positive (blue) estimates. Clubs with only 1 analyzable item do not have corresponding log-ratio values. Log ratio values have no associated null hypothesis tests associated with them, so their points are denoted by diamonds to avoid confusion.

Club 1

Club 1 had no analyzable item types.



Club 2

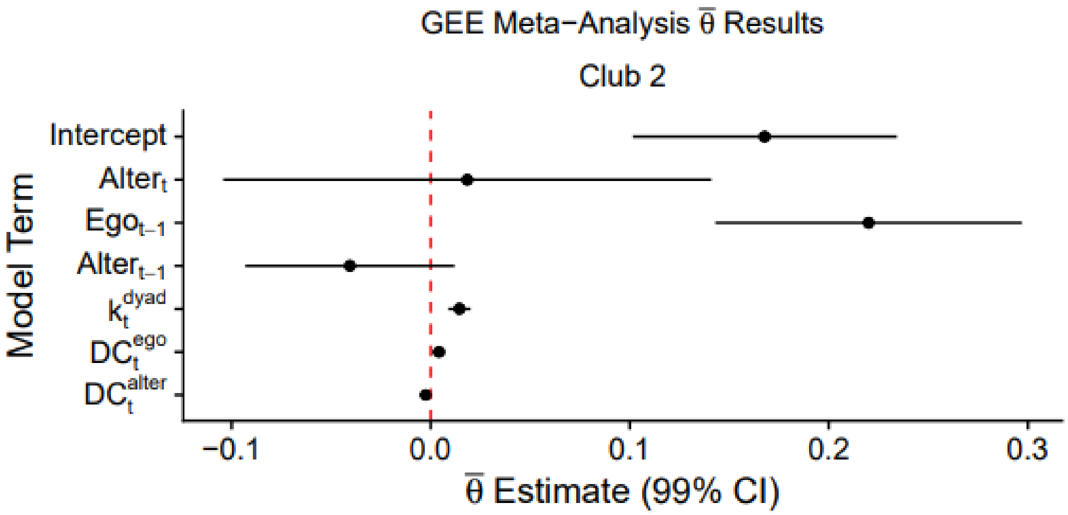
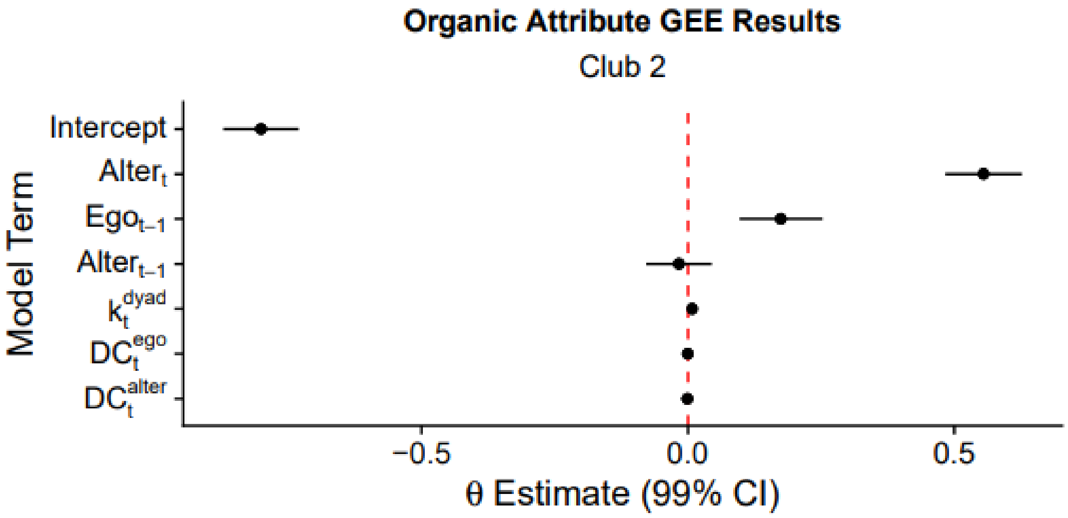


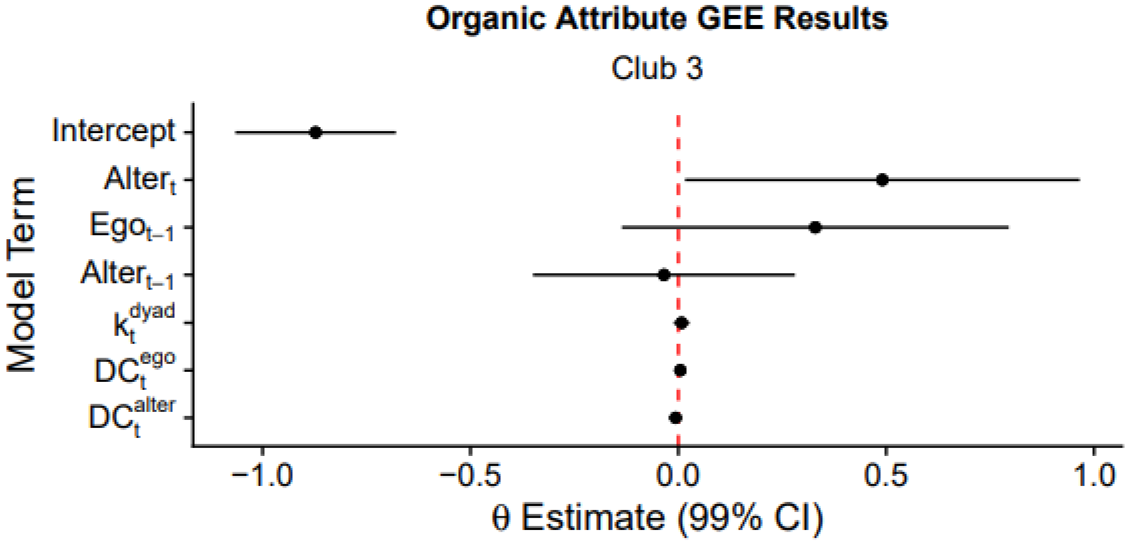
Table 2: Club 2 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
$Intercept$	39	12084.89***	333.28***	0.89
$Alter_t$	39	61.92*	844***	0.95
Ego_{t-1}	39	28625.05***	548.69***	0.93
$Alter_{t-1}$	39	1057.39***	227.06***	0.83
k_t^{dyad}	39	3517.22***	80.61***	0.53
DC_t^{ego}	39	24157.65***	424.68***	0.91
DC_t^{alter}	39	9519.18***	337.19***	0.89



Club 3

Club 3 had no analyzable item types



Club 4

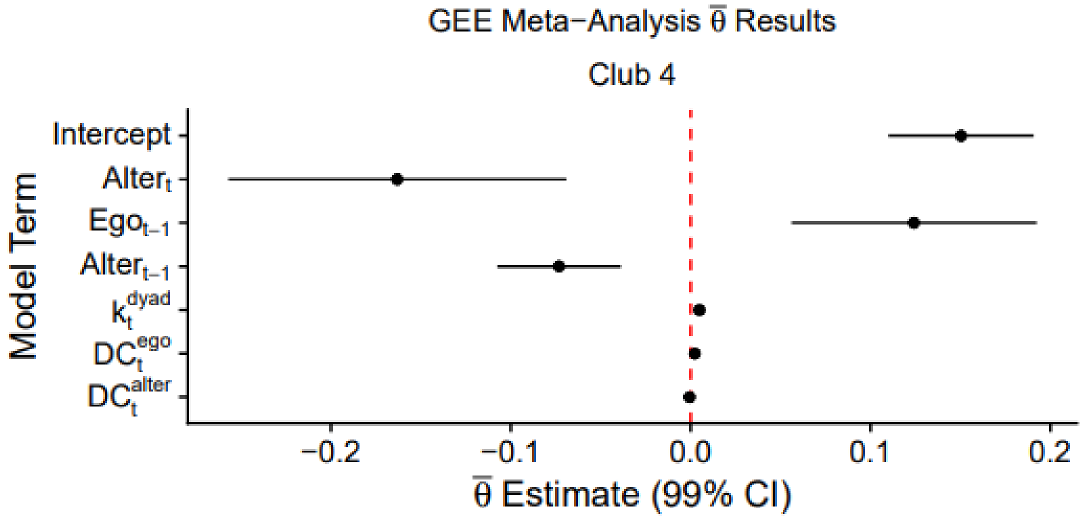
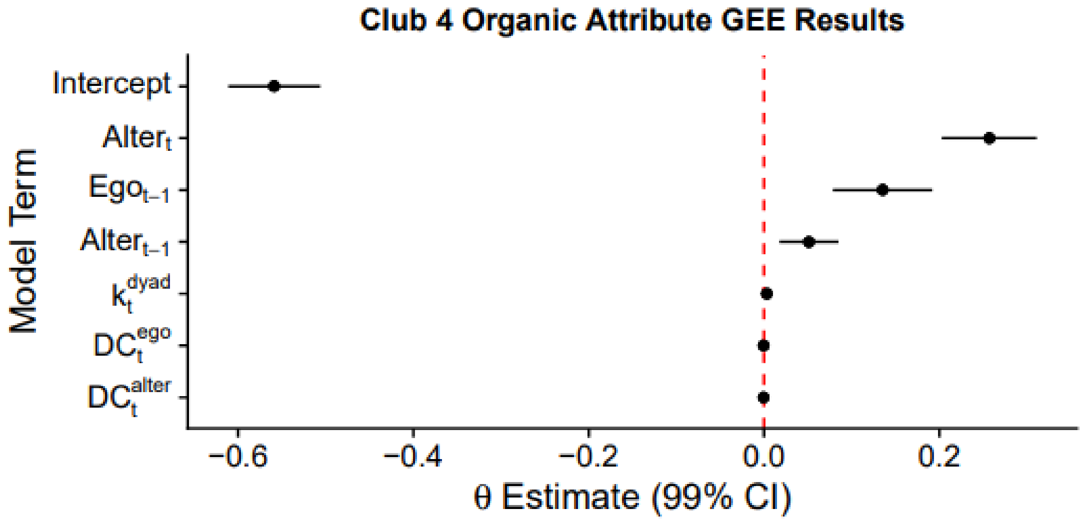


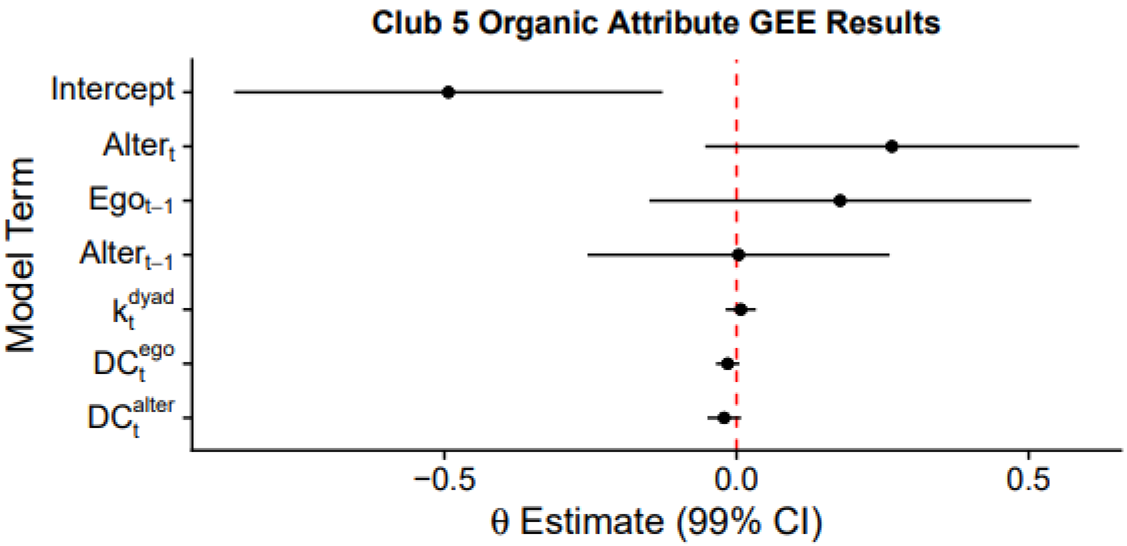
Table 3: Club 4 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
$Intercept$	102	80288.63***	1276.98***	0.92
$Alter_t$	102	153049.75***	5209.28***	0.98
Ego_{t-1}	102	70109.2***	3679.06***	0.97
$Alter_{t-1}$	102	19733.71***	945.26***	0.89
k_t^{dyad}	102	7269.26***	238.45***	0.58
DC_t^{ego}	102	203196.63***	1501.32***	0.93
DC_t^{alter}	102	12595.71***	861.39***	0.88



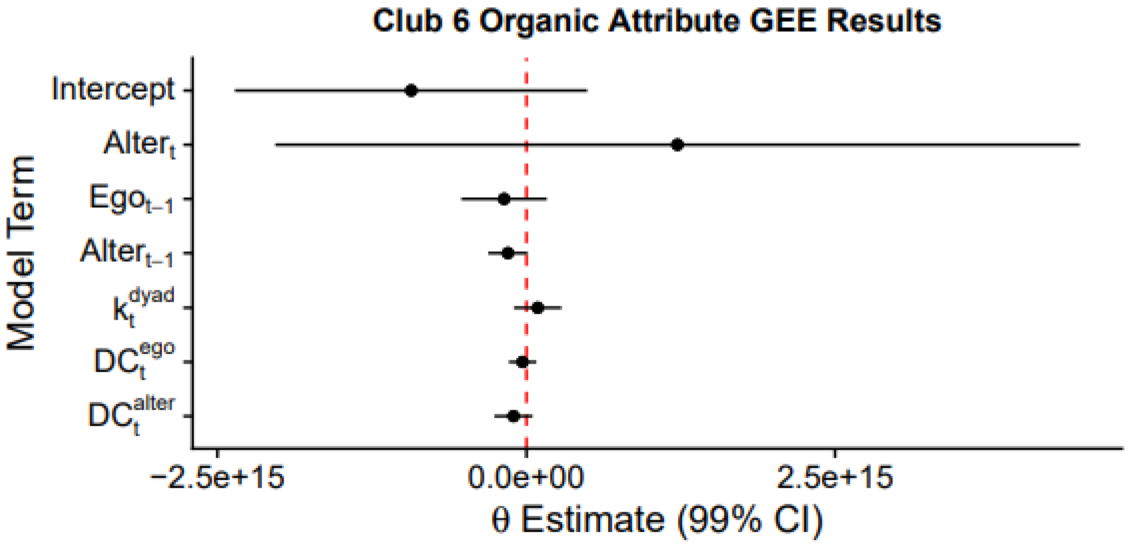
Club 5

Club 5 had no analyzable item types.



Club 6

Club 6 had no analyzable item types.



Club 7

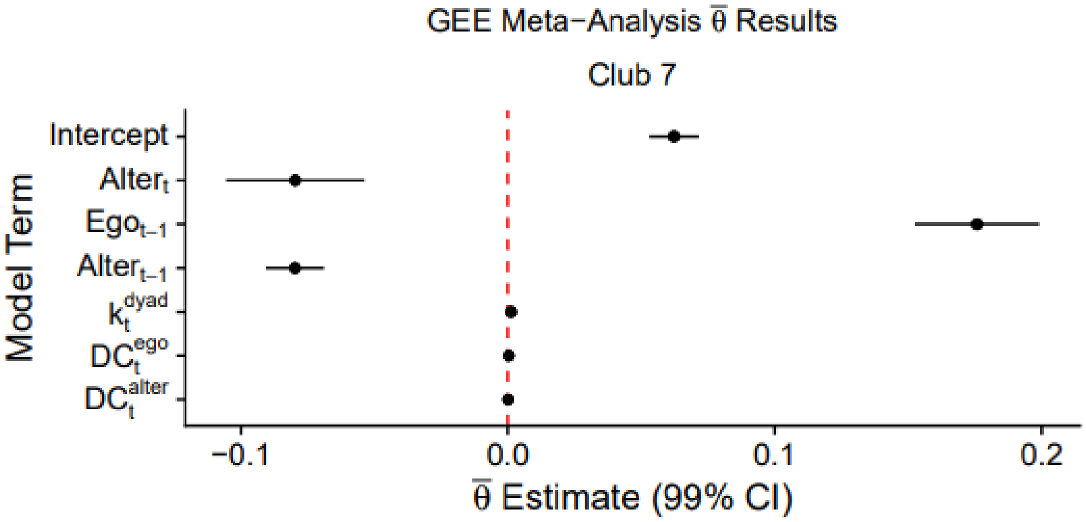
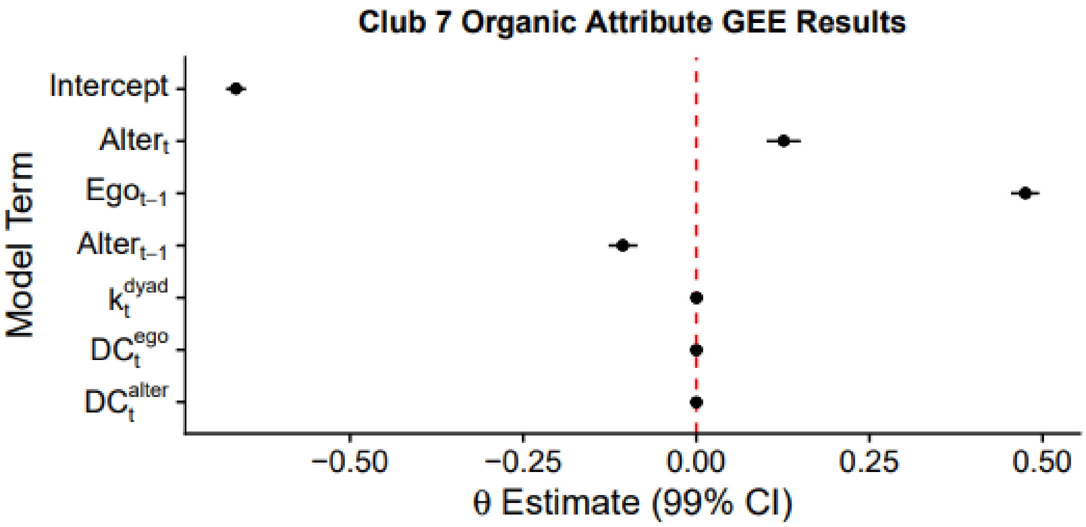


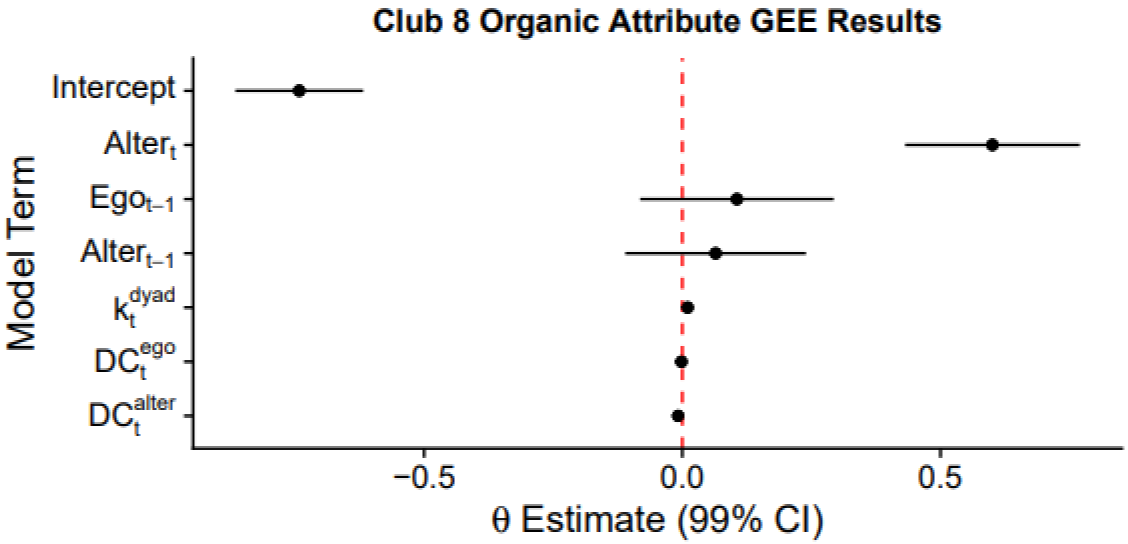
Table 4: Club 7 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
$Intercept$	399	4578869.53***	31598.76***	0.99
$Alter_t$	399	5344288.27***	61290.42***	0.99
Ego_{t-1}	399	17869181.76***	69645.57***	0.99
$Alter_{t-1}$	399	5617984.04***	18308.47***	0.98
k_t^{dyad}	399	347160.27***	3966.62***	0.90
DC_t^{ego}	399	14826786.46***	38397.85***	0.99
DC_t^{alter}	399	606604.78***	12576.37***	0.97



Club 8

Club 8 has no analyzable item types.



Club 9

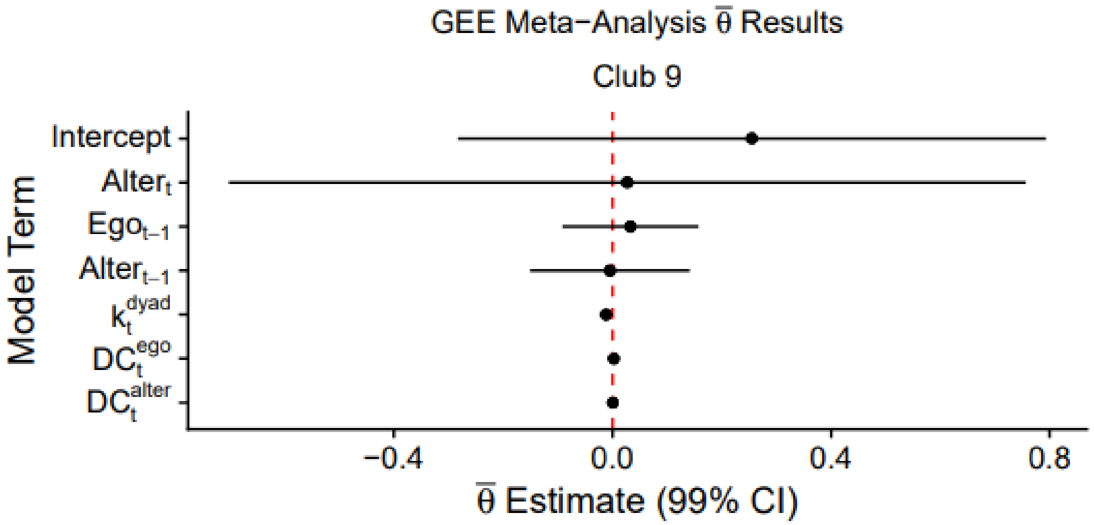
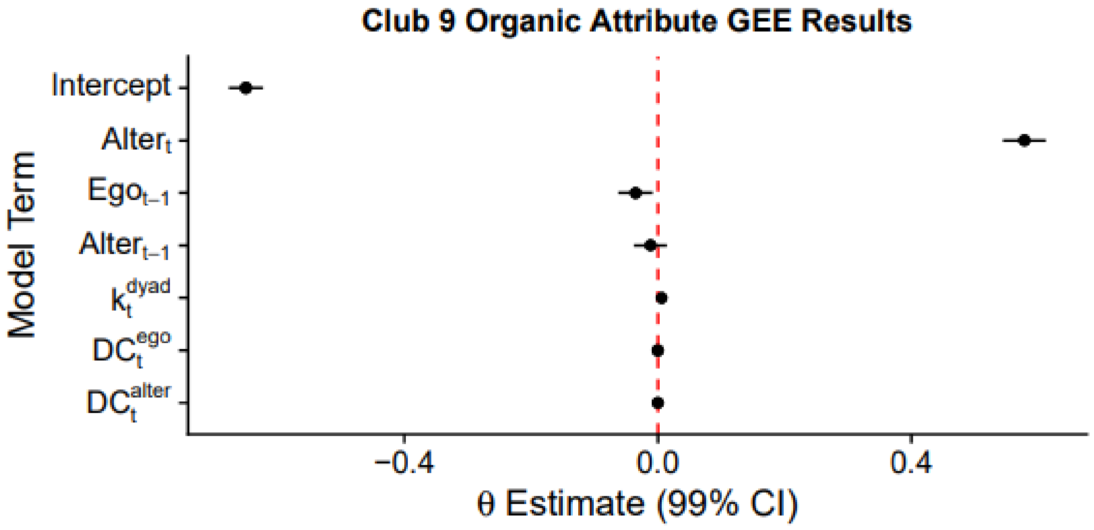


Table 5: Club 9 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
$Intercept$	5	691.71***	463.89***	0.99
$Alter_t$	5	213.95***	1874.9***	1.00
Ego_{t-1}	5	59.71***	60.79***	0.93
$Alter_{t-1}$	5	0.41	87.68***	0.95
k_t^{dyad}	5	109.23***	19.97***	0.80
DC_t^{ego}	5	5078.96***	169.87***	0.98
DC_t^{alter}	5	138.58***	225.94***	0.98



Club 11

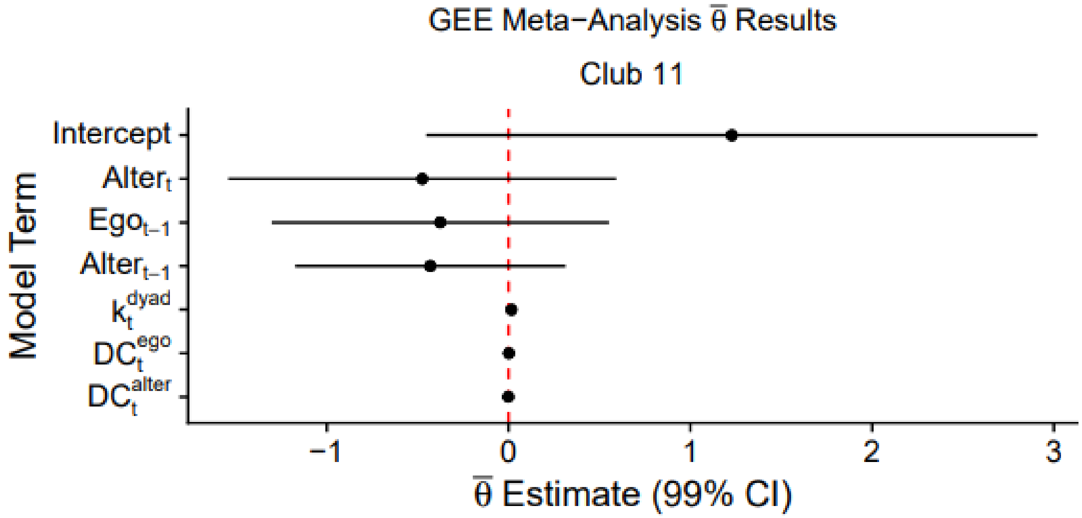
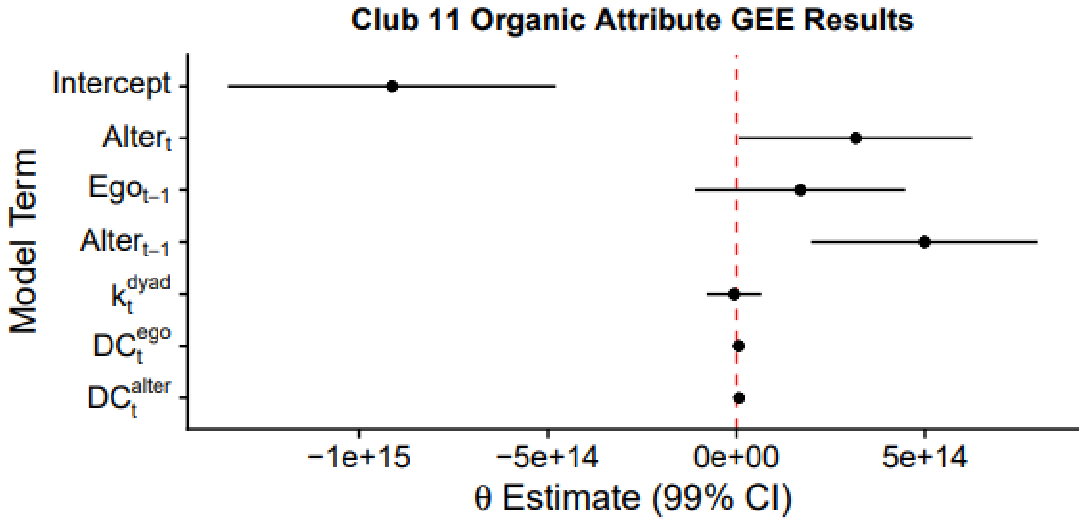


Table 6: Club 11 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
$Intercept$	3	947.93***	248.37***	0.99
$Alter_t$	3	1492.98***	638.38***	1.00
Ego_{t-1}	3	164.84***	249.1***	0.99
$Alter_{t-1}$	3	347.39***	162.24***	0.99
k_t^{dyad}	3	13.14**	1.36	0.00
DC_t^{ego}	3	142.33***	40.74***	0.95
DC_t^{alter}	3	71.39***	11.43**	0.83



Club 12

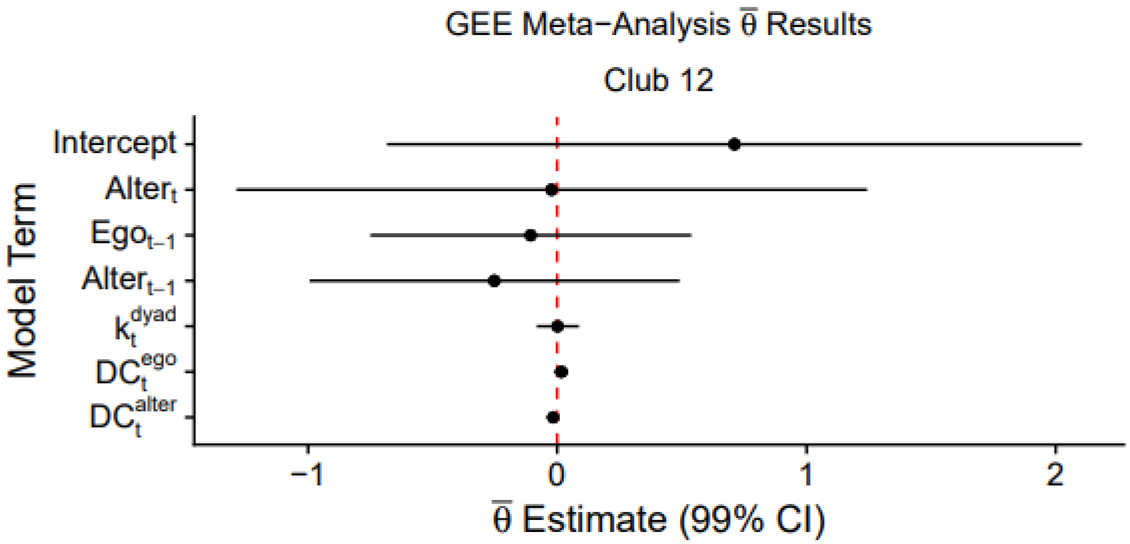
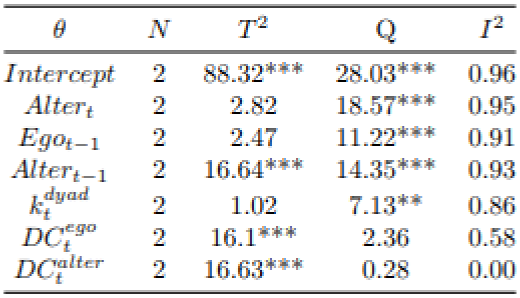


Table 7: Club 12 Meta Analysis Heterogenaity Estimates

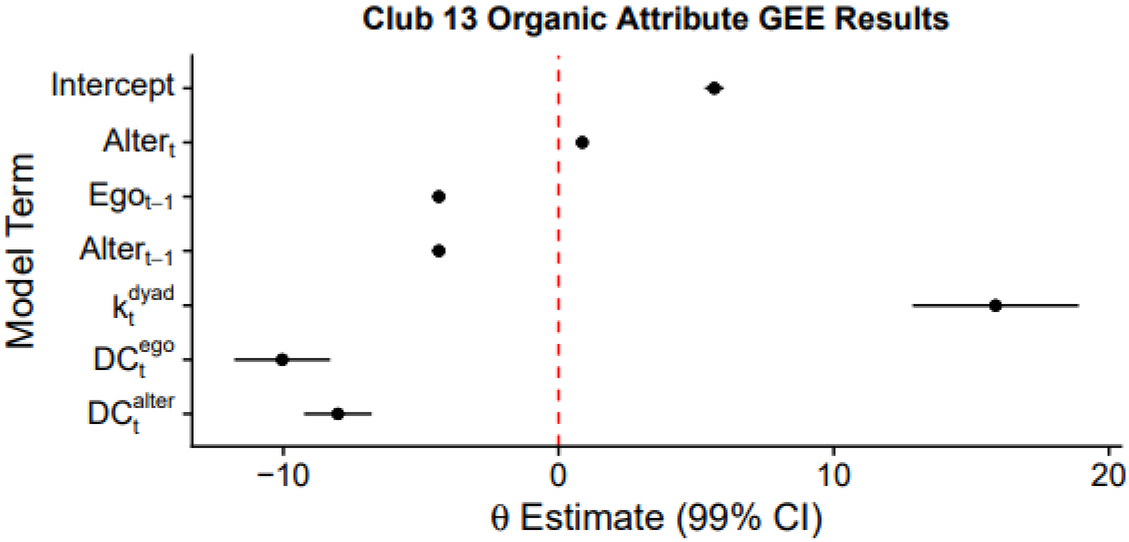


θ	N	T^2	Q	I^2
$Intercept$	2	88.32***	28.03***	0.96
$Alter_t$	2	2.82	18.57***	0.95
Ego_{t-1}	2	2.47	11.22***	0.91
$Alter_{t-1}$	2	16.64***	14.35***	0.93
k_t^{dyad}	2	1.02	7.13**	0.86
DC_t^{ego}	2	16.1***	2.36	0.58
DC_t^{alter}	2	16.63***	0.28	0.00

Club 12 purchased very few organic items and had several orders where none were purchased. This prevented an organic GEE from being estimated.

Club 13

Club 13 had no analyzable item types.



Club 14

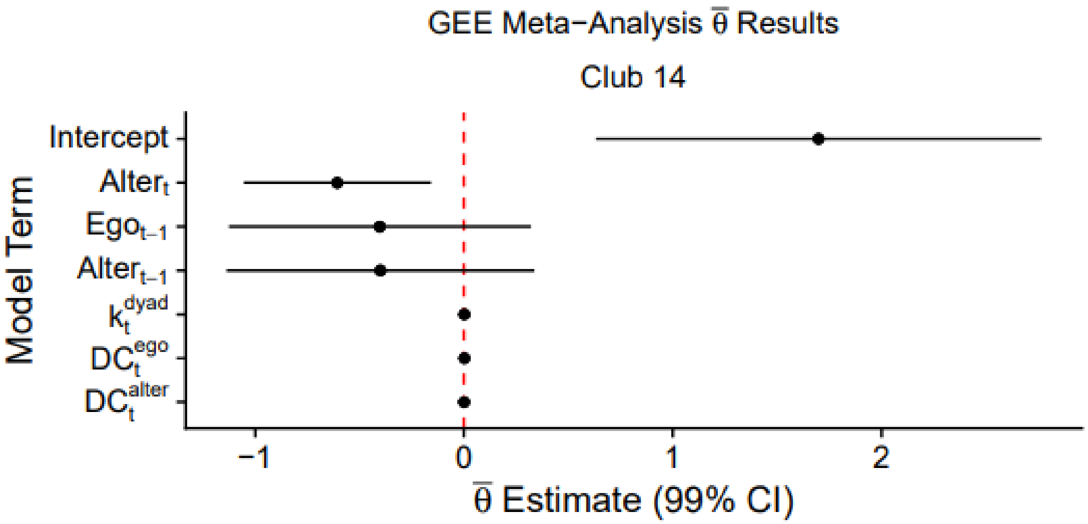
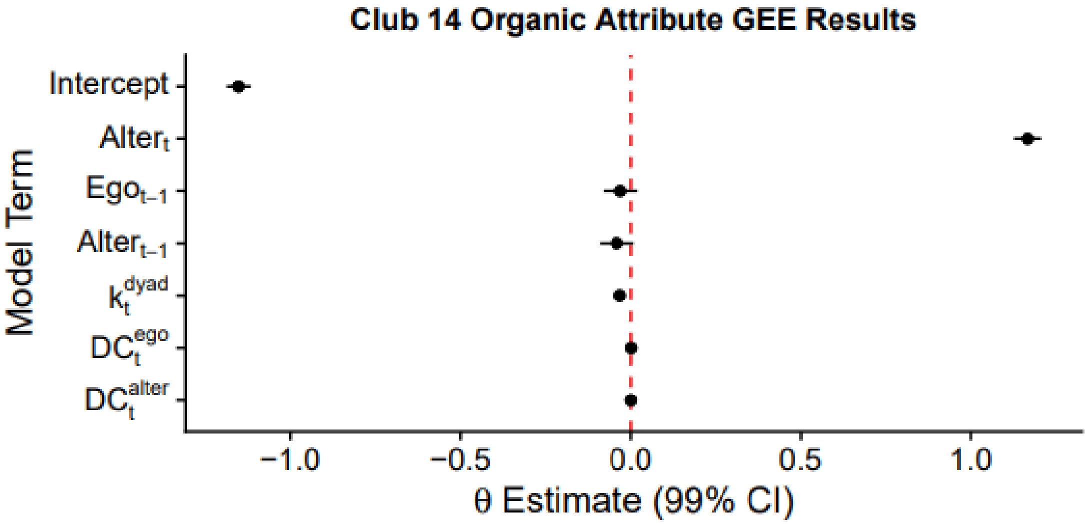


Table 8: Club 14 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
$Intercept$	4	9049.58***	387.71***	0.99
$Alter_t$	4	75028141.66***	509.86***	0.99
Ego_{t-1}	4	1976374.16***	1469.68***	1.00
$Alter_{t-1}$	4	1980015.34***	1754.9***	1.00
k_t^{dyad}	4	0	10.12*	0.70
DC_t^{ego}	4	564.79***	174.89***	0.98
DC_t^{alter}	4	151.87***	78.2***	0.96



Club 15

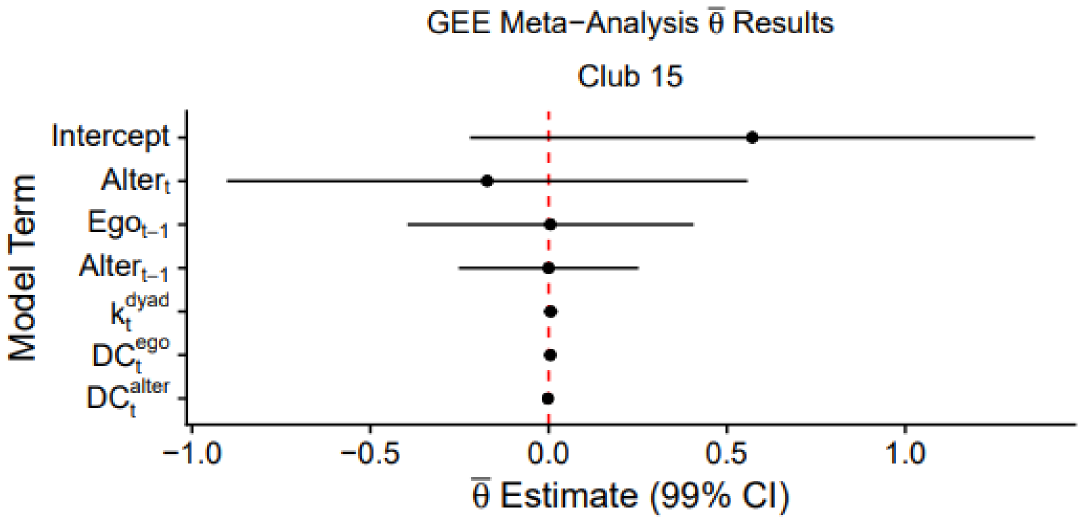
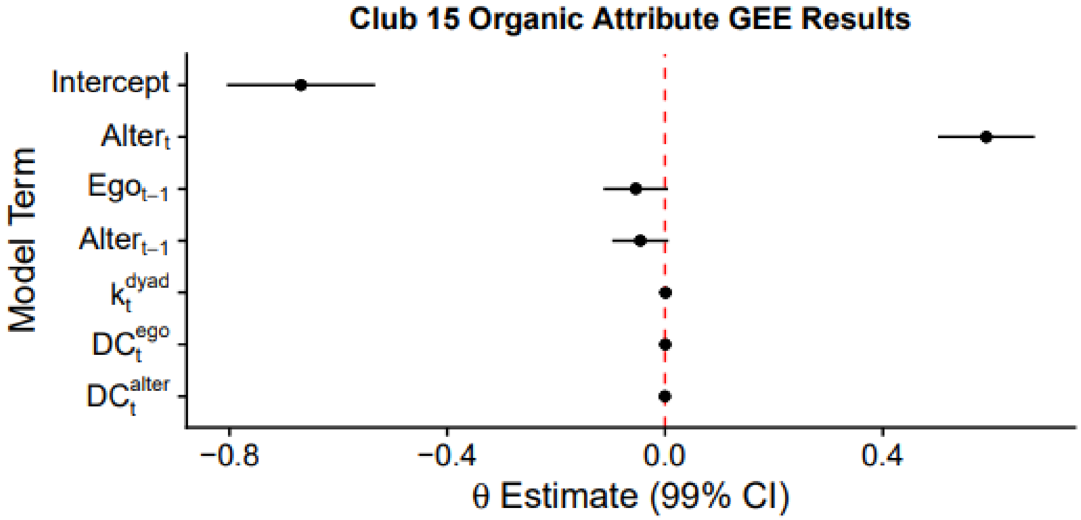


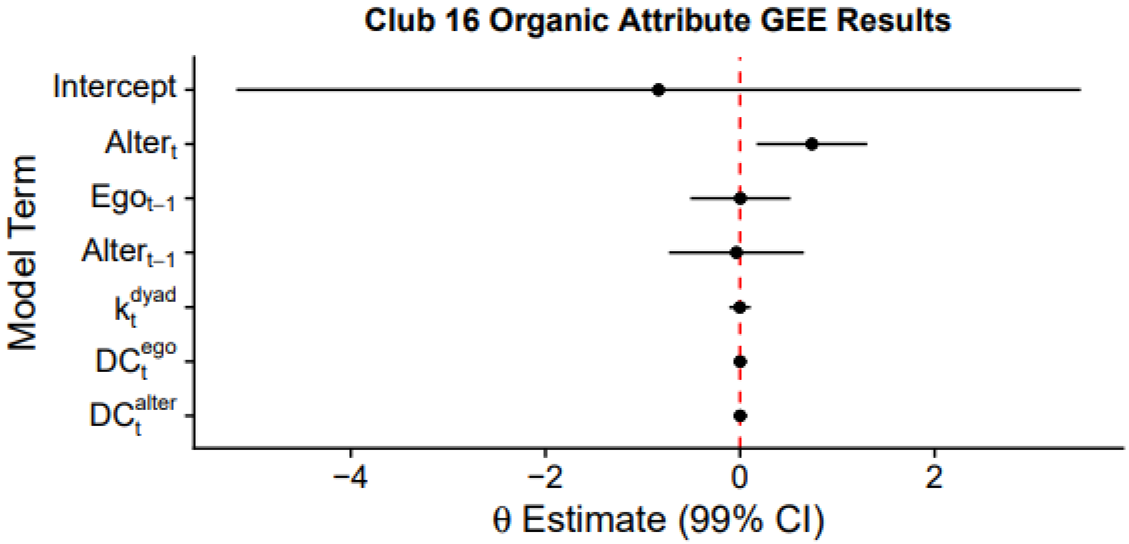
Table 9: Club 15 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
$Intercept$	5	164.62***	71.43***	0.94
$Alter_t$	5	4630.84***	707.19***	0.99
Ego_{t-1}	5	0.66	69.86***	0.94
$Alter_{t-1}$	5	0.87	29.07***	0.86
k_t^{dyad}	5	2.29	5.51	0.27
DC_t^{ego}	5	185.52***	18.72***	0.79
DC_t^{alter}	5	14.35*	37.18***	0.89

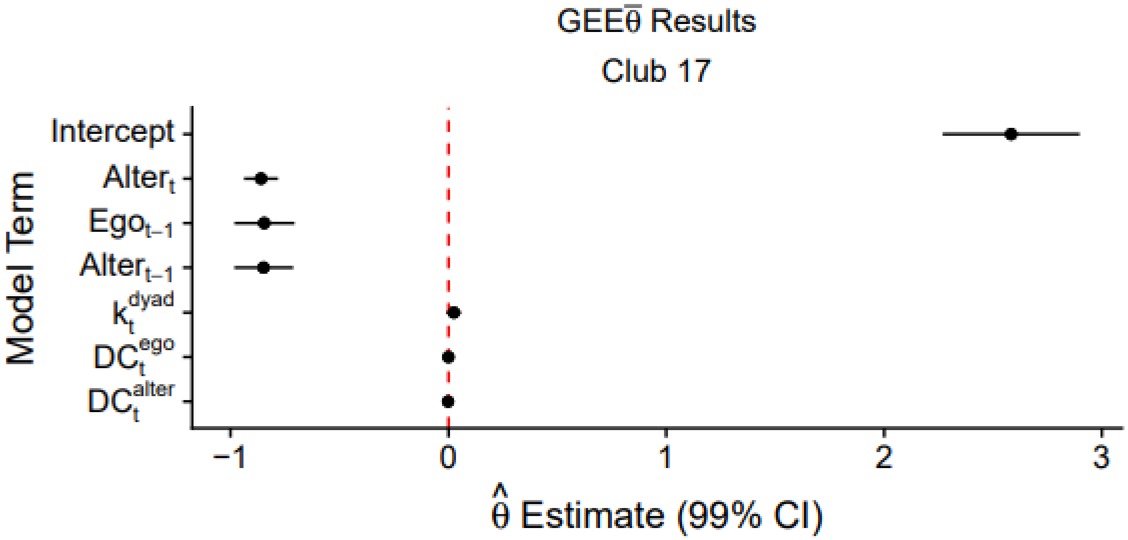


Club 16

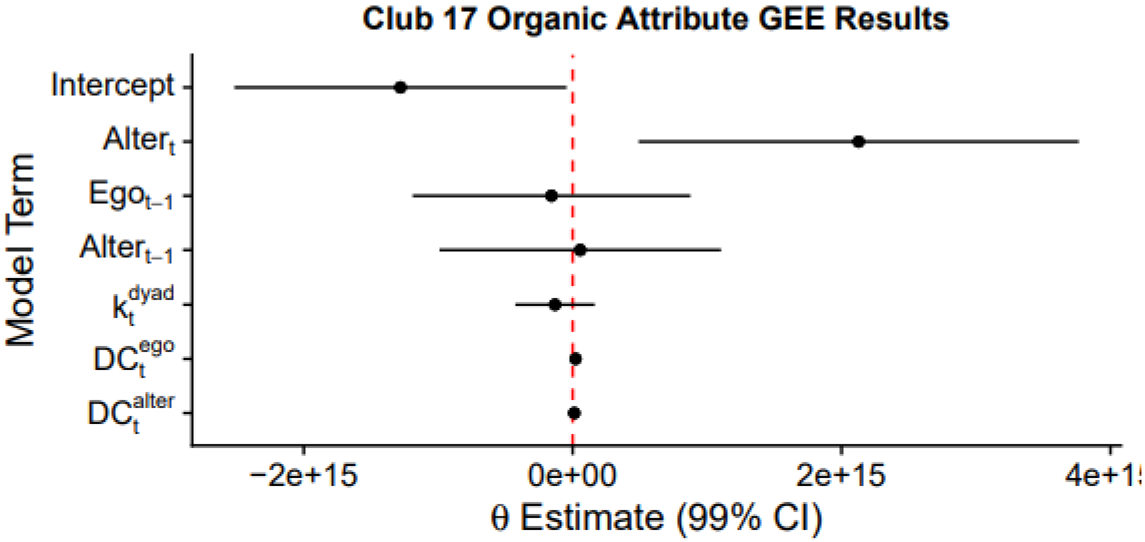
Club 16 had no analyzable item types.



Club 17



Club 17 only had 1 analyzable item type, so meta-analysis technique was not required.



Club 18

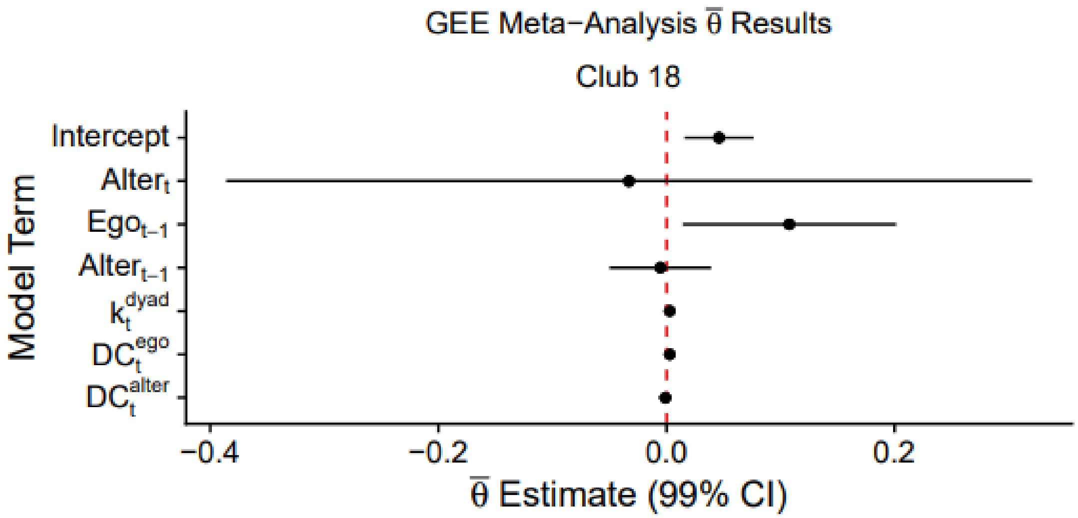
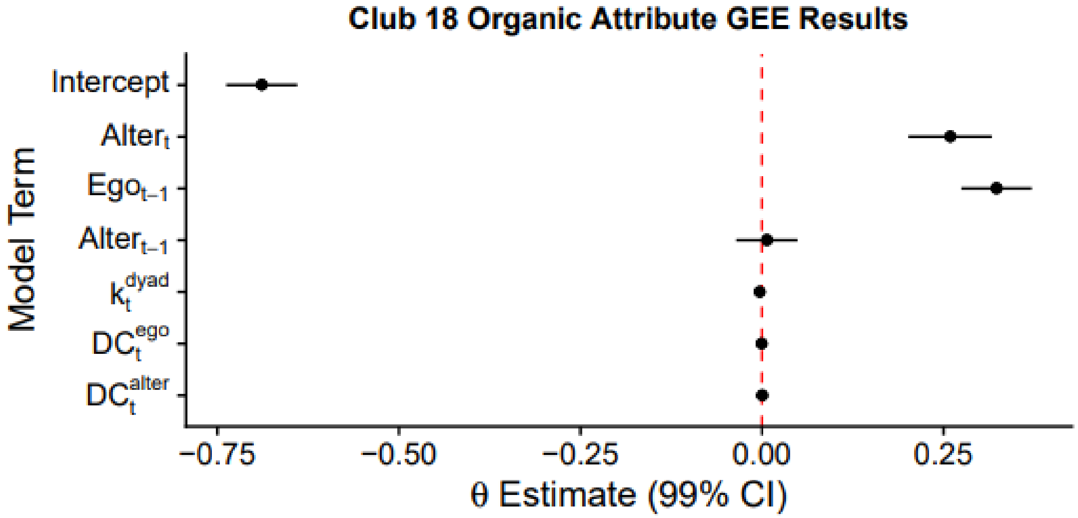
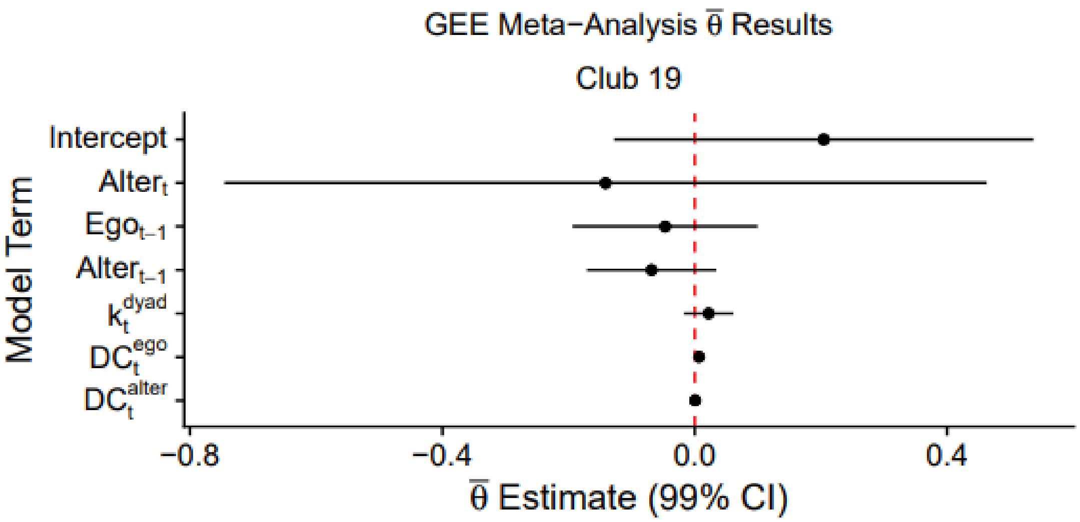


Table 10: Club 18 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
$Intercept$	41	3611.87***	564.13***	0.93
$Alter_t$	41	1504.39***	33134.62***	1.00
Ego_{t-1}	41	12933.23***	1499.34***	0.97
$Alter_{t-1}$	41	47.93	294.15***	0.86
k_t^{dyad}	41	109.53***	121.61***	0.67
DC_t^{ego}	41	30812.83***	916.16***	0.96
DC_t^{alter}	41	3252.94***	368.17***	0.89



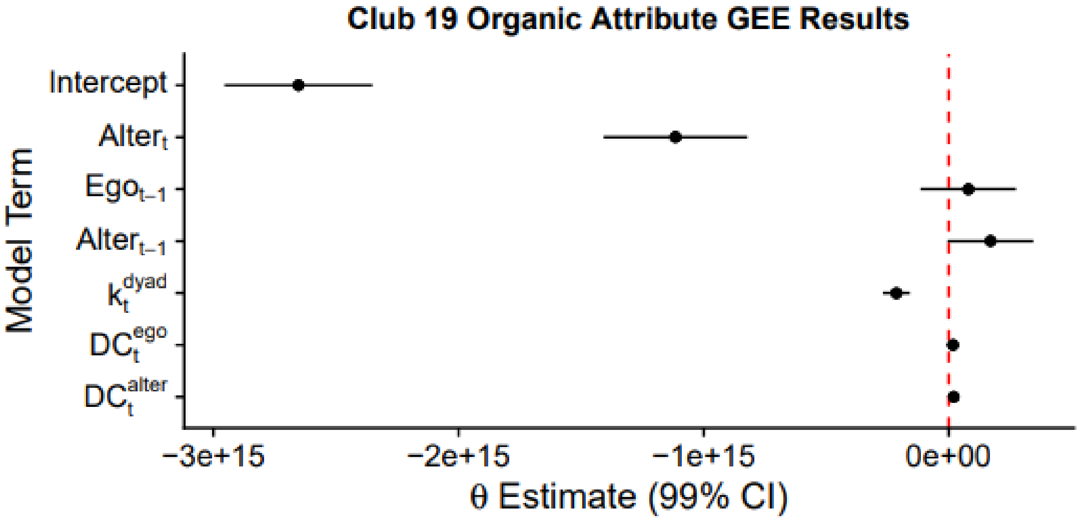
Club 19


GEE Meta−Analysis $\overline{\theta}$ Results

Club 19

Table 11: Club 19 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
$Intercept$	6	84.22***	49.97***	0.90
$Alter_t$	6	1677.04***	682.55***	0.99
Ego_{t-1}	6	8.74	38.56***	0.87
$Alter_{t-1}$	6	65.09***	18.62**	0.73
k_t^{dyad}	6	34.5***	28.48***	0.82
DC_t^{ego}	6	1646.43***	45.08***	0.89
DC_t^{alter}	6	2.95	101.99***	0.95


Club 19 Organic Attribute GEE Results

Club 20

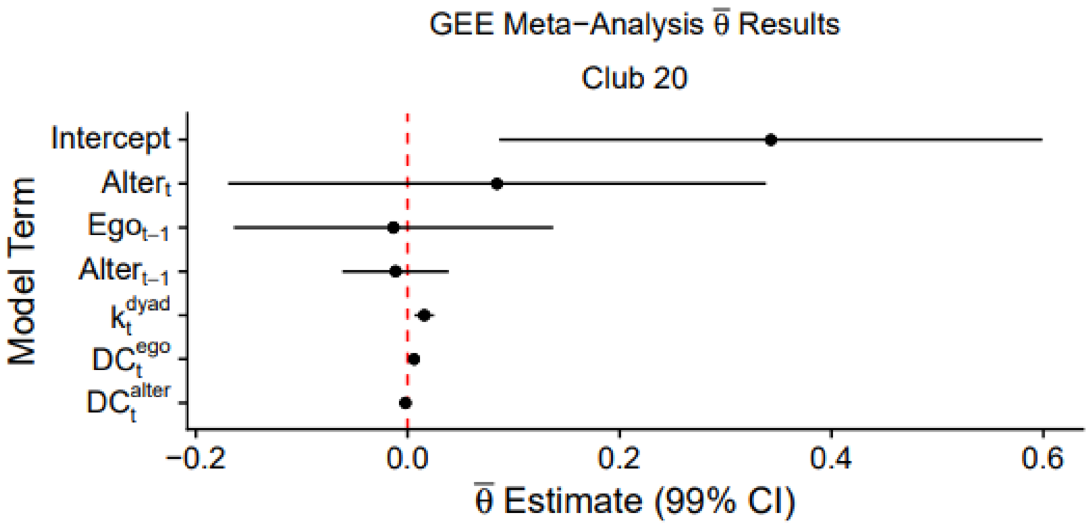
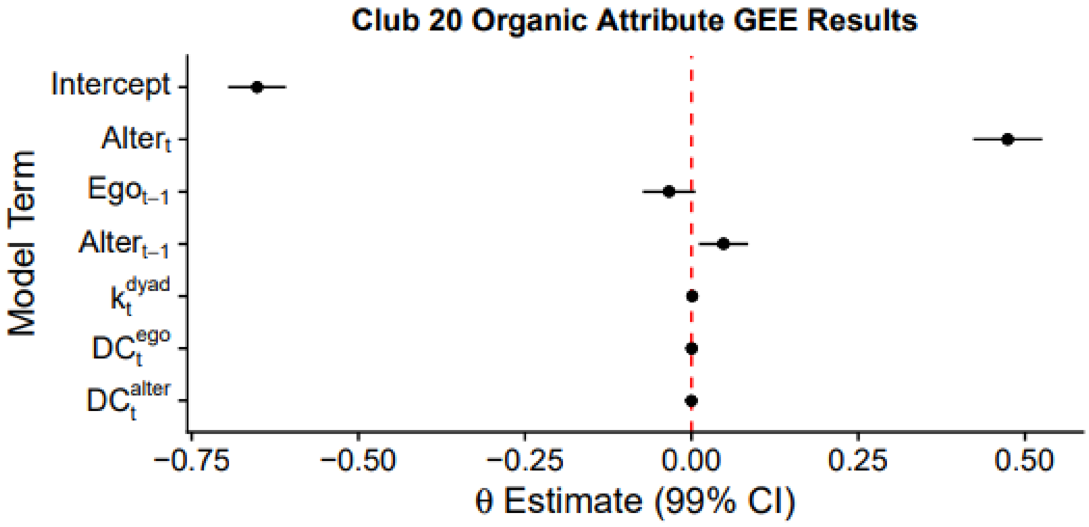


Table 12: Club 20 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
Intercept	5	505.52***	34.8***	0.89
$Alter_t$	5	33.8***	37.04***	0.89
Ego_{t-1}	5	3.65	33.66***	0.88
$Alter_{t-1}$	5	1.49	2.78	0.00
k_t^{dyad}	5	82.43***	2.28	0.00
DC_t^{ego}	5	2161.59***	25.7***	0.84
DC_t^{alter}	5	143.95***	19.71***	0.80



Club 21

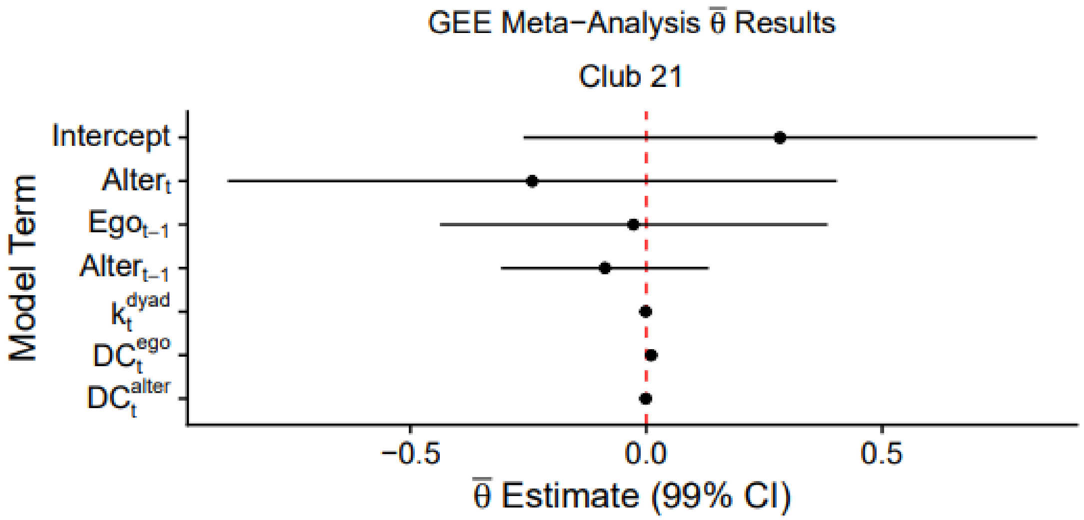
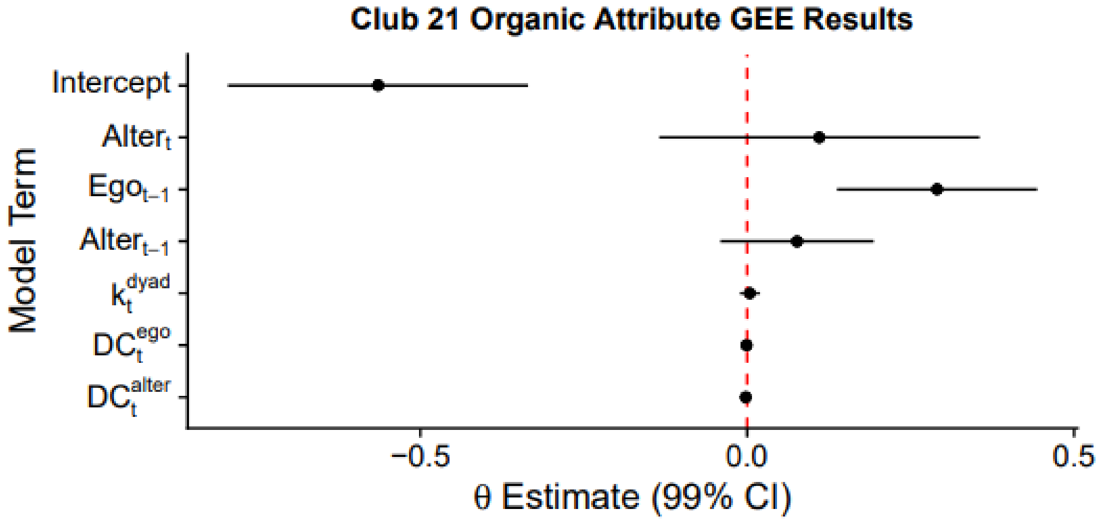


Table 13: Club 21 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
$Intercept$	6	110.75***	67.49***	0.93
$Alter_t$	6	13056.21***	319.12***	0.98
Ego_{t-1}	6	0.31	285.29***	0.98
$Alter_{t-1}$	6	29.11***	44.3***	0.89
k_t^{dyad}	6	4.93	5.35	0.07
DC_t^{ego}	6	133.19***	55.05***	0.91
DC_t^{alter}	6	0.26	6.4	0.22



Club 22

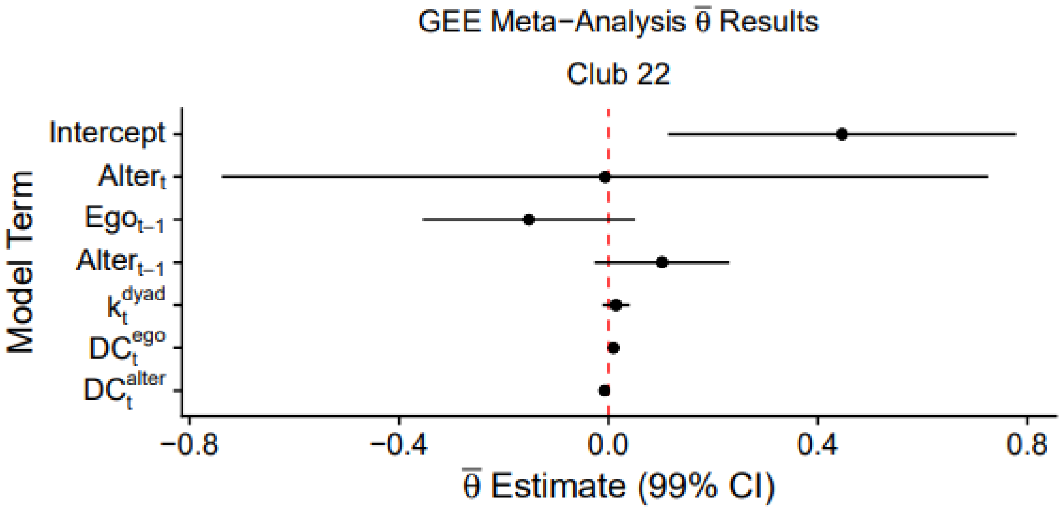
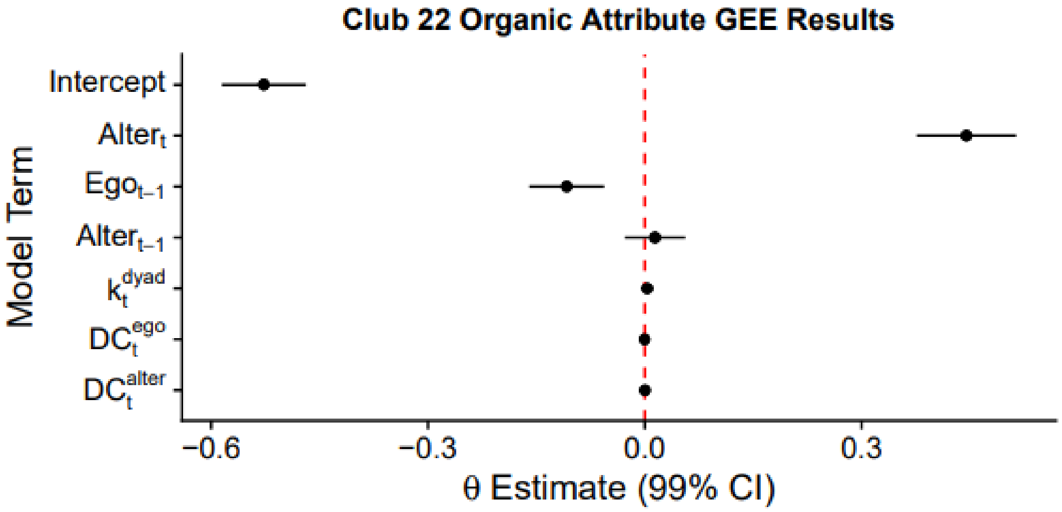


Table 14: Club 22 Meta Analysis Heterogenaity Estimates

θ	N	T^2	Q	I^2
$Intercept$	7	437.95***	38.71***	0.85
$Alter_t$	7	604.74***	372.7***	0.98
Ego_{t-1}	7	301.28***	49.54***	0.88
$Alter_{t-1}$	7	71.32***	15.19*	0.60
k_t^{dyad}	7	8.74	4	0.00
DC_t^{ego}	7	913.72***	46.62***	0.87
DC_t^{alter}	7	271.89***	46.14***	0.87



Club 23

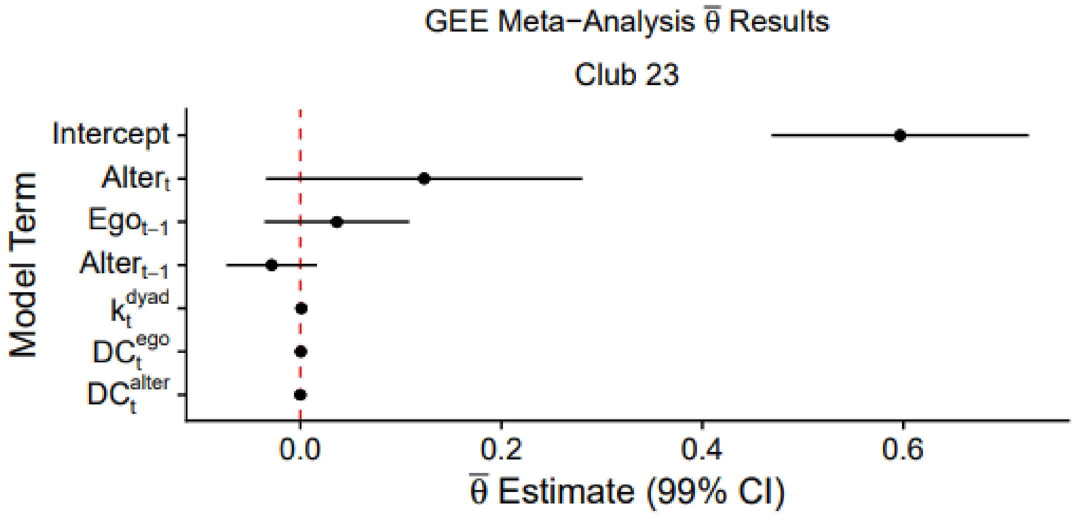
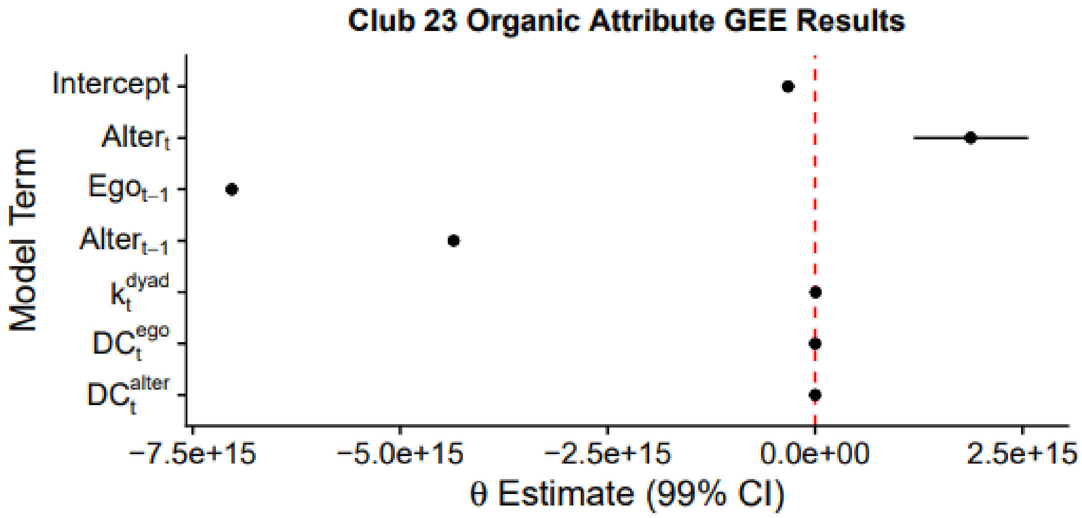
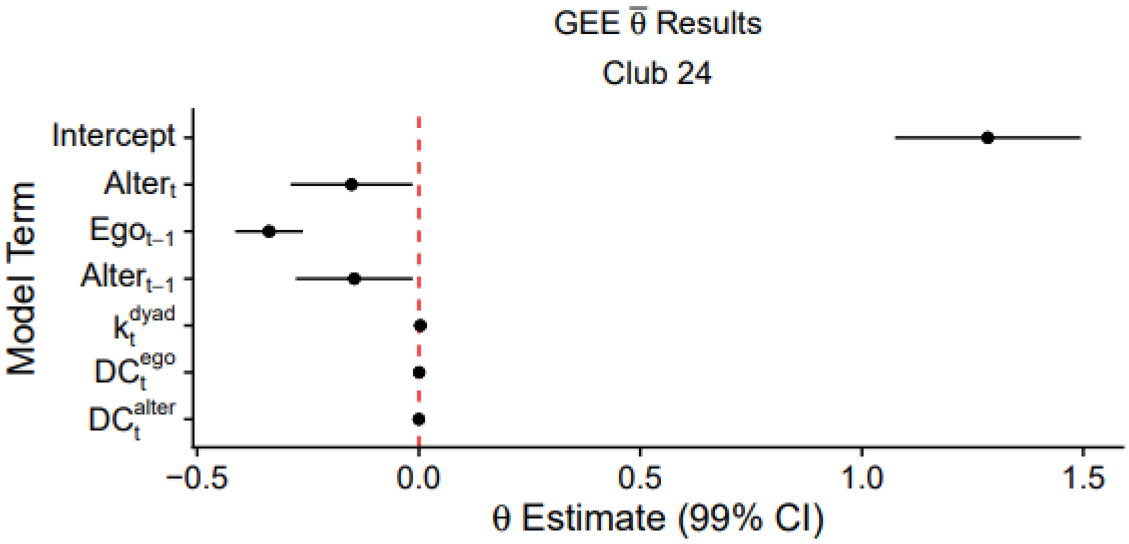


Table 15: Club 23 Meta Analysis Heterogenaity Estimates

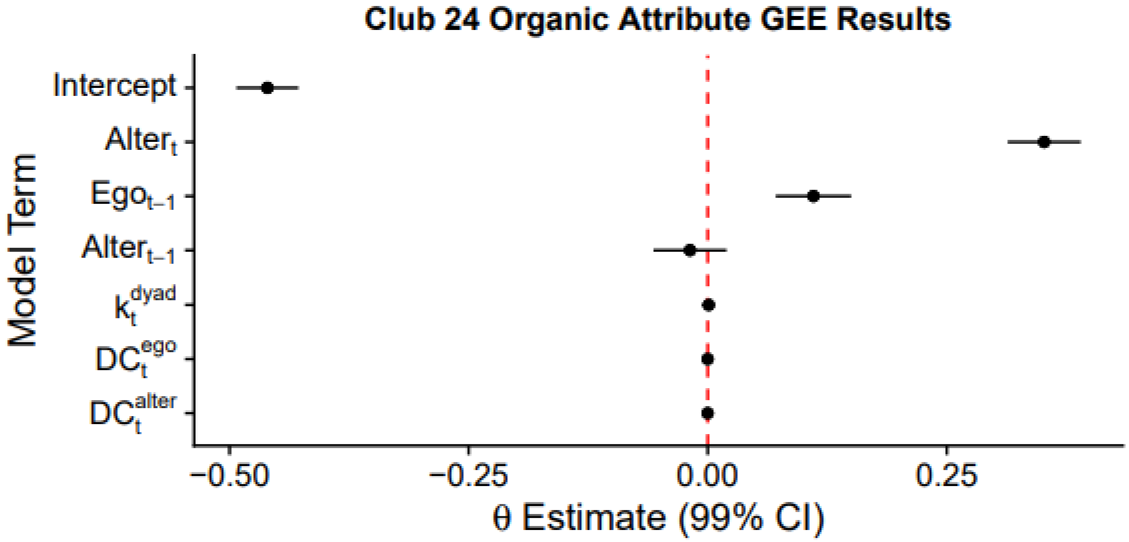
θ	N	T^2	Q	I^2
$Intercept$	5	15350.63***	78.75***	0.95
$Alter_t$	5	755.54***	181.84***	0.98
Ego_{t-1}	5	220.91***	62.43***	0.94
$Alter_{t-1}$	5	72.52***	31.65***	0.87
k_t^{dyad}	5	15.28**	109.39***	0.96
DC_t^{ego}	5	8334.49***	286.16***	0.99
DC_t^{alter}	5	189.74***	98.01***	0.96



Club 24

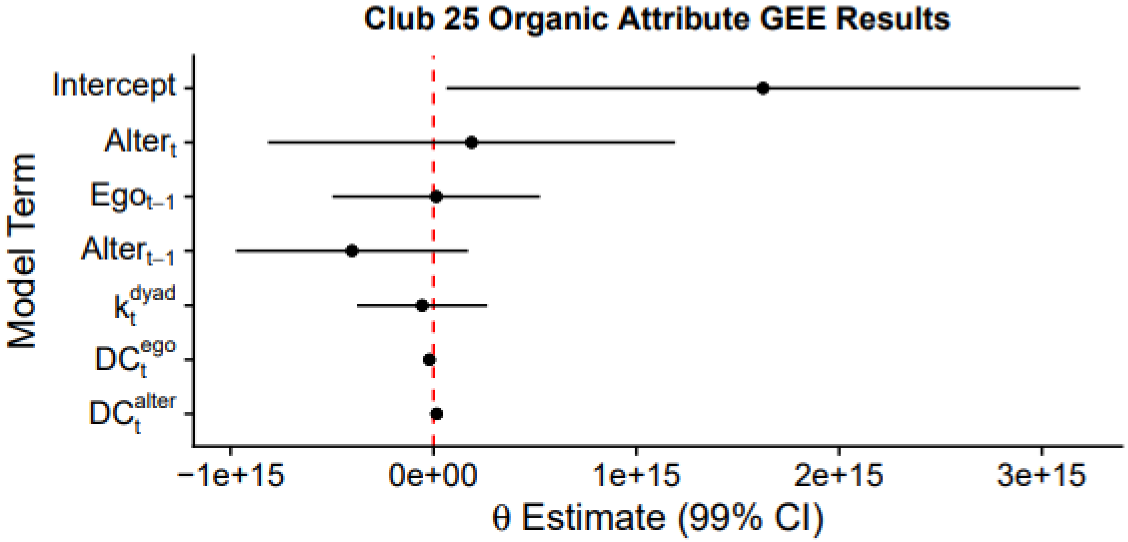


Club 24 ornly had one analyzable item type so meta analysis techniques were not required.

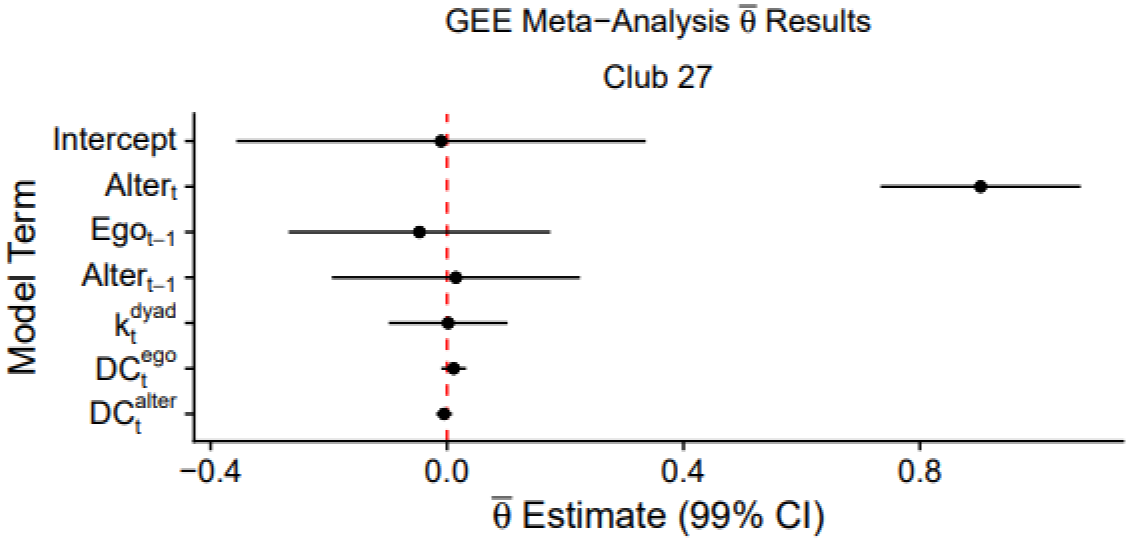


Club 25

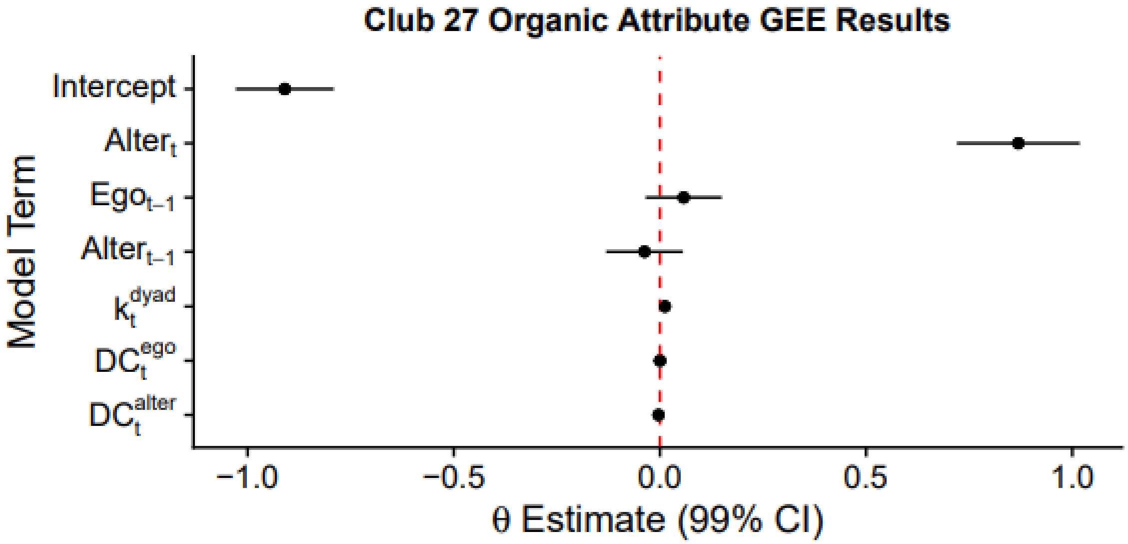
Club 26 had no analyzable item types



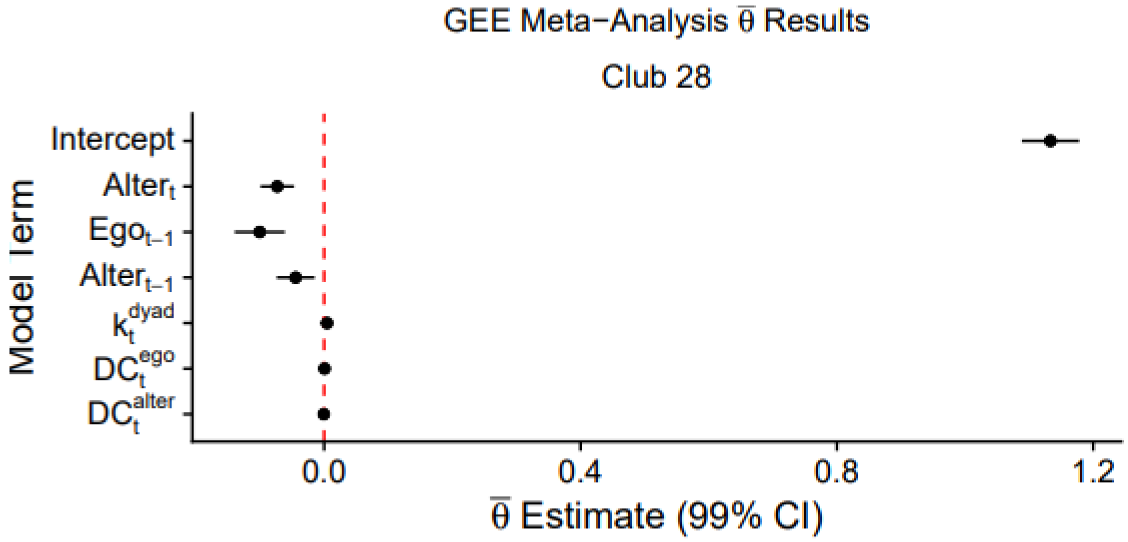
Club 27



Club 27 only had one analyzable item type, so meta analysis techniques were not required.



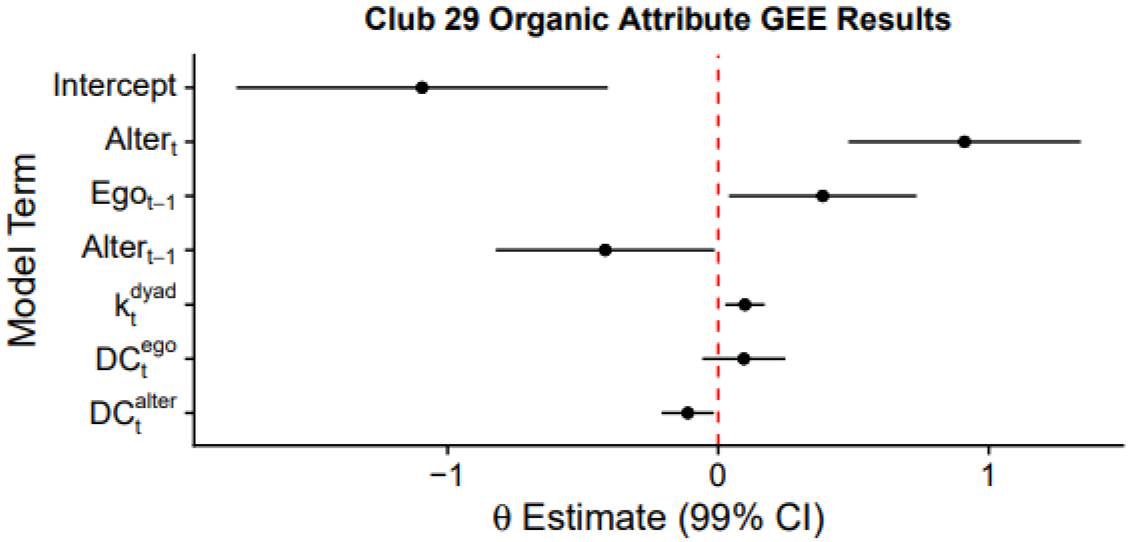
Club 28



Club 28 only had one analyzable item type, so meta analysis techniques were not required. Additionally, club 28 did not purchase a substantial amount of organic items, with some orders having none purchased at all. Thus an Organic GEE could not be computed.

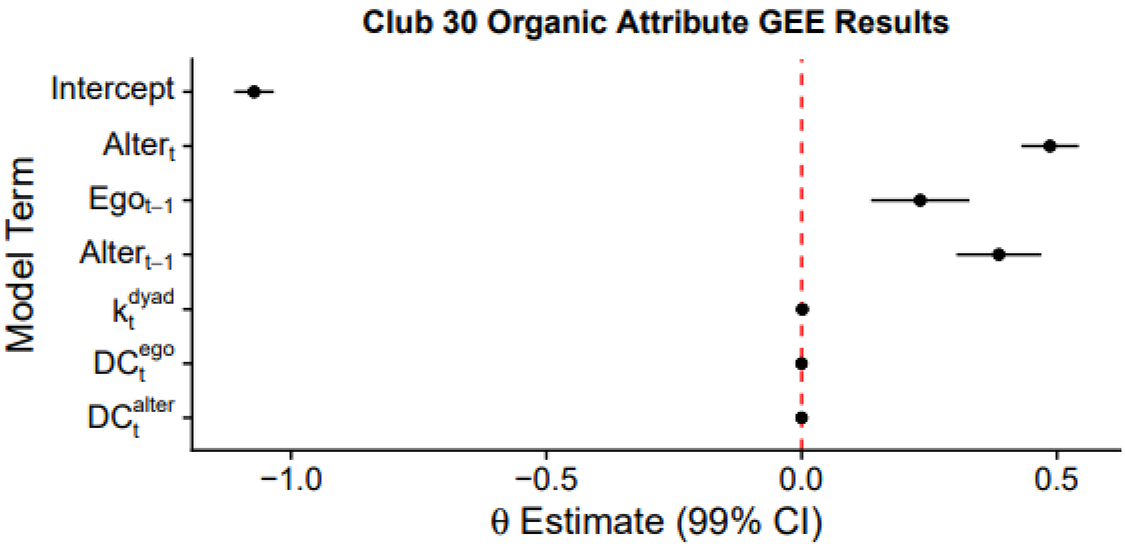
Club 29

Club 29 had no analyzable item types.



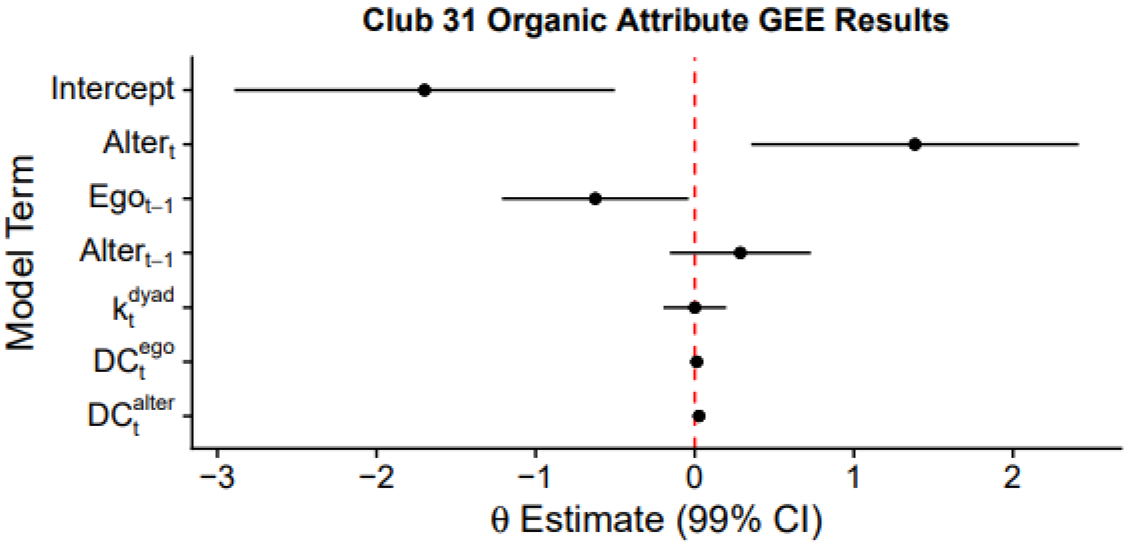
Club 30

Club 20 had no analyzable item types.



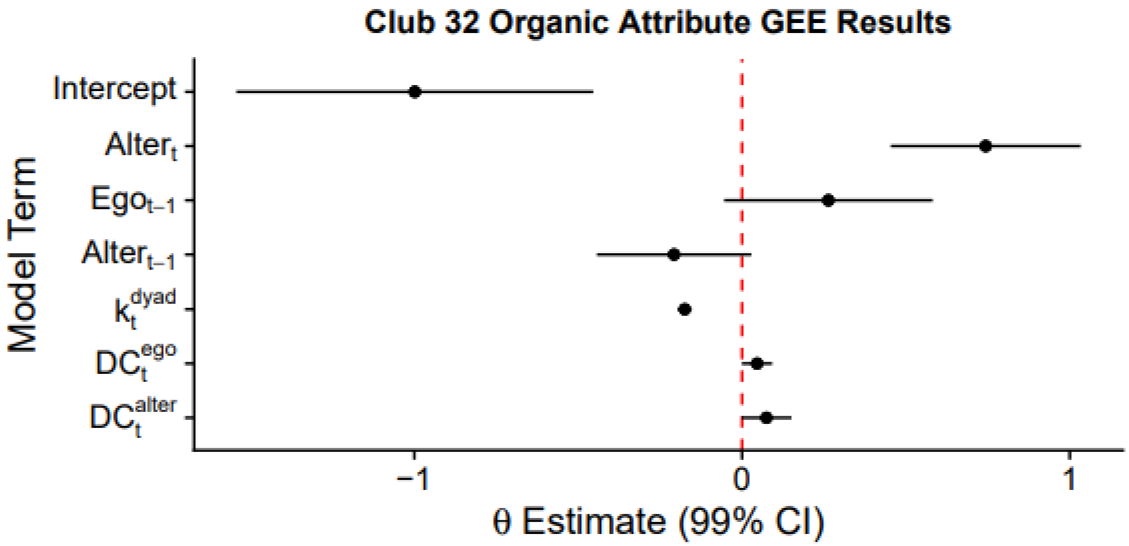
Club 31

Club 31 had no analyzable item types



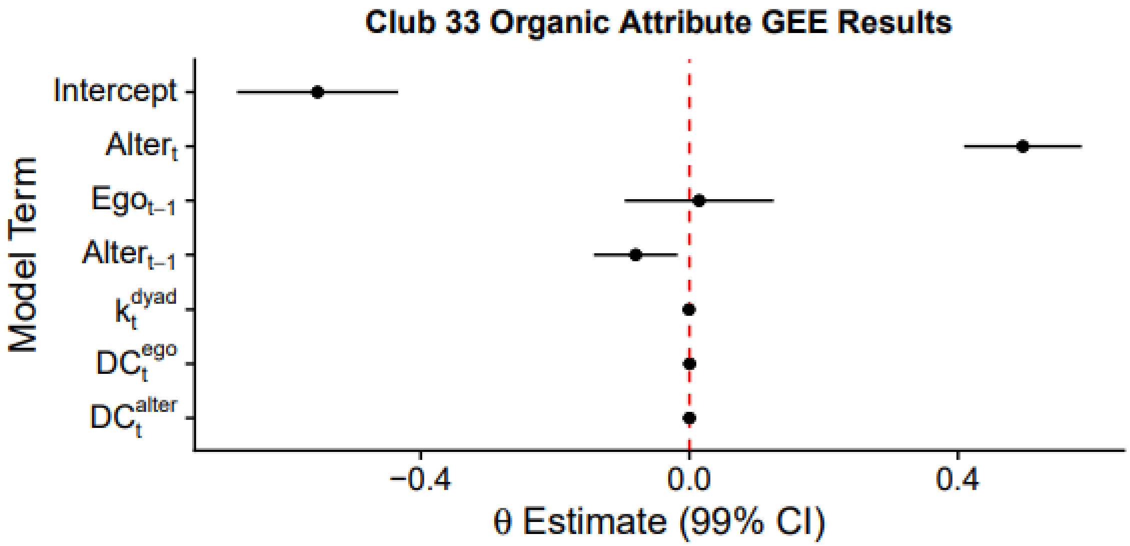
Club 32

Club 32 had no analyzable item types



Club 33

Club 33 had no analyzable item types

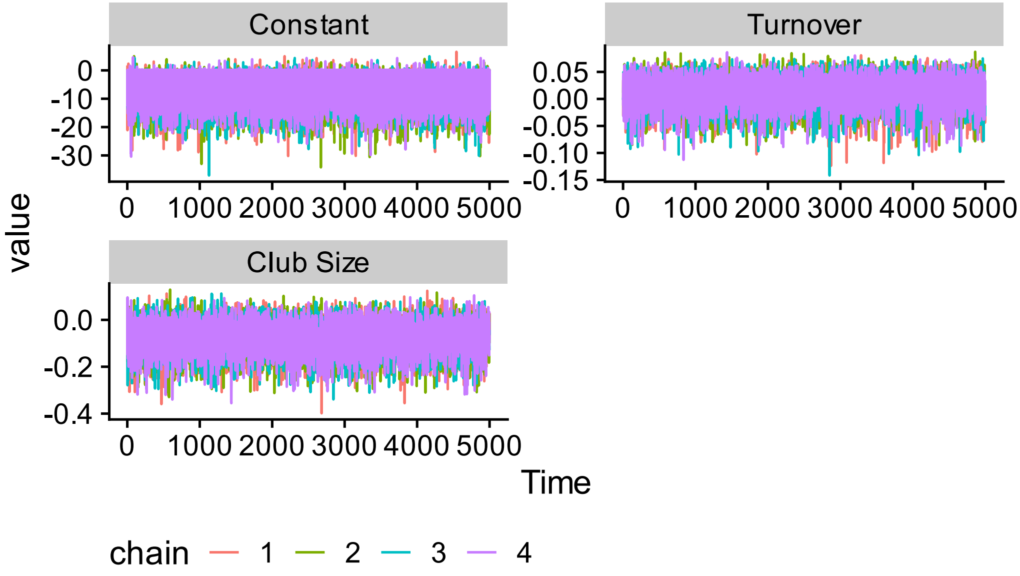


APPENDIX 3
SUPPLEMENT TO CHAPTER 4

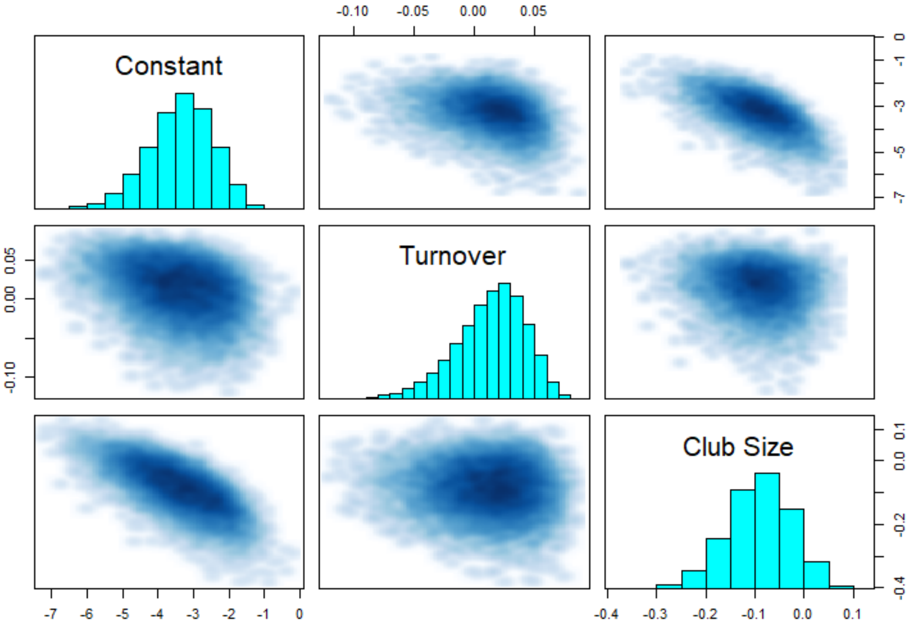
Model Trace and Pairs Plots

Base model

Trace Plot

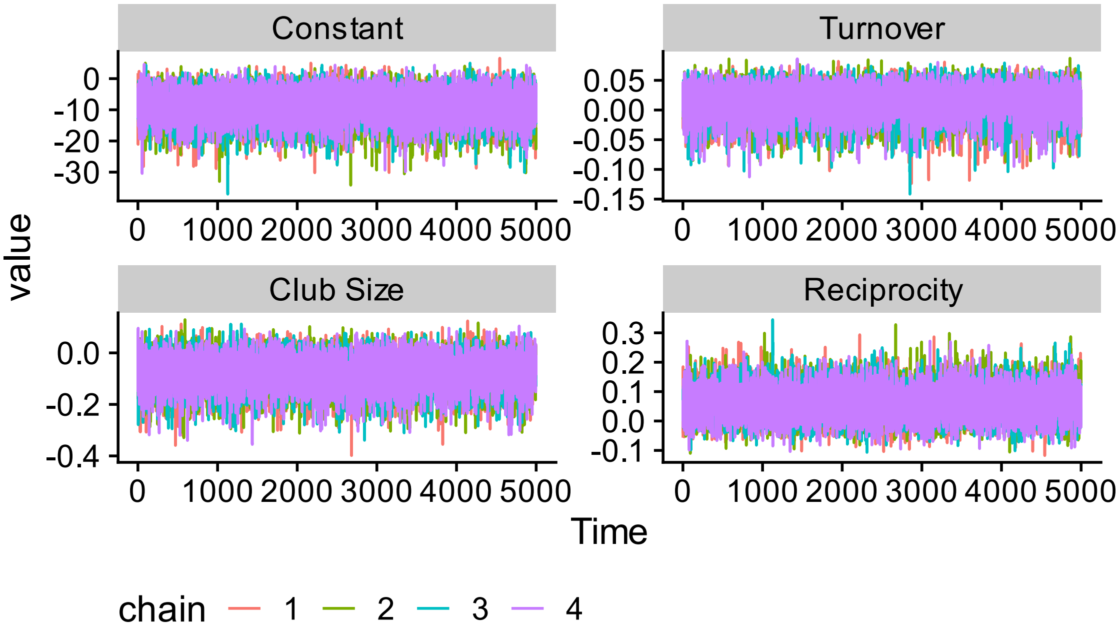


Pairs Plot

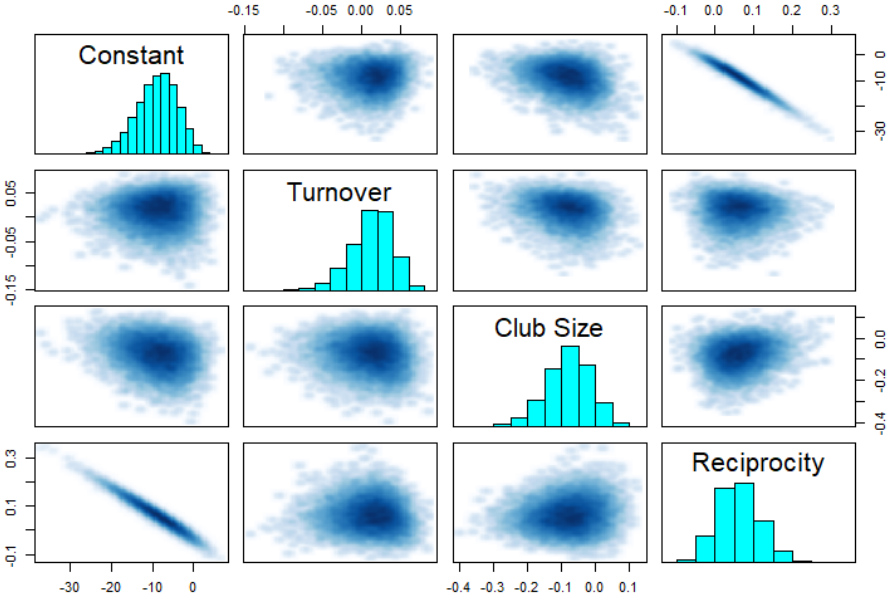


Reciprocity Model

Traceplot

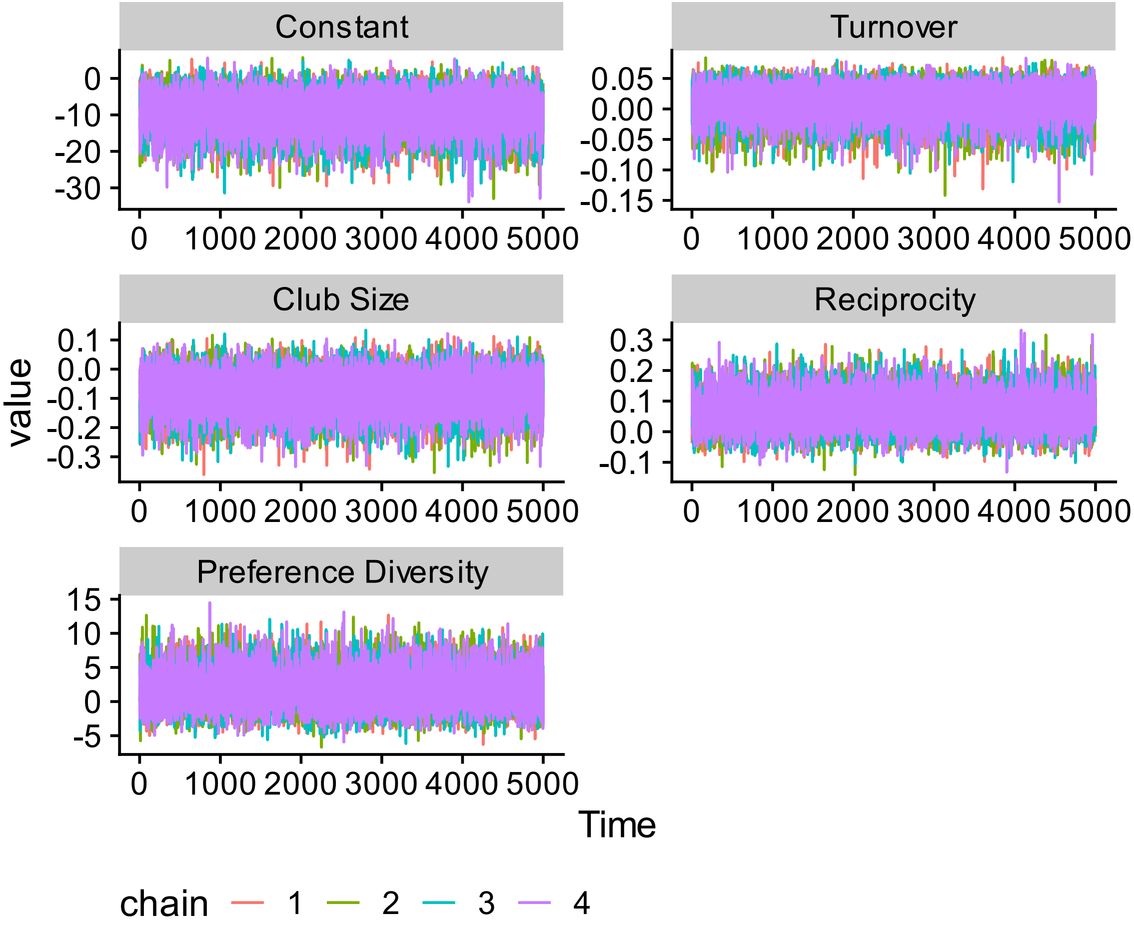


Pairs Plot

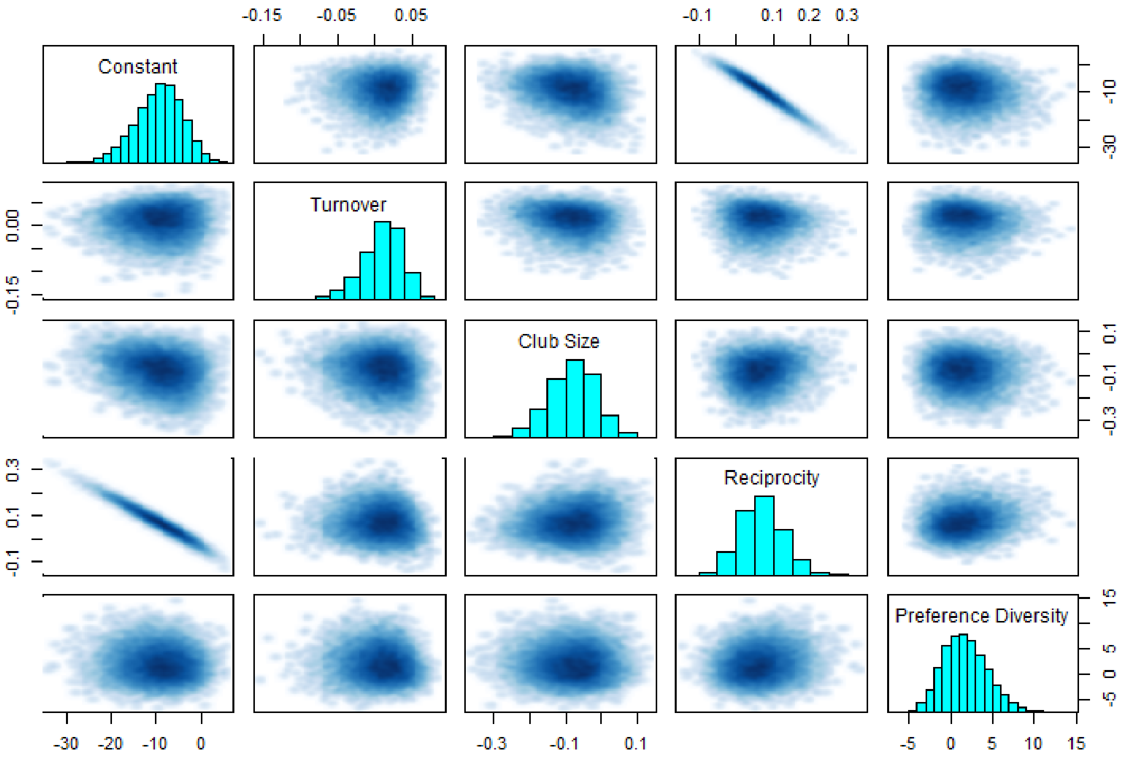


Preferences Model

Trace Plot



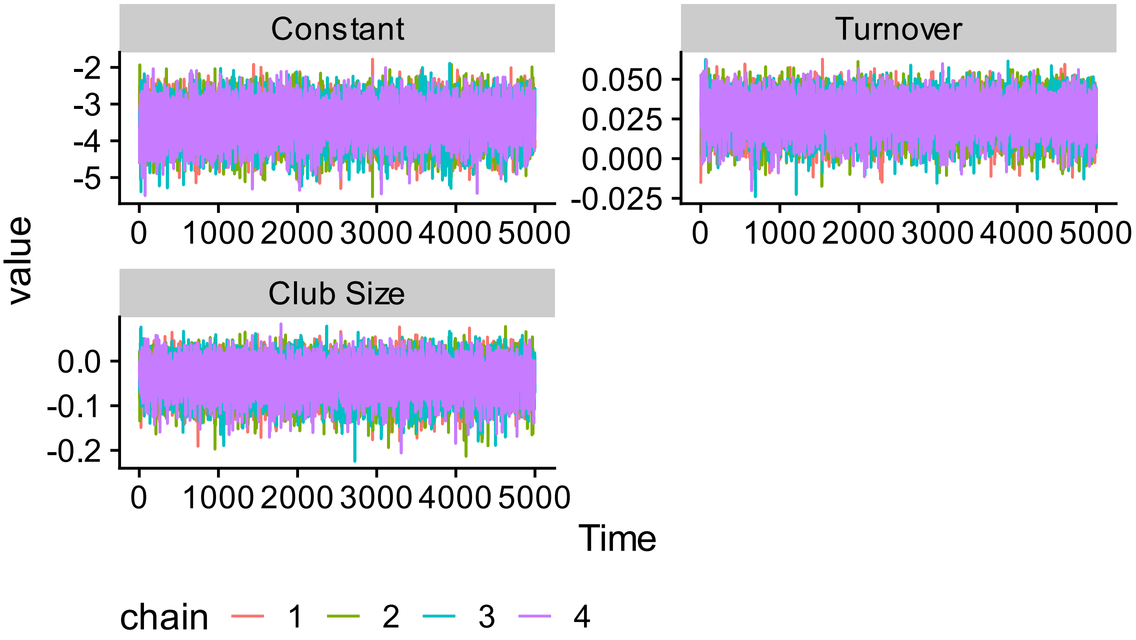
Pairs Plot


Constant
Turnover
Club Size
Reciprocity
Preference Diversity
-0.15
-0.05
0.05
-0.1
0.1
0.2
0.3
-10
-30
0.00
-0.15
0.1
-0.1
-0.3
0.3
0.1
-0.1
15
5
0
-5
-30
-20
-10
0
-0.3
-0.1
0.1
-5
0
5
10
15

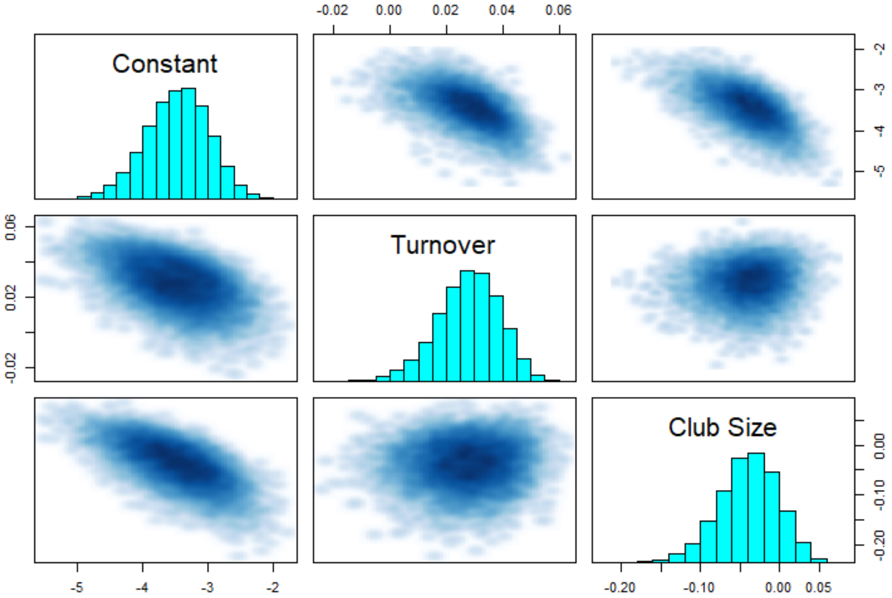
Robustness Check Model Trace and Pairs plots

Base model

Trace Plot

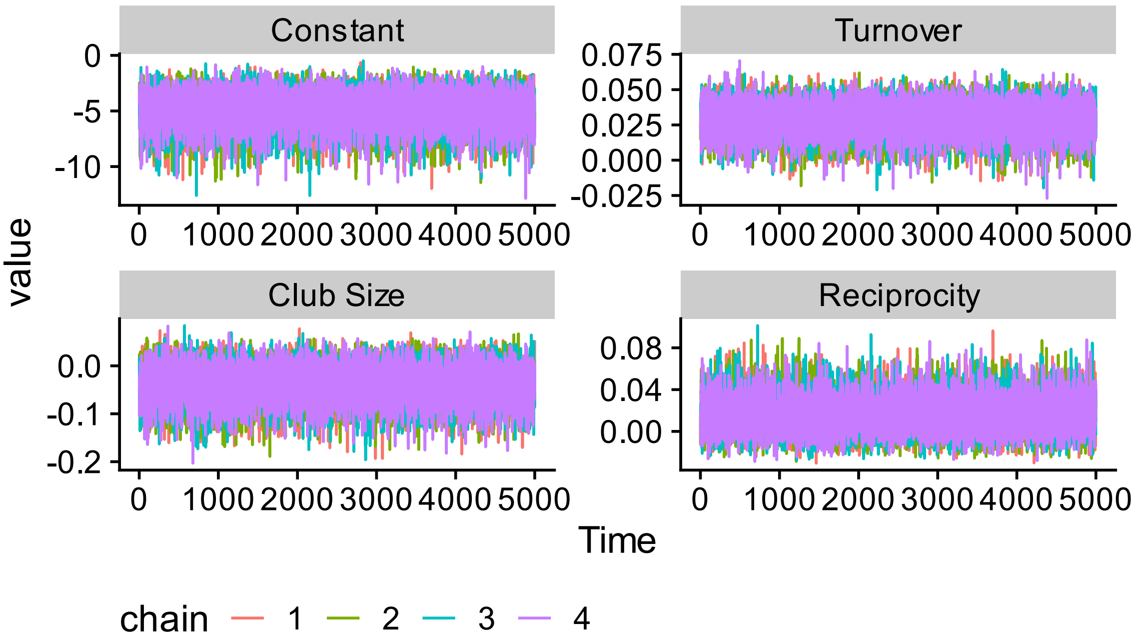


Pairs Plot

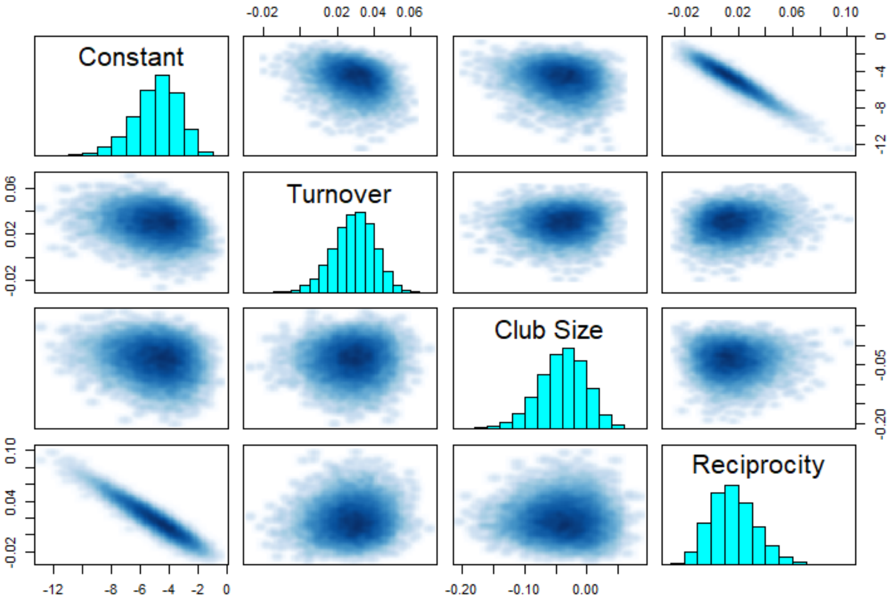


Reciprocity Model

Trace Plot



Pairs Plot



BIOGRAPHY OF THE AUTHOR

Taylor Z. Lange was born in Binghamton, New York on February 4th 1991 to Mark and Cherie Lange. He attended Chenango Valley High School and graduated 10th in his class in 2009. He earned a Bachelor of Arts in Environmental Planning from SUNY Binghamton University in 2013. He then completed a Master of Arts in Geography with a concentration in Natural Resources Management at SUNY Binghamton University in 2015. During his doctoral work at the University of Maine, he earned a Master of Science degree in Resource Economics and Policy in 2020. He is a candidate for the Doctor of Philosophy degree in Ecology and Environmental Science from the University of Maine in May 2022.