Middle manager’s innovative work behavior and their social network position

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DOI:
10.33612/diss.128363888
10.33612/diss.128363888

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A search on slippery ice

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Printed by: Haveka, Alblasserdam

ISBN (printed): 978-94-034-2731-7
ISBN (ebook): 978-94-034-2732-4

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PhD thesis

to obtain the degree of Doctor at the University of Groningen
on the authority of the
Rector Magnificus, Prof. C. Wijmenga
and in accordance with
the decision by the College of Deans.

This thesis will be defended in public on

Monday 6 July 2020 at 14.30 hours

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1 Introduction

1.1 Motivation of the topic and problem statement

This research project is based on a personal curiosity into the innovative behavior of managers. Students all over the world are all taught the same theories and methods in business schools. After graduating they are expected to manage an organization according to its manuals and Standard Operating Procedures. They are advised by consultants who use uniform approaches, and have to comply to standard formats in their management reports. Still, despite such pressures to uniformity, we see organizations in comparable conditions following different strategies. As if Weber or DiMaggio and Powell had never existed and institutional theories were null and void. We can observe similar differences in other fields, for example in military strategies.

Although there are several reasons why organizations differ from each other, organizational innovation is always based on individual behavior that generates innovative ideas (Scott & Bruce, 1994). Hence my particular interest is in the question why managers sometimes come up with the new ideas that drive change and lead to differences in organizational strategies. One case that inspired me in particular is about Hilton Amsterdam and is described in Box 1.1.

> Box 1.1 Roberto Payer and Hilton Amsterdam
>
> Hilton Hotels are well-known for offering highly standardized services that are based on equally highly standardized processes. For a frequent traveler this is wonderful because there are no surprises. From a (corporate) management perspective the benefit is the strong control of operational processes. When in 2005 I met Roberto Payer, the then General Manager of Hilton Amsterdam, I asked him how the strategy of Hilton Amsterdam was formulated in such a strict setting. Mr. Payer replied by explaining the annual budgeting process. When I replied that strategy is more than a budget, he told me that every seven years a consultancy firm was hired to formulate an investment plan. And after some more probing, he told me about his role and day-to-day activities. These involve speaking with guests, trainees, other hoteliers, government officials, and business people. They also include monitoring new developments and having a close eye on internal processes. According to Mr. Payer, all the information gathered from these diverse activities ultimately are transformed into creative ideas that lead to innovative behavior. He concluded with one example: As a newly appointed GM, he had to manage a hotel without a proper restaurant. Nevertheless, despite having hardly any seed-money and against all company policies, he built a beautiful Italian restaurant in the hotel that later would later become one of the hotel’s unique features.

This example describes how one middle manager deviates from existing practices and comes up with a major change, leading to a substantially different organization. In more general terms it shows how the innovative behavior of middle managers influences the course and direction of an organization. This case illustrates Janssen's (2000) definition of innovative work behavior as the intentional creation, introduction and application of new ideas within a work role, group or organization, in order to benefit the organization. The example shows the role of creativity in innovative work behavior, but equally emphasizes the importance of realizing those ideas. It also shows that innovative work behavior has an element of deliberately deviating from the existing standard practices, though clearly with the aim to benefit the organization. And most of all, it shows that it is the actual individual behavior to generate and realize innovative ideas that lies at the origin of organizational innovation (Scott & Bruce, 1994).

There is a growing recognition for the important role middle managers play in innovation. The relevance of middle managers' innovative work behavior is based on their key positions in organizations and their influence on organizational performance. In particular, recognition has increased for middle managers' contribution to an organization's strategy, their entrepreneurial role, and their contribution to innovation (Balogun, 2003; Floyd & Wooldridge, 2017; Floyd, Schmid, & Wooldridge, 2008; Hornsby, Kuratko, & Zahra, 2002). But not all middle managers are as innovative as this General Manager from Hilton in Box 1.1. If we want to understand organizational innovation, it is key to recognize the relevance of middle managers. Hence, the question is: what drives middle managers' innovative work behavior? This question will be the main focus of this thesis, and can be formulated as follows in the problem statement:

Problem Statement: What explains variation in middle managers' innovative work behavior?

To understand the relevance of a middle manager perspective on innovative work behavior, I will first describe the context of this thesis by briefly discussing theoretical insights on middle managers, leading to three research questions that guide this research thesis. I will then elaborate on these research questions to describe the scope of this thesis, to be followed by a section describing stochastic actor oriented models, a statistical analysis method I used extensively in my research. I conclude this introductory chapter with a section that summarizes the individual research projects that together constitute the core of this thesis.

1.2 Context of the study: Middle Managers

There are several definitions of a middle manager. A simple definition is that a middle manager is a manager below top management and above first level supervisors (Dutton et al., 1997). A second definition describes middle managers as having access to top management and close contact with operations as well. This enables them to relate strategy and operations (Floyd, Schmid, & Wooldridge, 2008). While middle managers have responsibility for only a limited part of the organization, top managers are primarily decision makers on a corporate level and responsible for the whole organization. Compared to top management, middle managers have detailed knowledge of market developments, daily competition, as well as the internal strengths and weaknesses of their organizations (Chen et al., 2018; Floyd, Schmid, & Wooldridge, 2008). Middle managers primarily implement strategies, gather information and exchange information between top and operational levels (Glaser, Fourné, & Elfring, 2015; Huy, 2001; Kuratko et al., 2005). In this traditional view, based on a top-down and control perspective of management, a middle manager is a bureaucratic filter (Hope, 2010). It sees middle managers as costs, as obstacles to change, and sources of inertia (Floyd & Wooldridge, 1994, 2000). According to some authors, this is the reason why middle managers' value to the organization declined during the past decades. Middle managers' jobs became increasingly routinized (Redman, Wilkinson, & Snape, 1997), control over middle managers increased (Ogbonna & Wilkinson, 2003) and many middle managers have been laid off due to organizational restructuring and delayering (Rajan & Wulf, 2006). Some authors (e.g., Meyer, 2006) claim that middle managers are primarily interested in pursuing their own goals, even if these are detrimental to the organization. It is not a surprise that according to this view, middle manager autonomy should be limited so they have just enough freedom to implement top management's policies.

In contrast to this traditional and negative view on middle managers, there is a positive view that sees them as strategic assets and as personally involved entrepreneurs with a strategic focus (Balogun, 2003; Floyd & Wooldridge, 1990, 1997; Huy, 2001). Burgelman (1983) argues that middle managers contribute to an organization's strategy by championing or selling new initiatives to top management. Involving middle managers in strategic planning has a positive impact on an organization's performance because their knowledge leads to improved and more realistic planning (Floyd & Wooldridge, 2000). Middle managers contribute to an organization by identifying opportunities, they develop initiatives, and they build and renew organizational capabilities (Ren & Guo, 2011). In particular in companies that emphasize corporate entrepreneurship, the role of middle managers in innovation is strongly emphasized. Their familiarity with market developments and internal strengths and weaknesses is assumed to facilitate entrepreneurial roles for middle managers (Huy, 2001; Kuratko, 2017; Kuratko et al., 2005; Mustafa, Martin, & Hughes, 2016).

In this positive perspective, middle managers are considered crucial for an organization's performance and success. One of the fundamental *raisons d'être* for a middle manager is to implement strategies and other decisions taken by top level managers. Middle managers collect and filter information from inside and outside the organization, interpret it and convey relevant issues to top management. Their detailed knowledge of operational processes enables them to propose new plans to top management or to initiate new actions themselves (Zandberg, 2018). In this role, middle managers not only connect top management and operations, but they also connect to other middle managers and other units, or with other organizations (Kleinbaum & Stuart, 2013; Pappas & Wooldridge, 2007; Shi, Markoczy, & Dess, 2009). Being connected to all kind of different actors enables middle managers to stay ahead of new developments and to ensure proper coordination in proposing new ideas and implementing plans.

To understand better why middle managers are more or less innovative, I will focus on the following three research questions.

1. A core role of middle managers is communication and forwarding information. Not only between higher and lower levels in the organization, but also with peers and other stakeholders. In this process, middle managers strongly rely on their internal and external network relationships (Pappas & Wooldridge, 2007; Shi, Markoczy, & Dess, 2009). Following Cohen & Nair (2017), I want to explore how a middle managers' social network position influences their innovative work behavior.
2. Research on a micro level suggests that individual characteristics and traits influence the extent to which middle managers are able to translate new information into innovative behavior (Anderso, Potocnik, & Zhou, 2014). Therefore, the second question is how individual characteristics influence innovative work behavior
3. A middle manager is a cog in the wheel of a large organization. This means a middle manager is constrained in his/her autonomy (Acar, Tarakci, & van Knippenberg, 2019). Research on corporate entrepreneurship has shown that a key condition for middle managers to be entrepreneurial, is a sufficient level of autonomy to make decisions, including space to make errors (Kuratko et al., 2005). The question how autonomy influences middle managers' innovative behavior will be the third research question.

After discussing innovative work behavior first, I will discuss these research questions in greater detail in the next section.

1.3 Scope of the thesis

1.3.1 Innovative Work Behavior

Innovative work behavior is related to innovation. OECD (2018, p. 20) defines **business innovation** as *"a new or improved product or business process (or combination thereof) that differs significantly from the firm's previous products or business processes and that has been introduced on the market or brought into use by the firm."*

At the foundation of all organizational innovation lies actual individual behavior to generate and realize these ideas (Scott & Bruce, 1994). Innovative work behavior refers to intentional and individual behavior to create and implement new ideas, processes, procedures, and products. This may be done within an organization, a smaller unit or department within an organization, or even relate to specific work roles (Janssen, 2000). Janssen distinguishes three behavioral elements in innovative work behavior: idea generation, idea promotion, and idea realization. Idea generation relates to new ideas about processes, products etc. Often problems, new developments, or increased competition lead to new ideas. Idea promotion is about organizing support and resources, and idea realization represent the final phase of implementation. Other authors (e.g., Anderson, Potocnik, & Zhou, 2014) distinguish between idea generation and implementation, where implementation is the combination of idea promotion and realization.

Innovative work behavior differs from creativity. Amabile (1983) and Amabile and Pillemer (2012) define creativity as the production of new ideas. Creativity can be seen as a crucial component of innovative work behavior, most evident in the beginning of the innovation process when problems or performance gaps are recognized and ideas are generated in response to a perceived need for innovation. In addition, creativity is also often necessary when implementing innovations. Unlike creativity, innovative work behavior is explicitly intended to provide some kind of benefit. It has a clear applied component and is expected to result in innovative output. This can be seen in the example of the Hilton manager in Box 1.1. Here, the middle manager's goal was to open an innovative hotel restaurant, leading to potential benefit for the organization. The example also shows that often innovation has an element of deviation from accepted practices and can be seen as the opposite of routines (Mainemelis, 2012; Soda & Bizzi, 2012; Vadera, Pratt, & Mishra, 2013).

1.3.2 A middle manager's social network

A middle manager is a liaison between different levels in the organization. Having timely access to new developments is important for generating new ideas. Middle managers also play a critical role in establishing and maintaining the organizational linkages that are needed for the communication and coordination underlying successful implementation of innovations (Taylor & Helfat, 2009). This suggests that a middle manager's social context is crucial for a middle managers performance in general, and a middle manager's innovative work behavior in particular. This is the reason I want to focus on the social network of a middle manager as a first factor in understanding innovative work behavior.

Innovative work behavior is to a certain extent a social process, in which communication and interaction with others support and lead to creativity (Perry-Smith, 2006). This is typically a role for middle managers, which differs from top management in several key aspects (Kauppila, Bizzi, & Obstfeld, 2018): top managers often consider only a limited number of options and respond quickly to external developments. Conversely, middle managers who bring people and their diverse ideas together, have more impact on an organization's creative performance and innovation. Because their network and their structural position are crucial for a middle managers' innovative work behavior, social network analysis (SNA) enables us to analyze the interaction of innovative work behavior with structural position and personal characteristics (Cohen & Nair, 2017). The structural position of a middle manager in his or her social network may result in constraints or in opportunities for innovative work behavior (Long, Cunningham, & Braithwaith, 2013). For example, Burt's (1992, 2001) theory of structural holes suggests that middle managers in brokerage positions have early access to and control of information, which enables them to be more innovative. Middle managers in dense networks find their contacts directly connected, which means they are poorly positioned to broker between otherwise unconnected (groups of) middle managers. This suggests that a network structure either enables or constrains the innovative work behavior of middle managers. This thesis investigates to what degree a middle managers' network position enables or hampers a middle manager's innovative work behavior.

The contribution of SNA to research on middle managers and innovative work behavior is relatively new and results are limited (Cohen & Nair, 2017). Several authors (Chen, Chang, & Chang, 2015; Floyd & Wooldridge, 1999; Turner & Pennington, 2015; Pappas & Wooldridge, 2007) have investigated the influence of social networks on organizational performance. However, many of the social network studies in organizational behavior are cross-sectional (Kalish, 2019) due to difficulties in collecting the necessary data for longitudinal studies and the specialized statistical analysis needed. Exploring the possibilities of SNA in organizational behavior, in particular in a longitudinal setting, will be an additional goal of this thesis.

1.3.3 Individual characteristics of the middle manager

Next to their social network structure, personal characteristics may help to explain why some middle managers are more innovative than others. In this thesis I focus on personality and on motivation and goal orientation.

Personality traits are relatively stable over longer periods of time and therefore suited to explain differences in innovative work behavior (see Anderson, Potocnik, & Zhou, 2014, for an overview of the research in this area). In particular, the relationship between traits and creativity received a lot of attention (Abdullah, Omar, & Panatik, 2016; Anderson, Potocnik, & Zhou, 2014; Perry-Smith & Mannucci, 2017). Research on the influence of personality traits on innovative work behavior has paid much attention to the relation between the personality traits of the Five Factor Model and innovative work behavior. Of these five factors, openness to experience and conscientiousness in particular have been found to be associated with innovative work behavior (Baer, 2010; Woods et al., 2018). Individuals scoring high on conscientiousness are more dependable and committed, therefore it is often assumed that people scoring high on conscientiousness are highly motivated to find new solutions to problems that arise, or to make use of opportunities that evolve (Judge et al.,

2013). Individuals scoring high on openness, often think divergent, are willing to work on new ideas, are curious, and are willing to explore the world (Judge et al., 2013), which leads to being more creative.
Besides the Big Five Personality traits, other traits such as generalized self-efficacy, innovativeness, stress tolerance, need for autonomy, dominance, proactivity (Rauch & Frese, 2007; 2008), and need for achievement (Collins, Hanges, & Locke, 2004; Rauch & Frese, 2008) are also found to be associated with innovative work behavior.

Besides personality traits, motivation and goal orientation are also found to influence innovative work behavior. In the componential theory of creativity, Amabile (1983), Amabile and Pillemer (2012) suggest that intrinsic motivation supports and fosters creativity. Additional research showed the positive relation between intrinsic motivation and creativity is even stronger when prosocial motivation is higher (Grant & Berry, 2011). Individuals have different goal orientations that influence how people behave in achievement situations. For example, a learning goal orientation emphasizes personal development and is positively related with creativity (Hirst, Van Knippenberg, & Zhou, 2009; Gong, Huang, & Farh, 2009). Similar, mastery orientation is positively related to innovative work behavior (Janssen & Van Yperen, 2004). The motivation to engage in innovative behavior is also influenced by the expected benefits. Yuan and Woodman (2010) found that expected performance outcomes and expected image risks or gains explained innovative work behavior.

1.3.4 The autonomy of a middle manager

Next to a middle manager's personal characteristics or social network position, the organizational context plays a role in explaining innovative work behavior. A middle manager is an actor in a larger organization and has only limited autonomy for innovative work behavior. It is generally believed that a lack of autonomy will constrain a middle manager's innovative work behavior. For example, theories on corporate entrepreneurship stress the importance of decentralization and discretionary space for middle managers (Foss, Lyngsie, & Zahra, 2015; Hornsby, Kuratko, & Zahra, 2002; Kuratko, Hornsby, & Covin, 2014). There are several reasons why autonomy and decentralization may lead to increased innovative work behavior. First of all, autonomy might motivate middle managers to become more innovative. According to self-determination theory (Deci & Ryan, 2000), control over a task, and responsibility for successful implementation will increase intrinsic motivation. Besides the motivating dimension, autonomy enables innovative work behavior. Middle managers are often directly connected to the market and familiar with opportunities and challenges. This knowledge can guide them in innovative work behavior (Foss, Lyngsie, & Zahra, 2015). But middle managers need a certain level of autonomy to benefit from their local knowledge, otherwise they are only able to stick to corporate rules and implement top level strategies. Autonomy and decentralization give middle managers the opportunity to use their market knowledge to adjust corporate strategies while implementing them.

1.4 Research strategy

The main goal of the study is to investigate if the social network position of a middle manager together with other (personal) attributes explain innovative work behavior. Until now, this is an unexplored area. While ample research has been conducted on either innovative work behavior or on social network studies, there has hardly been empirical research on the combination. To investigate this question, three empirical studies, each in a different context, were conducted: A longitudinal study among two cohorts of 42 and 47 international students who aspire to become (middle) managers, a longitudinal study among 110 middle managers in a listed company in Europe, and a cross-sectional study among 64 civil servants in Mexico City. In addition, a methodological study was conducted to investigate strategies to deal with missing attribute data in longitudinal social network studies.

In the longitudinal study among 47 international master students in the Netherlands, four surveys were conducted in weeks 1, 5, 13, and 21 after the start of the academic year 2012/2013. In each questionnaire, students were asked to whom of their fellow students they had turned for advice in the past three weeks, and to describe their relation with their peers. The answers to both questions were used to construct advice and friendship networks for all four surveys. As students cannot show innovative work behavior, in all surveys personal initiative, measured using the seven-item scale of Frese et al. (1997), was used as proxy. Personality traits using the NEO Five Factor Inventory test (Costa & McCrae, 1992) were measured in the first survey only. One year later the data collection was replicated with a second cohort of 42 new students. In this replication study the items in the questionnaire were identical to the original study.

The second empirical study is based upon a longitudinal panel study among middle managers of a Dutch company that operates 75 leisure parks in Europe. This company belongs to a larger holding in the USA that is listed at the stock exchange. Of the whole management team of the organization, consisting of seventy-five park managers plus sixty office managers, 110 managers participated in this panel study. The group of office-managers consisted of board members, area managers and managers of staff departments. In spring 2013 interviews were conducted with seven middle managers of this company and in October 2013 and May 2014 two surveys among all middle managers were conducted. In each survey, middle managers were asked to whom of their fellow middle managers they had turned for advice in the past six months. Based on these answers, advice networks were constructed. In addition, middle managers were asked about their innovative work behavior, using a six-item scale (Scott & Bruce, 1994) and job autonomy using a five-item scale (Hage & Aiken, 1967). The influence of the organizational structure was measured by describing the formal ownership structure of the leisure parks (parks fully owned or managed, parks under a management contract, or franchised parks) or whether the middle manager was working at the head office. The influence of spatial distance was measured by taking the logarithm of the distance in kilometers from the park to the head office.

The third empirical study is a cross-sectional study among 64 middle managers in Milpa Alta, a semirural municipality in Mexico City in which managerial positions are often appointed using discretionary and political instead of professional criteria. The study was conducted online (response rate = 69%) in June 2012 and the first time such a research method was conducted in this environment. The variables representing innovative work behavior were based on the innovative roles of middle managers (Floyd & Wooldridge, 1996). Tests for common method variance were negative.

Next to these three empirical studies, a simulation study was carried out to analyze seven different methods to deal with missing attribute data in social network studies. In a simulation study based on four real-life data sets, the impact of these methods was investigated. Missing behavior data were created for four different missingness mechanisms and four different levels of missingness. The generation of the observed and missing data resulted in 4 (data sets) × 500 (replications) = 2,000 complete data sets (two waves of network and behavior two waves), and 4 (data sets) × 500 (replications) × 4 (proportion missing) × 3 (missingness mechanism) = 24,000 incomplete data sets. The resulting re-estimated parameters of the pre-defined models for these data-sets were then compared to the original model-parameters. The effect of the missing data methods was evaluated using three criteria: model convergence, parameter bias, and parameter coverage.

The strong empirical focus on network studies caused three major challenges. First, while many common statistical methods are based on samples, a longitudinal network study requires that all network relations of the complete network (population) to be collected at two different moments at least. Achieving a sufficient response in a sequence of surveys poses the first challenge. The second challenge is dealing with the missing data that were encountered during the data collection process and statistical analyses. While there are several strategies to deal with missing data in cross-sectional social network studies, little is known about the performance of these strategies in longitudinal settings. To address this question, a methodological study (see section 5) was conducted to select an optimal strategy to deal with missing data. The third challenge is the nature of network data, which prohibits the use of common statistical methods that analyze relations between attributes only. The remaining part of this section describes a method to deal with this third challenge.

From a methodological perspective analyzing social network data is a challenge because in network studies the behavior of middle managers not only depends on their own attributes, but also on their network and therefore also on the attributes and behavior of their peers. The complex dependencies (relationships) between the respondents (actors) prevent the use of more common statistical methods, that are based on the assumption of independent observations, and we have to use social network analysis to quantify the relations between middle managers (Cohen & Nair, 2017). However, the large majority of social network analysis in management studies is based on cross-sectional data, preventing the analysis of causal relations. To enable the longitudinal analysis of the dynamic interaction between network and behavior, a specific family of stochastic actor-oriented models (SAOM) was developed (Snijders, 2017). SAOMs are particularly well suited to model the co-evolution of network and behavior.

A SAOM is based on observed panel data, and assumes the observed data are "visualizations" of an underlying and unobserved process of small sequential changes or mini steps in network and behavior. Each mini step gives one randomly selected actor the opportunity to change either one network tie (adding or dropping a tie to another actor, or no change) or to change his behavior variable (increasing or decreasing one level, or no change). The decisions of actors to change a network tie or behavior score are modeled by objective functions that are linear combinations of effects that represent the current network structure and behavior. These effects are functions of the network of the focal actor, as well as the behavior of that actor and the behavior of his network partners. One example of an effect is reciprocity: If A goes to B for advice, it may become more likely that B will also approach A for advice. A second example is outdegree: A middle manager who approaches many peers for advice may be considered well informed and hence more likely to be innovative. In this manner, the changes in the network can also be related to the state of the actors' behavior, and vice versa, and a mutual dependence between the network dynamics and the behavior dynamics can be established.

Because these mini steps between observed waves are unobserved, the SAOM uses simulations to model the sequence of mini step as a Markov process. The simulation starts with the first observation of the network (W1) and simulates a series of sequential changes until the second observation (W2) is reached. The simulated network at W2 is then compared to the observed network at W2. Based on a comparison of simulated and observed W2 network, the parameters are updated. With these updated parameters the simulation is repeated. This iterative process is repeated until the model has reached convergence and parameters are stable. Once convergence has been achieved, the final parameter estimates are used to generate a number of additional sets of simulated mini steps that are used to estimate standard errors.

Kalish (2019) and Snijders, van den Bunt, and Steglich (2010b) provide accessible introductions to SAOMs. Adams and Schaefer (2018) provide a clear visualization of the sequential mini steps underlying a SAOM. More theoretical background can be found in Snijders (2001, 2017).

1.5 Thesis structure

The thesis consists of three parts. Part one is this introductory chapter. Part two is the main part and addresses the research questions. This part consists of four chapters that are reprints of published articles or submitted manuscripts. Part three is the final chapter in which I discuss the contribution of the individual chapters in answering the problem statement.

Part 2, consisting of chapters 2 to 5, is a combination of three empirical studies plus a supportive methodological study. The empirical studies are set in three different contexts and in different international settings, each focusing on a specific aspect of the problem statement.

Chapter 2 is a methodological study that aims to find an optimal method to deal with missing attribute data in longitudinal network studies. Stochastic actor oriented modelling, the main analytical method I have used in my research, is a relatively new technique, and only a few studies investigated the effects of missing data treatments in longitudinal social network data, where missing attribute data in social network analysis remained mainly unstudied (Krause, 2019). For field studies as reported in this dissertation, missing data are common, and therefore we have conducted a simulation study to determine the best method to deal with such missing data.

Chapter 3 is a longitudinal study among two classes of respectively 42 and 47 students of a business school. Many of these students will likely become middle managers at some point in their career. Unlike a work context, the class setting comes with relatively low levels of functional interdependence between students. This setting therefore provides a good opportunity to disentangle the relation between personal initiative, personality, and the structural autonomy stemming from their social network position. Since students are not yet in a professional setting in which they have the opportunity for innovative decisions and behavior, we investigated their personal initiative instead of their innovative work behavior.

Chapter 4 is a longitudinal study among 110 middle managers of an international company that operates 75 leisure parks. The main focus of this study is on the influence of autonomy on middle managers' innovative work behavior. This study attempts to increase our understanding of autonomy's influence by distinguishing four dimensions of autonomy: structure, structural (network) constraint, spatial distance, and governance structure.

Chapter 5 is a cross-sectional study among 64 middle managers in Milpa Alta, a municipality in Mexico City. According to public management and Public Service Motivation theories, public managers have a collective orientation aimed at producing public goods. Therefore, we investigated if, next to intra-organizational networking, an individual career motive or a collective motivation for networking explains innovative work behavior.

2 Missing behavior data in longitudinal network studies: the impact of treatment methods on estimated effect parameters in stochastic actor oriented models

This chapter has previously been published as: Zandberg, T. and Huisman, M. (2019). Missing behavior data in longitudinal network studies: the impact of treatment methods on estimated effect parameters in stochastic actor oriented models. *Social Network Analysis and Mining*, *9*(1), 8.

Abstract

Research into missing network data is growing, with a focus on the impact of missing ties on network statistics or network model parameters. Longitudinal network studies using stochastic actor-oriented models (SAOMs) focus on the co-evolution of network structure and behavior/attributes to disentangle influence and selection mechanisms. Still little is known about the impact of missing behavior data on estimated effect parameters in SAOMs. This paper examines seven different methods that are currently available to deal with missing behavior data: complete cases, three single-imputation procedures (imputing the mean, random hot deck, nearest neighbor hot deck), one multiple-imputation procedure (based on predictive mean matching), and two methods available in the SIENA software to estimate SAOMs (default method based on imputation and available cases, and a method based on dummy variables). In a simulation study based on four real-life data sets, the impact of these methods on estimated parameters of SAOMS was investigated. Missing behavior data were created under different conditions (proportions, mechanisms), and the missing data methods were used to estimate SAOMs on the incomplete data. The effect of the missing data methods was inspected using three criteria: model convergence, parameter bias, and parameter coverage. The results show that, in general, the default method available in the SIENA software gives the best outcomes for all three criteria. The dummy-based method generally performed worse than the default method, as did the imputation procedures. The multiple-imputation procedure sometimes outperformed the single imputations and the three single-imputation methods often gave the same results. The effects of missing data mechanism and data set were small.

2.1 Introduction

Social scientists often face the problem of missing data when analyzing empirically collected data. In the analysis of social networks, missing data constitute even a larger problem, because the complexity of collecting the network data and survey items are more likely to generate missing data (Burt, 1987; Borgatti & Molina, 2003). Moreover, due to the dependencies in the network, network analysis is especially sensitive to missing data, as the missingness not only limits the modeling of the local network of the actors involved, but also limits the modeling of the local network structures of all neighboring actors (Robins, Pattison, & Woolcock, 2004).

In recent years, the effects of missing data in network studies are often studied, especially for cross-sectional data (e.g., Kossinets, 2006; Žnidaršič, Ferligoj, & Doreian, 2012; Smith & Moody, 2013; Smith, Moody, & Morgan, 2017). The general conclusion that can be drawn from these studies is that missing data has a negative impact on describing and estimating the structural properties of the network, underestimating the strength of relationships, centrality measures, degree measures, or clustering coefficients (e.g., Kossinets, 2006; Smith & Moody, 2013; Smith, Moody, & Morgan, 2017). However, due to the unique property of networks that information on missing actors is (at least partially) available through the out-going ties of observed neighboring actors, measures based on indegrees are reasonably robust for small amounts of missing data (Costenbader & Valente, 2003; Smith & Moody, 2013).

For longitudinal network data where respondents are repeatedly observed, missing data are even more likely to occur. Some respondents will not be available at every observation moment, a situation known as wave non-response (Huisman & Steglich, 2008), or they will even drop out completely from the study after a certain time point. Huisman and Steglich (2008) studied the effect of missing longitudinal network data within the framework of stochastic actor-oriented models (SAOMs), a family of models often used to analyze the dynamics of network and behavior (Snijders, van de Bunt, & Steglich, 2010). They found that restricting the analysis to completely observed cases leads to model convergence problems and generally gives biased parameter estimates. Non-convergence due to missing data was also encountered by de la Haye et al. (2017) while analyzing the complete cases, which lead them to propose and study different analytic strategies for longitudinal networks with missing data.

Simple treatment procedures for missing network data were already suggested by Burt (1987) and Stork and Richards (1992). More recent, model-based procedures were proposed by Robins, Pattison, and Woodcock (2004), Handcock and Gile (2010), Koskinen, Robins, & Pattison (2010), Koskinen et al. (2013), all based on modeling observed and missing data within the framework of exponential random graph models (ERGMs). Imputation-based procedures were proposed and studied by Huisman (2009), Wang et al. (2016), Huisman and Krause (2017), and Krause, Huisman, Steglich & Snijders, (2018). All these procedures treat missing actors and ties in cross-sectional network data. For longitudinal network data, missing data procedures for analyses based on SAOMs were investigated by Huisman and Steglich (2008), Hipp et al. (2015), and de la Haye et al. (2017). Huisman and Steglich (2008) use simulations to study simple imputation schemes, one of which is the built-in (default) missing data treatment in SIENA, the software to estimate SAOMs (Ripley et al., 2017). This SIENA method was found, in general, to result in small biases in model parameters for small to medium missingness levels (up to 20% per wave). In the studies of Hipp et al. (2015) and de le Haye et al. (2017), analytical strategies are proposed that are based on inclusion of different subsets of actors depending on the availability of data in particular waves. Some of the strategies rely on the simple default imputations in SIENA, and one of the strategies proposed by Hipp et al. (2015) expand these simple imputations by including ERGM-based imputations for missing values in the first wave. This procedure creates the opportunity for multiple imputation (of the first wave), as suggested by Hipp et al. (2015). Krause, Huisman, and Snijders (2018) present a full multiple-imputation procedure based SAOMs.

Although research in missing data procedures for social networks is increasing in the past decades for both cross-sectional and longitudinal data, all methods are designed to treat missing ties in the network data and very few do address the problem of missing actor behaviors or behavior data. Missing actor behavior could be regarded as ‘ordinary’ missing data in any non-network data set, and thus treated as such by one of the ample general missing data methods for survey data available in statistical literature. However, treating missing behavior without considering their (often strong) relationship with the structural properties of the network, may bias effects of behavior and may lead to biased estimates of the structural properties. Koskinen et al. (2013) illustrate the effect of missing behavior data and present an ERGM-based procedure to analyze the incomplete data. Ouzienko and Obradovic (2014) propose an ERGM-based imputation procedure for the case of longitudinal network data (i.e., temporal ERGMs). In a small simulation study, using simulated and real-life data, they showed that, in general, their imputations result in more accuracy in predicting tie and behavior variables (comparing observed and imputed scores) than simpler methods.

In this paper, we investigate the performance of several treatment methods to handle missing behavior data in longitudinal networks. More specifically, we analyze the impact of different treatment methods on estimated effect parameters in SAOMs that are used to model the dynamics of network and behavior (Snijders, van de Bunt, & Steglich, 2010). We restrict the missingness to the behavior variable, that is, the networks are completely observed. This means that any effect found can only be attributed to the missing behavior data and is not confounded by missing ties or actors. The network and behavior data are simulated under known co-evolution models (the base models in our study) and we examine missing data strategies that are available for SAOMs (complete case analysis, dummy variable adjustment in SAOMs, SIENA method) and some simple, ad hoc treatments (i.e., simple single imputations, based on means and hot deck, and somewhat more sophisticated multiple imputations using observed network statistics as predictors). The simulated data are based on four empirical, observed data sets, in the tradition of Smith and Moody (2013), Smith, Moody, and Morgan (2017), and others. In that respect, the current paper can be regarded as a continuation of the study of Huisman and Steglich (2008), focusing on missing behavior data.

The paper is organized as follows. Section 2 briefly describes the stochastic actor-oriented models for the dynamics of networks and behavior (Snijders, van de Bunt, & Steglich 2010) that are used to simulate the data sets and analyze the treated missing data to examine the effects of missing data treatments. Section 3 addresses the problem of missing data in networks and especially in behavior data and introduces the available missing data treatments of which the performance is studied. The design of the simulation study is described in Section 4, and the results are presented in Section 5. Finally, in Section 6 the results are discussed and some general recommendations are given.

2.2 stochastic actor-oriented models

A common model to analyze the dynamics of networks and behavior is the family of stochastic actor-oriented models (SAOMs; Snijders, 2005, 2017; Snijders, Koskinen, & Schweinberger, 2010), of which the estimation is implemented in the SIENA software (RSiena package, Ripley et al., 2017). In this paper, we consider directed networks where the tie variable x_{ij} is binary with values 1 (indicating a tie going from actor *i* to actor *j*) or 0 (absence of a tie between actors *i* and *j*). For example, the tie variable is friendship, where x_{ij} = 1 means that actor *i* nominates actor *j* as a friend. Self-nominations are not allowed, that is, x_{ii} = 0. The behavior variable is assumed to be an ordinal discrete variable representing levels of some behavior (e.g., smoking). In the SAOM approach, the network dynamics part in the co-evolution process constitutes the social selection process, and the behavior dynamics part constitutes the social influence process.

Stochastic actor-oriented models (SAOMs) model the co-evolution of network and behavior. A SAOM is based on panel data, and assumes that the observed data are snapshots of an underlying and unobserved process of continuous change in network and behavior between the observation moments. This change process is modelled as a continuous-time Markov chain of small sequential mini steps, where the first observation is taken as starting point. Each mini step gives a randomly selected actor the opportunity to change either a tie or the value of the behavior variable. For the tie variable, a change means adding a tie to another actor or dropping an existing tie, or no change. For the behavior variable, a change means increasing or decreasing the value with one unit, or no change. See Adams and Schaefer (2018) for a visualization of the model mini steps.

The change processes consist of two steps. First, a stochastic rate function determines when an actor gets the opportunity for a new change (mini step). Secondly, the probabilities of the changes for both tie and behavior variables are determined by objective functions that are modeled as linear combinations of effects that represent the current network structure and behavior. These effects are functions of the network of the focal actor, as well as the behavior of that actor and the behavior of his network partners. Because the changes in the network are also dependent on the state of the actors' behavior, and vice versa, a mutual dependence between the network dynamics and the behavior dynamics is established. Examples of effects and the corresponding parameters are given in Section 4; for a more elaborate discussion of the objective functions and examples and illustration of effects, see Snijders, Koskinen, and Schweinberger (2010) and Snijders (2017).

Because the mini steps between observed measurements are unobserved, a SAOM is used to simulate the Markov chains of mini steps. The simulation starts with the first observation of network and behavior (W1), and, using an initial set of model parameters, simulates changes until the second observation (W2). Based on a comparison of the simulated data at W2 and the observed data at W2, the model parameters are updated. With these updated parameters the simulations are repeated. This iterative process is repeated until the model has reached convergence. After convergence, the final parameter estimates are used to generate additional series of simulated mini steps to estimate standard errors of the parameter estimates (for details see Snijders, 2001, 2017).

2.3 Non-response in longitudinal network studies

2.3.1 Missing behavior data

In this paper, we focus on missing data due to non-response. Other types of missing network data are described by Kossinets (2006) and Žnidaršič, Ferligoj, and Doreian (2012), for example missingness caused by boundary specification problems. We consider two observation moments where the networks are completely observed and one behavior variable that is missing for some actors at both observation moments. The non-response pattern is important because it determines the amount of data available to estimate the SAOMs.

Another important aspect of the non-response is the relationship of the missingness to the data. According to the typology of Rubin (1976; see also Schafer & Graham, 2002), three different mechanisms can be distinguished, depending on the relation between being missing on a behavior variable and the scores on (the behavior or tie) variables. If the missingness is unrelated to the value of the behavior variable itself, the data are called *missing at random* (MAR). In this situation, the non-response can be related to the observed tie variables, or function thereof, but not to the behavior itself. If the missingness is even unrelated to the observed tie variables (or, in general, to any other variable in the data), the data are called *missing completely at random* (MCAR). If the missingness is related to the unknown value of the behavior itself, the data are *missing not at random* (MNAR). In this latter situation, parameters related to the behavior may be severely biased due to the systematic difference between responding actors and non-respondents.

2.3.2 Treatments for missing behavior data

In recent years, missing data treatment procedures have received ample attention, for both cross-sectional and longitudinal network data. In general, missing data treatments can roughly be categorized in three classes of treatments (e.g., Schafer & Graham, 2002)[1]: 1) deletion methods (also known as available case methods), 2) model-based methods, and 3) imputation. Model-based methods for missing cross-sectional network data were proposed by Robins, Pattison, and Woodcock (2004), Handcock and Giles (2010), Koskinen, Robins, & Pattison (2010), Koskinen et al. (2013), all within the family of exponential random graph models. Imputation methods for cross-sectional network data were proposed and examined by Huisman (2009), Wang et al. (2016), Huisman and Krause (2017), and Krause, Huisman, and Snijders (2018), and for missing longitudinal network data by Huisman and Steglich (2008), Ouzienko and Obradovic (2014), Hipp et al. (2015), and Krause, Huisman, and Snijders (2018). A combination of available case strategies and imputation within SAOMs (i.e., the default method implemented in the SIENA software) was examined by Hipp et al. (2015), de la Haye et al. (2017), and Krause, Huisman, and Snijders (2018).

The problem of missing actor behavior data has received far less attention in network analysis. One possible strategy to handle the non-response is treating the behavior or behavior variables as “ordinary” survey data and using general missing data methods. The advantage of this strategy is that general missing data treatments have been investigated extensively and there are well-known and sophisticated methods, for example, multiple imputation using stochastic regression imputation with actor attributes or other behavior variables as predictors (as illustrated for actor behavior data by Huitsing et al. (2014). A major disadvantage is that the network structure is not taken into account and the associations between behavior and ties are ignored. Unless network and behavior are completely independent, this can lead to biased estimates of these relationships as well as biases in the estimates of network properties. To prevent the results from becoming biased, either network properties should be incorporated in general missing data procedures, or missing data treatments should be based on network models.

For missing behavior data, an ERGM-based estimation method was proposed by Koskinen et al. (2013). In this method, ERGMs are estimated on partially observed data (both network and behavior data) using Bayesian procedures that take into account the relations between network and behavior. Imputation methods for behavior data are scarcely investigated. Ouzienko and Obradovic (2014) present an ERGM-based imputation model for imputing

[1] Often a fourth class of treatments is distinguished, i.e., (re)weighting procedures, which are not considered for missing network data.

both missing tie variables and missing actor behaviors for longitudinal network data. For missing behavior variable in SAOMs, Ripley et al. (2017) propose a simple imputation scheme in which either the previous observation, the next observation, or the mode of the variable is imputed, in order of availability. These imputed values are then used to simulate the mini steps that constitute the behavior (and network) dynamics, but not for the calculation of the target statistics to estimate the model parameters, preventing a direct effect of the imputed values on model estimation.

In this paper, we consider procedures that are currently available to handle missing behavior data within the SAOM framework. This means that we investigate the possibilities in the SIENA software and compare these with either simple (complete case analysis or single-imputation) methods, or with more elaborate multiple-imputation methods in which the missing behavior variable is regarded as “ordinary” survey data in non-network analyses. Specific details about the use of the methods in the simulation study are given in Section 4.

Complete case analysis

Complete case analysis is based on the smaller network of complete cases. This means that all actors with missing behavior data are removed from the analysis, including the ties to or from them. The reduction in the data can be considerable and the results of the method will be highly sensitive to the proportion missing data. This may result in biased estimates of network characteristics even if data are MCAR. Moreover, model estimation is difficult if the remaining complete data set is small and may lead to convergence problems.

Single imputation

To avoid the loss of data due to complete case analysis, the missing data can be replaced by suitable values in order to create a completed data set. A simple procedure is to replace the missing values by the mean of the observed data. Although this method is simple and therefore attractive, it will lead to biased estimates even when data are MCAR, as it seriously underestimates variances and covariances (e.g., Schafer & Graham, 2002). In order to preserve variation in the data, imputations can be generated by drawing from the distribution of the (missing) data. One way to generate such distributions, is by using observed donor cases and replacing the missing values by the observed values of the donors. These methods are known as hot deck imputations. Although hot deck partially solves the problem of underestimating variances, it still gives biased results for relations between variables (effects).

Multiple imputation

A drawback of single imputations is that they do not take into account the extra variability due to missing data and imputation. This leads to underestimation of standard errors and therefore biased inferences. By imputing multiple times, the increased variability is accounted for and valid inferences are obtained (Rubin, 1987; Schafer & Graham, 2002; Van

Buuren, 2012). With multiple imputation, *m* (*m* > 1) completed data sets are created using stochastic single-imputation methods. This leads to *m* completed data sets, which will be different from each other due to the stochastic nature of the imputations, the extent of which reflects the uncertainty due to missing data and imputation.

After imputation, the *m* completed data sets are analyzed separately (i.e., the parameters of the specified model are estimated for each of the data sets) and the results are combined using Rubin's rules (Rubin, 1987). For parameter estimates, this simply means averaging the *m* parameter estimates for each imputed data set: $\bar{\theta} = \frac{1}{m}\sum_{i=1}^{m}\hat{\theta}_i$, where $\hat{\theta}_i$ is the estimated parameter for the *i*th imputed data set. For the variances of the estimates (i.e., standard errors), the average within-imputation variance is combined with the between-imputation variance to reflect increased variability due to non-response and imputation: $T = \overline{U} + \left(1 + \frac{1}{m}\right)B$. Here $\overline{U} = \frac{1}{m}\sum_{i=1}^{m} U_i$ equals the average variance within each imputed data set, with U_i the variance in each imputed data set, and $B = \frac{1}{m-1}\sum_{i=1}^{m}(\hat{\theta}_i - \bar{\theta})^2$ equals the variance between the *m* estimated parameters. The factor $\frac{1}{m}$ in the equation of the total variance T reflects the finite number of imputations. Standard errors for parameters are obtained by taking the square root of the variance T.

SIENA procedures

The last two methods investigated in the simulation study, are procedures within the framework of SAOMs that are available in the SIENA software. The first procedure is the model-based hybrid imputation method for ties (Huisman & Steglich, 2008) extended to behavior variables, the default procedure for missing data treatment in the SIENA software. The method is called hybrid because in estimating the SAOM parameters, it uses imputed values during the simulation of the Markov chains of mini steps, but during the calculation (updating) of the estimates, the imputations are not used. This means that during the simulation of the Markov chains of mini steps between two consecutive waves, all actors (observed and missing) are allowed to make changes. At the end of the simulation runs when the simulated and observed data of the second time point are compared, the parameter updates are based on the observed data only, and imputations are not taken into account. As a result, the imputations only have indirect effects on the estimates through the Markov process in the simulation phase of the procedure. In the default procedure, imputation consists of replacing missing values with previous observations from an earlier wave, if available, otherwise the mode of the variable (for the corresponding wave) is imputed.

The second procedure investigated in the simulation study is handling missing behavior data by using dummy effects in the SAOM. In this procedure, a dummy variable is created that indicates whether an actor is missing (value 1) or observed (value 0). The dummy is included in the SAOM by specifying a dummy effect in the objective function of the behavior part of model, where the value of the parameter is fixed at a large negative value. In this way, a large (artificial) negative effect on the objective function of the missing actor is created if this actor would choose to make a change in the behavior variable (i.e., take a mini step in the Markov process modeling the behavior dynamics). As a result the actor will decide not to change his behavior. The missing actor will thus not influence the behavior dynamics in the model.

This dummy variable procedure differs from the traditional dummy variable adjustment of missing values in regression models. In the traditional setting, a dummy variable is created indicating missing values on the predictor and a new predictor variable X^* is constructed with values equal to X for the observed cases, and c (any constant) for the missing cases. The estimated parameter of the dummy variable represents the influence of missing predictors on the outcome variable. The estimated parameter for the new predictor X^* represents the estimated effect of X for the observed cases. This procedure redefines the parameters estimates and generally produces biased estimates of the coefficients (Allison, 2001; Schafer & Graham, 2002).

2.4 Simulation study

In order to investigate the impact of various missing data treatments on the parameter estimates of the SAOMs, a simulation study was performed. In this study, a modified version of the general pattern of the simulation study by Huisman and Steglich (2008) was followed:

1. Select a data set consisting of both network and behavioral data. In line with Smith and Moody (2013) and Smith, Moody, and Morgan (2017), data sets representing a variety of commonly studied networks were selected, limited to small networks (smaller than 65 nodes), which are typically found in empirical research using SAOMs.
2. For each data set, estimate a SAOM, the so-called base model, on the first two observed waves. This base model represents the 'true' model and is based on the complete data set, before generating missing actors.
3. Using the selected data set and the base model, generate complete (i.e., non-missing) sets of longitudinal data consisting of two waves.
4. Generate missing data in both waves by deleting the behavioral data of a fraction of the actors. Note that the network data are not deleted.
5. Use the procedures outlined in Section 2.3.2 to handle the missing data and re-estimate the SAOM.
6. Investigate the effect of missing data handling on the estimation procedure and the estimated parameters of the SAOM by comparing the parameters of the re-estimated models after treating for the missing (deleted) behavior, with the parameters of the base model. This comparison is based on the following three

criteria: convergence of the estimation procedure, parameter bias, and parameter coverage.

Details and specifications of various steps in the simulation process are given in the following subsections.

2.4.1 Selection of data sets and generation of longitudinal data

Four different data sets were selected to be used in the simulation study. Each data set consists of at least two waves of network and behavioral data. To limit computation time and convergence problems, from each data set, the first two waves of one network and one behavioral variable are used. The sampled networks are similar in size, ranging from 50 to 63 actors, and consist of friendship or advice relations. Data sets one and two are subsets of the friendship networks from the *Teenage Health and Lifestyle* study (Michell & Amos, 1997; Pearson & West, 2003). The first consists of 50 girls (labeled s50) with the behavioral dependent variable alcohol consumption, which is coded on a five-point frequency scale ranging from 1 (“I don’t drink”) to 5 (“I drink more than once a week”). This data set was also used by Adams and Schaefer (2018) for a visualization of the mini steps in SAOMs and in the simulation studies of Huisman and Steglich (2008), Huisman (2009), and Krause, Huisman, and Snijders (2018). The second data set consists of a subset of 58 boys from the same study (labeled G58), also with friendship defining network ties and alcohol consumption as dependent behavioral variable.

The third data set comes from a study among 63 managers of an international company (labeled L63; Zandberg, Huisman, & Wittek, 2020) It consists of two waves of an advice network and the behavioral variable is information synthesizing, which involves gathering, evaluating, and distributing strategic information to the top management of an organization (Floyd & Wooldridge 1997). Synthesizing is coded on a six-point frequency scale ranging from 1 (“hardly synthesizing information”) to 6 (“regularly synthesizing”). The fourth data set (labeled H57) comes from a study among 57 staff members of a housing corporation in the Netherlands (Whitmeyer & Wittek, 2010). It consists of an advice network and dependent behavioral variable stress at work. The behavioral variable is coded on a five-point frequency scale ranging from 1 (“not or hardly ever stressed at work”) to 5 (“very often or always stressed at work”).

Some data characteristics of the first and second observation of the data are presented in Table 2.1, and a visual presentation of the first wave of each network is given in Figure 2.1. In Table 2.1, density is calculated as the number of actual ties divided by potential number of ties, and degree is the number of ties of each actor. Moran’s *I* is the spatial autocorrelation index that measures the association between behavior and network (i.e., the correlation of behavior between actors that are related to each other). The Jaccard index is the Jaccard distance between two successive networks (wave 1 and wave 2) and measures stability between the waves.

The networks are comparable in terms of size, but differ in density, with the friendship networks s50 and G58 having the lowest densities. The advice networks are denser, with the H57 network showing some cliques and some actors in (very) central positions. The L63 network is rather dense showing high levels of interaction between the actors. In the s50 data, Moran's I, the network autocorrelation, equals 0.43 and 0.40 for wave 1 and wave 2, respectively, which means there is a strong association between network and behavior. In the G58 data, Moran's I decreases from 0.33 to 0.05, signifying a decrease in association between network and behavior. In the L63 data, Moran's I equals 0.12 and -0.04, for wave 1 and 2, respectively, and 0.05 and 0.03 in the H57 data, which signifies a rather low association between the network and behavior in both data sets (Veenstra et al., 2013). The Jaccard index measures the amount of change in the network between two waves, and should be large enough to provide enough information to estimate the parameters. A value of 0.3 is usually considered adequate (Ripley et al., 2017). The Jaccard index varies from 0.30 to 0.67, indicating there is enough change between the waves to enable estimation of a SAOM in all data sets.

Table 2.1 Sample network descriptive statistics for all three data sets (S50, G58, L63, H57): Network size, density, average degree, Moran's *I*, the Jaccard index, and relative frequencies of the categories of the behavioral variable.

Network	s50		G58		L63		H57	
	Wave 1	Wave 2	Wave 1	Wave 2	Wave 1	Wave 2	Wave 1	Wave 2
Network size (n)	50		58		63		57	
Density	0.05	0.05	0.05	0.04	0.38	0.39	0.10	0.10
Average degree	2.26	2.32	2.69	2.33	23.40	24.10	5.32	5.70
Moran's I	0.43	0.40	0.33	0.05	0.12	–0.04	0.05	0.03
Jaccard Index	0.33		0.30		0.67		0.39	
Behavior relative frequencies								
1	0.10	0.06	0.05	0.03	0.27	0.19	0.14	0.14
2	0.32	0.32	0.48	0.33	0.19	0.24	0.14	0.07
3	0.24	0.24	0.29	0.40	0.02	0.27	0.37	0.38
4	0.28	0.22	0.14	0.21	0.00	0.11	0.21	0.24
5	0.06	0.16	0.03	0.03	0.00	0.13	0.14	0.15
6	-	-	-	-	0.52	0.06	0.00	0.00

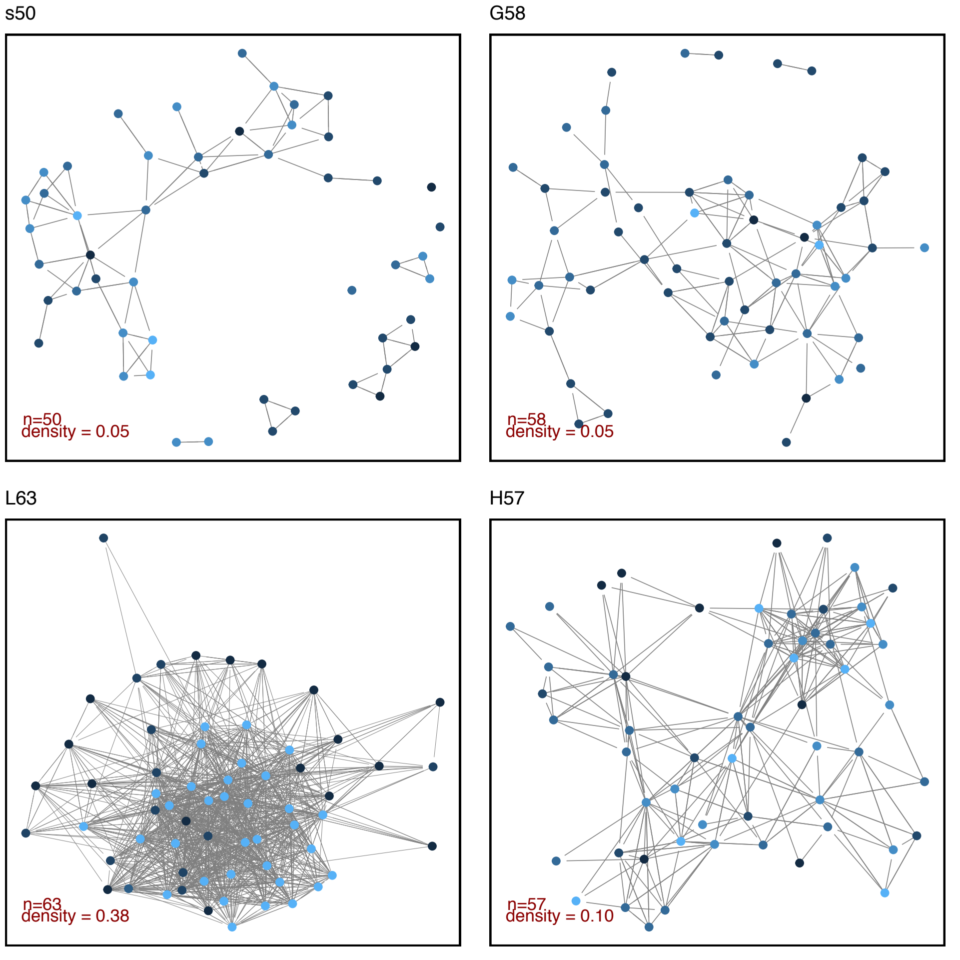


Figure 2.1: Graphs (wave 1) of the networks used in the simulation study: Friendship networks s50 and G58 (top row) and advice networks L63 and H57 (bottom row).

The first two waves in each data set were used to generate simulated co-evolution processes of networks and behavior. On each data set, a SAOM was estimated that is used as the base or 'true' co-evolution model to generate the data in the study. These base models are presented in Table 2.2. As the data sets differ in type of network and behavior, we tried to keep the base models as similar as possible by using the following set of standard effects:

The first three effects specify the dynamics of the network.

- Density (outdegree), the basic tendency of actors to have ties.
- Reciprocity, the tendency of relations to be returned. If actor A asks actor B for advice, this increases the probability of B asking A for advice.

- Transitive triplets, the tendency to form transitive triplets. If actor B is a friend of actor A, and actor C is a friend of actor B, the probability of A becoming a friend of C will increase (friends become friends with their friends' friends).

The following three effects model the influence of behavior on network structure.

- Behavior alter describes the effect of behavior on the actor's popularity to attract other actors; a positive parameter indicates a tendency that actors with high levels of behavior will receive more incoming tie requests. For example, spending lots of money might be a reason for getting befriended.
- Behavior ego describes the influence of an actor's level of behavior on extending ties to others. For example, being successful leads to more easily approaching others.
- Behavior similarity describes the effect of forming a tie with actors with similar levels of behavior, like non-smokers befriending non-smokers.

The following three effects model the influence of network structure on behavior.

- Behavior total similarity describes the actors' preference to be similar to their alters.
- Behavior indegree describes the tendency that popular actors (with more incoming ties) have higher values for behavior.
- Behavior outdegree describes the tendency that more active actors (with more outgoing ties) have higher values for behavior.

In a first attempt, a model containing all the described effects was estimated on each data set. In order to obtain acceptable convergence results for all data sets, in a second round some effects were removed from the model of some data sets. This resulted in simple base models that have slightly different specifications for all data sets, good convergence qualities, do not take too much computing time, and are able to generate empirically informed simulations. A drawback is that some parameters are not significant. All four base models satisfy the common convergence criteria (Ripley et al., 2017), with convergence statistics for individual parameters smaller than 0.10 and *t*-statistics for overall convergence smaller than 0.25. It should be noted that the satisfying convergence of the base models is also due to the relatively simple model specifications.

Table 2.2. Specification of base models to generate longitudinal data for networks and behavior for the four data sets: Estimated parameters *b* (with standard errors) and convergence *t* statistics. The t-statistic is the average deviation between simulated values of the statistics and their target values in the final phase of the estimation phase where the standard errors of the statistics are estimated.

	Effect	s50		G58		L63		H57	
		b (SE)	*t*	*b* (SE)	*t*	*b* (SE)	*t*	*b* (SE)	*t*
1	Network rate	5.94 (0.99)	–0.01	5.78 (0.70)	–0.02	14.63 (0.90)	0.01	7.68 (0.64)	0.02
2	Density	–2.59 (0.17)	0.01	–2.49 (0.23)	0.02	–1.70 (0.08)	–0.01	–1.36 (0.07)	0.00
3	Reciprocity	2.06 (0.26)	0.02	2.27 (0.29)	0.00	1.17 (0.09)	–0.02	0.99 (0.14)	0.00
4	Transitive triplets	0.61 (0.12)	0.02			0.04 (0.00)	–0.02		
5	Behavior alter	–0.14 (0.11)	–0.05	0.58 (0.28)	0.03	–0.20 (0.05)	–0.02	0.05 (0.05)	0.03
6	Behavior ego			–0.15 (0.28)	0.01			–0.12 (0.06)	0.01
7	Behavior similarity	1.60 (0.75)	–0.03	2.10 (1.60)	0.01			–0.78 (0.32)	0.04
8	Behavior rate	1.02 (0.40)	0.03	1.76 (0.54)	–0.01	6.64 (1.59)	0.02	0.92 (0.27)	0.02
9	Behavior linear	–0.35 (1.23)	0.05	–0.38 (0.54)	0.04			–0.20 (1.01)	0.03
10	Behavior quadratic	–0.16 (0.36)	0.00	–0.21 (0.20)	0.01			0.61 (0.75)	0.00
11	Behavior total similarity			2.36 (1.85)	0.03			2.26 (2.95)	0.00
12	Behavior indegree	–0.69 (1.46)	0.03	0.01 (0.43)	0.03			–0.05 (0.20)	0.03
13	Behavior outdegree	1.10 (2.16)	0.03	0.29 (0.54)	0.04	–0.05 (0.02)	0.01	0.17 (0.31)	0.02
	Overall convergence t-statistic		0.10		0.09		0.06		0.06

The four estimated base models are used to simulate the co-evolution processes. The first observation of each network and corresponding behavioral variable are taken as initial state of the process and using the estimated model parameters, the co-evolution process was simulated 500 times. This resulted in 500 simulated networks and 500 simulated behavioral variables at the second time point. These simulated data (network and behavior) are taken as wave two data in the simulation study (after generating missing data).

2.4.2 Generating missing data

As the study is restricted to missing behavior (endogenous) variables, missing data were created by selecting actors according to some stochastic procedure and deleting the values of the behavioral variable of these actors. Four proportions of non-response were generated: 0.1, 0.2, 0.4, and 0.6. For each proportion, actors were sampled using one of the selection mechanisms described below, and missing values were created in the behavior variable at both time points. That is, an actor with non-response on behavior, has missing values on both time points. In line with Huisman and Steglich (2008) and using the typology defined by Rubin (1976), we used three different mechanisms to select the actors with missing behavioral values.

1. Missing completely at random (MCAR): Completely random selection, where missingness is not related to characteristics of the network or the actors.
2. Missing at random (MAR): Probability of selection is proportional to $1/(\text{outdegree} + 1)^2$, where missingness is related to an observed network characteristic.
3. Missing not at random (MNAR): Probability of selection is proportional to $1/(\text{behavior} + 1)^2$, where missingness is related to the behavioral variable itself.

In the second and third mechanism, the selection is such that actors with lower scores on the characteristic (outdegree and behavior, resp.) have a larger probability to have missing data. While these may not be the only realistic mechanisms to select actors with missing behavior data, they are very suitable to illustrate the impact of the different types of mechanisms.

The generation of the observed and missing data resulted in 4 (data sets) × 500 (replications) = 2,000 complete data sets (two waves of network and behavior two waves), and 4 (data sets) × 500 (replications) × 4 (proportion missing) × 3 (missingness mechanism) = 24,000 incomplete data sets.

2.4.3 Treatment of missing data and re-estimation of SAOM

For each network, the data were analyzed using the SAOM that was used to generate the data (see Table 2.2). Next, the same SAOM was fitted to the incomplete data, were the missing behavior data were treated using one of the missing data procedures described in Section 3.2:

1. Complete cases (CC).
2. Single imputation by imputing the mean of the observed data (AV).
3. Single imputation by imputing the value of a randomly selected donor case (RAN). For each missing actor, a donor case is selected at random from the set of observed actors and the value of the behavior variable of the donor actor is used to replace the missing data.
4. Single imputation by imputing the value of a selected donor case (hot deck imputation; HD). As in the previous procedure, the missing behavior is imputed by the behavior value of a donor actor. The donor actor, however, now is an actor resembling the actor whose behavior is missing. The selection of a matching donor is based on the absolute difference in outdegree between the actor with missing behavior data and the donor actor (the smaller the difference, the higher the probability of the donor to be selected).
5. Multiple imputation based on predictive mean matching (MI). Predictive mean matching (Little, 1988) is a hot deck procedure in which donor actors are selected of which the observed values are imputed. The selection of the donors is based on matching predictions from regression models. In the case of missing behavior data, a set of three observed donor actors is found of whom the predicted behavior scores are close to the predicted value of the missing actor, and from this set one donor is randomly drawn (van Buuren, 2012). The regression models on which the predictive mean matching is based, consist of additional behavioral or attribute variables and network effects, depending on the data set that is imputed (one of the four described in Section 4.1). For all four networks, the network statistics that were used in the imputation model are indegree, outdegree, number of reciprocal ties, number of transitive ties, number of three-cycles, and number of two-paths. The additional behavior variables that were used in the imputation model are use of tobacco, use of cannabis, sports participation (s50 data set), use of tobacco, use of cannabis, amount of pocket money, having a romantic relation, distance to school (G58 data set), proactive behavior, discretionary space, organizational support, organizational commitment, and organizational connectedness (L63 data set). For the H57 data set no additional behavioral variables were used as predictors in the imputation model, as none were available. The multiple imputation for each incomplete data set was performed using the R software package mice (van Buuren & Groothuis-Oudshoorn, 2011), based on *m* = 5 imputations. These imputations were simulated until five convergent runs were obtained. When less than five convergent runs were obtained after twenty-five attempts, simulation was stopped. In that case, if we had achieved four convergent runs, multiple imputation was based on these four imputations, and in case we had obtained less than four convergent single imputations, this particular simulated data set was discarded for further analysis.

6. The default SIENA method (SIENA) based on imputation and restricted parameter estimation (as described for ties by Huisman & Steglich, 2008).
7. The dummy variable procedure for SAOMs (DUM). The parameter for the effect of the dummy variable (indicating missing actors) was fixed at the value –40, which proved large enough (in absolute value) to prevent missing actors from making a change in the dynamic processes.

2.4.4 Analysis of the simulation outcomes

Three measures of performance were used to investigate the effect of the missing data procedures for behavioral variables on modeling the longitudinal data: convergence (number of converged estimation runs), relative bias (compared to true score, i.e., the parameter of the data-generating SAOM), and coverage (percentage of intervals containing the true parameter value). A convergent simulation is a prerequisite for a reliable parameter estimation in SIENA. Convergence indicates that the statistics of the simulated networks in the estimation procedure, are close to their target values. In our study, we considered a simulation run converging if after one simulation run the *t*-statistic for overall model convergence is smaller than 0.25 (Ripley et al., 2017). While one usually reruns a simulation when convergence is not satisfactorily in a first attempt, we did not rerun simulations as we considered the number of convergent runs in a first attempt a good indication of the effect of a missing data treatment on convergence characteristics. For multiple imputation, the approach is slightly different because MI is based on five (or four) convergent sub runs. Therefore, obtaining a MI-result for a specific run automatically implies that it is based on convergent sub runs. The difference with the other methods is that we had more opportunities in obtaining convergent runts. If a run was not converging, it was discarded for further analysis.

To evaluate the robustness of the missing data handling methods, the relative bias of the estimated parameters was calculated: bias = (treated – true) / true, where treated is the estimated parameter for the treated missing data, and true is the estimated parameter in the original base model. Because for some combinations of data set, parameter, mechanism, and method, the number of convergent simulation runs was very low, only those combinations with at least 100 converging runs were considered.

To evaluate the distribution of the estimated parameters, the proportion of population parameters (base model) within two-standard-errors distance from the estimated parameter was calculated. In case of a normal distribution of estimated parameters, this distance would be smaller than two standard errors in approximately 95% of the cases. Although the distribution of estimated parameters in SAOMs is unknown, we will use this procedure to approximate parameter coverage. Similar to the relative biases, this is based on combinations with at least 100 convergent runs only.

2.5 Results

2.5.1 Convergence

The results are presented in Figure 2.2, which shows the number of convergent simulation runs for each combination of data, method, missingness mechanism, and level of missingness. Each combination has been simulated 500 times, and the graphs show how many of these 500 runs were convergent. For example, in the G58 data set, the number of convergent simulations is approximately 380 when there is no missing data, but below 100 for 60% missing data and complete case analysis (CC).

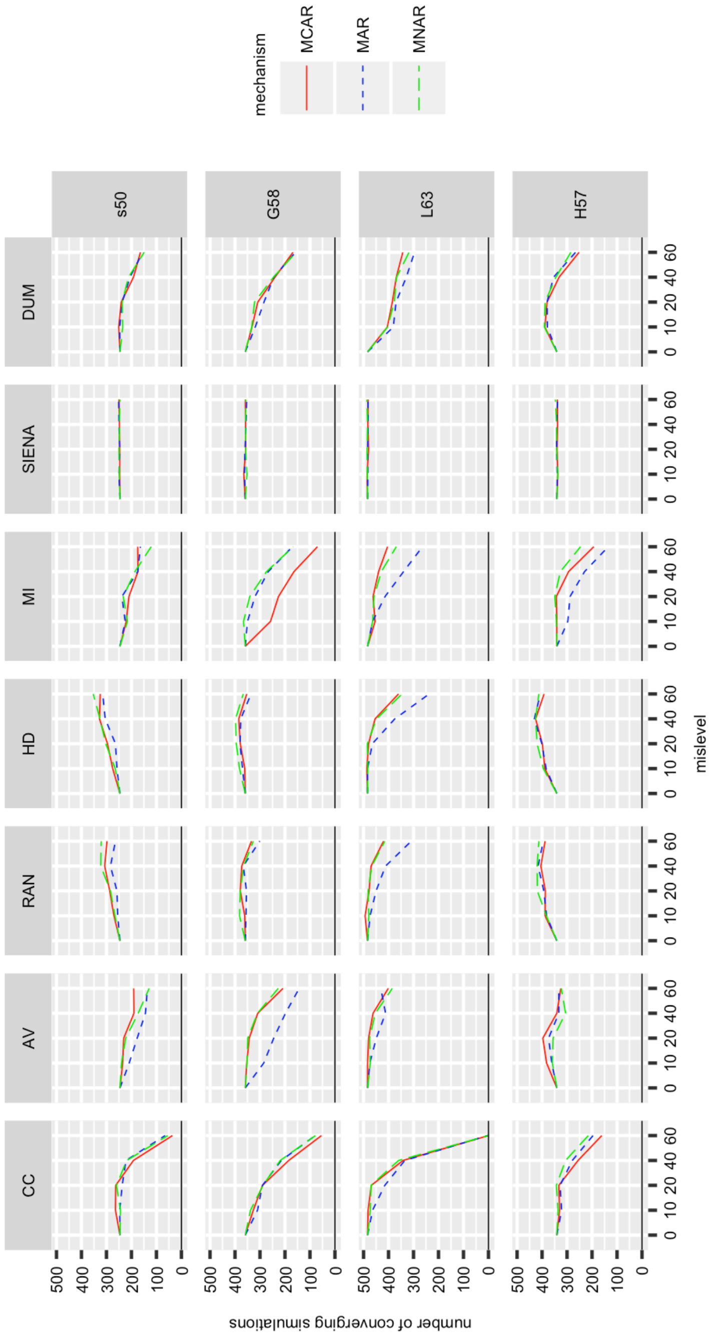


Figure 2.2: Number of converging simulation runs.

First, we observe that the missingness mechanism hardly matters in most cases. In the G58 data set, mean imputation (AV) shows the worst performance for the MAR mechanism, while multiple imputation (MI) performs worst for MCAR. In the L63 data set, MAR generally shows lowest convergence rates (especially for the imputations based on donor cases: RAN, HD, and MI) for high levels of missingness. As a general conclusion, we can say that the missingness mechanism seems to have only a small impact on convergence.

When we look at the convergence characteristics of the different methods, it can be observed from Figure 2.2 that for all data sets CC leads to low numbers of convergent simulations for higher levels of missingness. This is no surprise as the number of network relations declines exponentially and the remaining number of actors and ties quickly becomes too small. The implication is that CC is not a useful method to deal with missing data. The single imputation-methods AV, RAN, and HD replace the missing data by a value that is based upon the observed data. It is therefore no surprise that their convergence results show similar patterns. Multiple imputation shows patterns that are often similar to mean imputation (AV) and is frequently hardly better than complete case analysis. Although MI imputes observed information (based on donor cases), the variation in imputed values is probably too large to lead to stable estimation. The two single-imputation methods based on donor cases (RAN and HD) often result in increased numbers of convergent runs, indicating that they insert information that benefits model estimation, which may not actually reflect true data processes.

The default SIENA method shows rather strong convergence performance, even for high levels of missingness. However, using SIENA with the dummy option (DUM) leads to convergence problems with higher levels of missingness. The explanation of this difference might be due to the manner SIENA treats missing data. In the case of the default, the mode of the variable is imputed for the missing behavior data, and this value is allowed to change in the Markov sequence that models the behavior between the waves. This means that the incomplete cases still participate in the co-evolution of behavior and network between the waves, though they are excluded in the procedure for parameter estimation. In the dummy method, any change of the missing behavior is effectively prohibited, limiting the co-evolution process between waves. Especially for higher fractions of missing data this may lead to convergence problems.

The overall conclusion is that the SIENA method is least affected by convergence problems. Single imputation gives acceptable convergence rates for small numbers of missing data, but for higher percentages the performance gets worse. The same pattern can be seen for the multiple-imputation method, however the effects are even larger, especially for higher levels of missingness.

2.5.2 Parameter bias

The average relative biases of the estimated model parameters are presented in Figures 2.3a-d, which consists of one subfigure for each data set. Each of these subfigures in turn contains a number of graphs for different combinations of method and estimated parameter. These figures show the average relative bias of the estimated parameters as a function of missingness level for the three different missingness mechanisms.

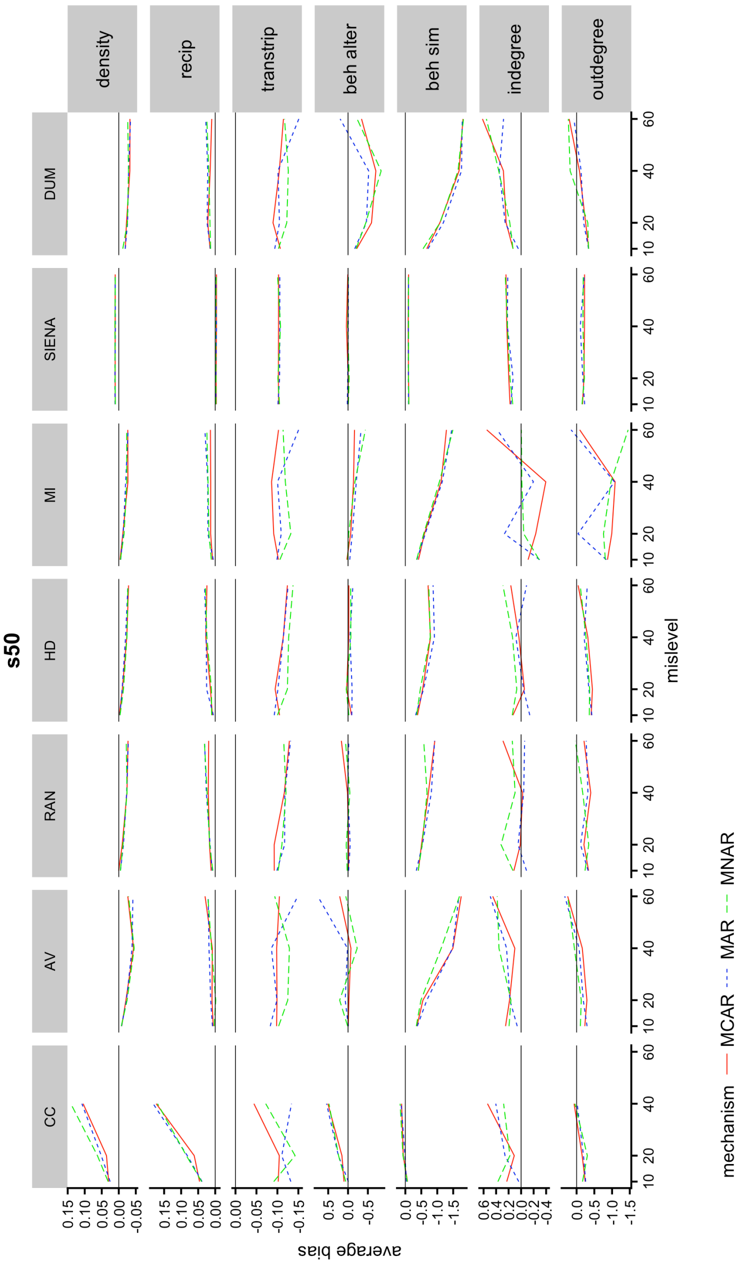


Figure 2.3a: Data set s50. Relative average bias in all data sets, for all missing data methods (columns) and parameters of the corresponding base models (rows), mechanisms (lines in figures), and percentages of missing data (*x*-axis).

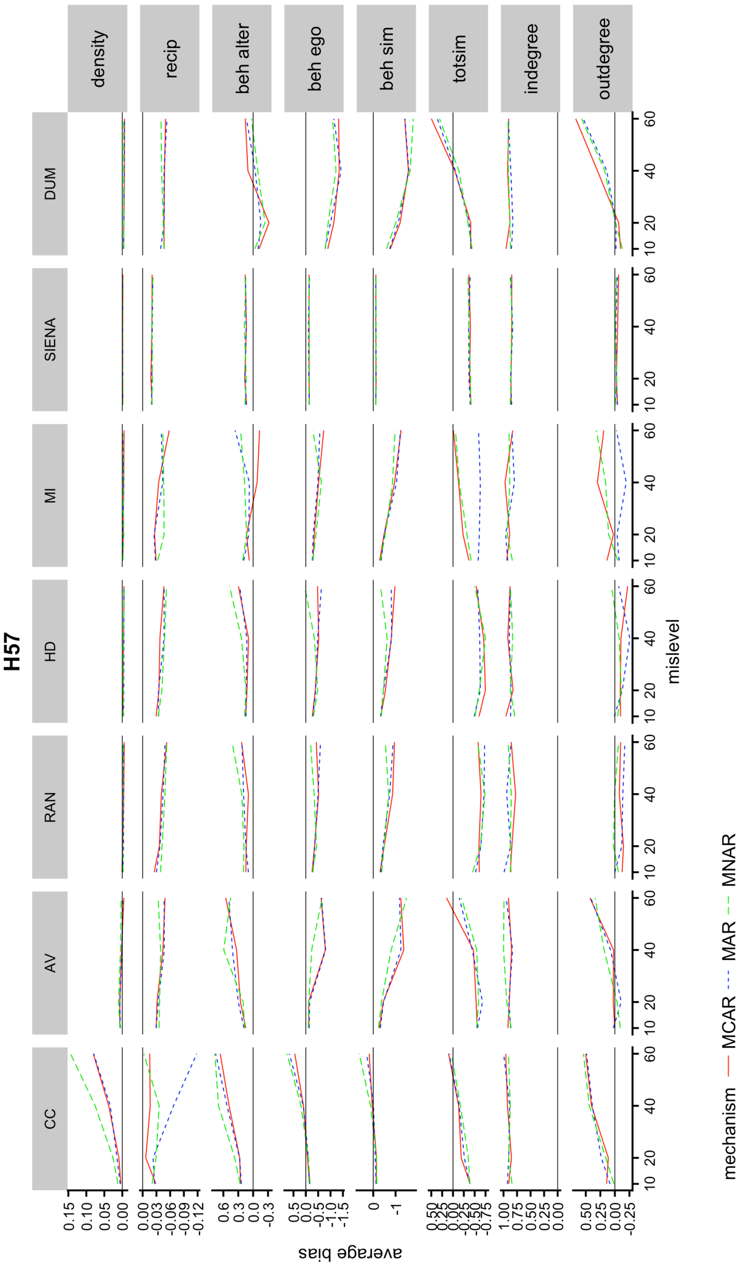


Figure 2.3b: Data set G58. Relative average bias in all data sets, for all missing data methods (columns) and parameters of the corresponding base models (rows), mechanisms (lines in figures), and percentages of missing data (*x*-axis).

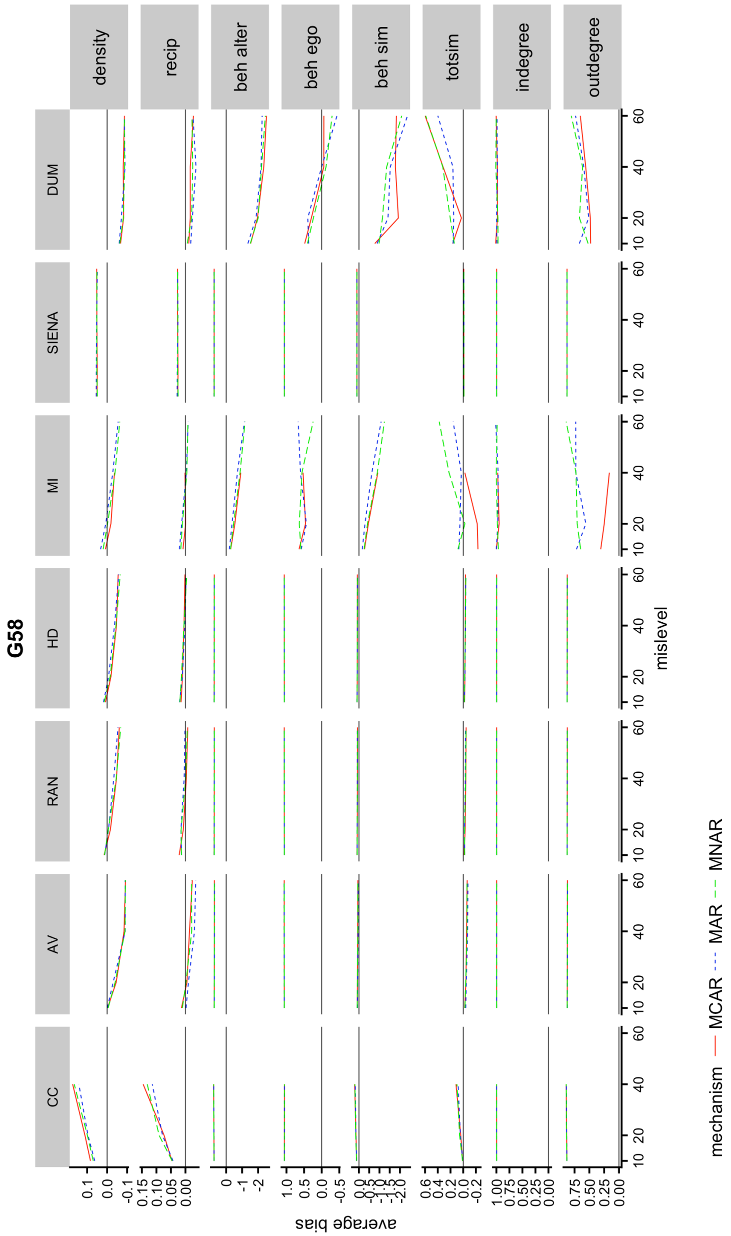


Figure 2.3c: Data set L63. Relative average bias in all data sets, for all missing data methods (columns) and parameters of the corresponding base models (rows), mechanisms (lines in figures), and percentages of missing data (*x*-axis).

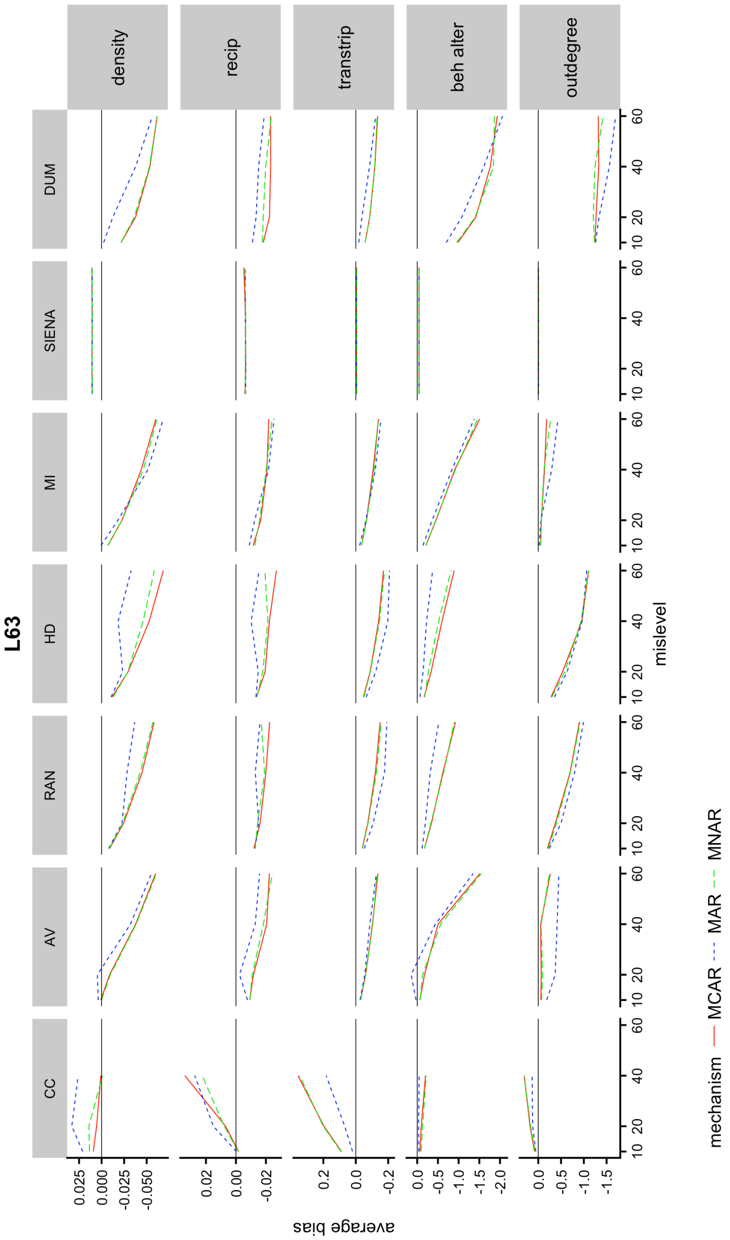


Figure 2.3d: Data set H57. Relative average bias in all data sets, for all missing data methods (columns) and parameters of the corresponding base models (rows), mechanisms (lines in figures), and percentages of missing data (*x*-axis).

From Figures 2.3a-d it can be seen that the missingness mechanisms (MCAR, MAR, and MNAR) seem to have little impact on the relative parameter bias. With some minor exceptions, there is some variation in performance, single-imputation methods (AV, RAN, and HD) perform rather similarly. Depending on the type of the relation and the strength of the effect in the data, some effects will be more sensitive to missing data than others, leading to a variation in relative biases. The performance of the multiple-imputation procedure is comparable to single imputations in a number of cases, but sometimes outperforms them, for example in the L63 data set. The default SIENA method clearly outperforms the other methods. The figures also indicate that the performance of this procedure seems to be rather independent of the level of missingness, whereas most methods show deteriorating performance for higher level of missingness. This is likely to be caused by the way SIENA deals with missing behavior values: While a value is imputed for the missing observation and behavior may change between the waves, the parameter estimation is based upon the non-missing cases only. This gives the SAOM a high level of flexibility and the possibility to adapt, while at the same moment only taking into account observed values for parameter estimation.

Factorial ANOVAs were performed to find the most important factors that affect the average relative bias of the estimated parameters. To reduce the amount of effects to be estimated and to increase clarity of interpretation, the ANOVAs were performed for each combination of data set and model parameter separately. That is, the main effects on bias of missingness mechanism, level of missingness, and treatment method were estimated, as well as all two-way and three-way interactions. The partial eta-squared values, η_p^2, of main, two-way and three-way effects are presented per parameter and per data set in Table 2.3.

In addition, for each data set a linear regression was performed to predict the relative biases of the estimated parameters using dummy variables representing the different categorical factors (only main effects, no interactions). In this analysis, the default SIENA method was chosen as the reference for method, because Figures 2.3a-d indicated this to be the best performing method. For the missingness mechanism, we chose MCAR, as a theoretical ideal situation. For the level of missingness, we chose 10 percent, the lowest percentage. And for parameter, at random, density. The results of the regressions are presented in Table 2.4.

Table 2.3. Partial eta squared values from factorial ANOVAs for each combination of data set and model parameter to compare the main effects of missingness mechanism (MCAR, MAR, MNAR), level of missingness (10, 20, 40, 60%), and treatment method (CC, AV, RAN, HD, MI, SIENA, DUM), and their two-way and three-way interactions on the average relative bias.

		density	recip	transtrip	beh alter	beh ego	Beh sim	Tot sim	Indegree	outdegree
s50	mechanism	0.00	0.00	0.00	0.00	-	0.00	-	0.00	0.00
	mislevel	0.01	0.01	0.00	0.00	-	0.04	-	0.00	0.00
	method	0.23	0.09	0.00	0.04	-	0.25	-	0.03	0.06
	mechanism*mislevel	0.00	0.00	0.00	0.00	-	0.00	-	0.00	0.00
	mechanism*method	0.00	0.00	0.00	0.00	-	0.00	-	0.00	0.00
	mislevel*method	0.13	0.04	0.00	0.01	-	0.09	-	0.00	0.00
	mechanism*mislevel*method	0.00	0.00	0.00	0.00	-	0.00	-	0.00	0.00
G58	mechanism	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00
	mislevel	0.00	0.00	-	0.01	0.00	0.00	0.01	0.00	0.00
	method	0.28	0.11	-	0.86	0.16	0.32	0.23	0.00	0.04
	mechanism*mislevel	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00
	mechanism*method	0.00	0.00	-	0.01	0.00	0.00	0.01	0.00	0.02
	mislevel*method	0.08	0.04	-	0.14	0.01	0.07	0.03	0.00	0.01
	mechanism*mislevel*method	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00
L63	mechanism	0.02	0.00	0.01	0.02	-	-	-	-	0.00
	mislevel	0.01	0.01	0.04	0.08	-	-	-	-	0.01
	method	0.02	0.03	0.26	0.29	-	-	-	-	0.27
	mechanism*mislevel	0.01	0.00	0.00	0.00	-	-	-	-	0.00
	mechanism*method	0.01	0.00	0.02	0.01	-	-	-	-	0.00
	mislevel*method	0.06	0.04	0.06	0.10	-	-	-	-	0.08
	mechanism*mislevel*method	0.01	0.01	0.01	0.01	-	-	-	-	0.00
H57	mechanism	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00
	mislevel	0.01	0.00	-	0.01	0.00	0.03	0.01	0.00	0.01
	method	0.07	0.00	-	0.02	0.13	0.18	0.03	0.00	0.02
	mechanism*mislevel	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00
	mechanism*method	0.01	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00
	mislevel*method	0.05	0.00	-	0.00	0.03	0.07	0.01	0.00	0.01
	mechanism*mislevel*method	0.00	0.00	-	0.00	0.00	0.00	0.00	0.00	0.00

Table 2.4. Estimated parameters (with standard errors) of the regressions predicting the average relative bias using dummy variables for missing data method, missingness mechanism, missingness level, and model parameter, for all four data sets.

	s50	G58	L63	H57
Intercept	0.063 (0.006)	0.075 (0.003)	0.190 (0.004)	0.067 (0.006)
CC	0.140 (0.005)	0.062 (0.003)	0.080 (0.004)	0.139 (0.005)
AV	–0.059 (0.005)	–0.037 (0.003)	–0.120 (0.004)	–0.063 (0.005)
RAN	–0.094 (0.005)	–0.022 (0.003)	–0.200 (0.004)	–0.130 (0.006)
HD	–0.109 (0.005)	–0.022 (0.003)	–0.214 (0.004)	–0.129 (0.006)
MI	–0.287 (0.007)	–0.325 (0.003)	–0.176 (0.004)	–0.174 (0.006)
DUM	–0.139 (0.005)	–0.237 (0.003)	–0.381 (0.004)	–0.185 (0.006)
MAR	–0.001 (0.004)	0.004 (0.002)	0.025 (0.003)	–0.002 (0.004)
MNAR	0.002 (0.004)	0.002 (0.002)	0.001 (0.003)	0.014 (0.004)
mis20	–0.020 (0.004)	–0.001 (0.002)	–0.036 (0.003)	–0.024 (0.004)
mis40	–0.019 (0.004)	0.013 (0.002)	–0.097 (0.003)	–0.020 (0.004)
mis60	0.043 (0.004)	0.034 (0.002)	–0.127 (0.003)	0.066 (0.004)
recip	0.033 (0.005)	0.004 (0.003)	0.019 (0.003)	–0.043 (0.006)
transtrip	–0.111 (0.005)	-	–0.044 (0.003)	-
beh_alter	0.002 (0.006)	0.468 (0.003)	–0.395 (0.003)	0.206 (0.006)
beh_ego	-	0.912 (0.003)	-	–0.357 (0.006)
beh_sim	–0.466 (0.006)	–0.014 (0.003)	-	–0.445 (0.006)
totsim	-	0.059 (0.003)	-	0.031 (0.006)
indegree	0.596 (0.006)	0.969 (0.003)	-	0.910 (0.006)
outdegree	0.449 (0.006)	0.818 (0.003)	–0.269 (0.003)	0.340 (0.006)

The first observation from the factorial ANOVA is that the η_p^2 values for the missingness mechanism are all very small. This indicates that of the variances in bias, the proportions associated with the missingness mechanism are very small. The largest values are found in the L63 data set with η_p^2 = 0.015 for the density effect and η_p^2 = 0.017 for the behavior alter effect. This is confirmed in the regression on the dummy variables in Table 2.4, where MAR and MNAR only add minor and often insignificant differences to MCAR. The results in Figures 2.3a-d also show often little differences between the missingness methods. The conclusion is that the differences between missingness mechanisms are very small for almost all cases and that the missingness mechanism is not a major factor to consider for the selection of a method to deal with missing data.

A second conclusion to be drawn from the ANOVAs is that the level of missingness is only limited associated with the variation in parameter bias. Large partial eta-squared values are η_p^2 = 0.044 for transitive triplets (transtrip) and η_p^2 = 0.080 for behavior alter effects in the L63 data set, η_p^2 = 0.037 for the behavior similarity effect in the s50 data set, and η_p^2 = 0.026 for the behavior similarity effects in the H57 data set. These results can also be seen in Figures 2.3a-d, where for the mentioned cases an increase in (negative) average relative bias can be seen.

Much larger partial eta-squared values can be found for method. Primarily for the main effect of method (e.g., η_p^2 = 0.231 and 0.283 for density in the s50 and the G58 data set, resp.), but as well for some two-way interactions between method and missingness level (e.g., for the behavior alter effect, η_p^2 = 0.138 in the G58 data set and η_p^2 = 0.103 in the L63 data set, and for the behavior similarity effect, η_p^2 = 0.088, 0.070, and 0.066 for the s50, G58, and H57 data sets, resp.). That the method to deal with missing data is the largest source of variation in parameter bias indicates that choosing the right method is the most important concern.

Looking at the different methods, CC shows relatively large deviations from the true model parameters. Further, in Figures 2.3a-d it can be seen that the four imputation methods (AV, RAN, HD, and MI) show comparable patterns, and especially RAN and HD almost give similar results. In data set s50, MI shows similar results as RAN and HD. In data set L63, MI performs better for reciprocity, transitive triplets and outdegree. In G58, MI differs slightly from the other three methods, showing less deviation for behavior ego, but more deviation for behavior similarity, total similarity, and outdegree. This is confirmed by the regression analyses, where again we see that RAN and HD show almost identical effects.

In most cases SIENA shows the smallest bias, and DUM is similar to the imputation methods. This is not unexpected, as with dummies the value of missing behavior is fixed to a constant level by using a high penalty for change. SIENA imputes the mode and carries out a simulation as if the data set was complete. The actual parameter estimation is then based on the non-missing data. The difference with the dummy method is the allowed change in the underlying sequences of mini steps. It appears that denying these micro changes for missing data, which effectively means putting a lock on behavior, results in larger biases relative to the true parameter.

2.5.3 Coverage

To evaluate the distribution of the estimated parameters, the proportion of population parameters (base model) within two-standard-errors distance from the estimated parameter was calculated. In case of a normal distribution of estimated parameters, this distance would be smaller than two standard errors in approximately 95% of the cases. Although the distribution of estimated parameters in SIENA is unknown, we will use this procedure to approximate parameter coverage. Similar to the relative biases, this is based on combinations with at least 100 convergent runs only.

The coverage results are presented in Figures 2.4a-d. These figures show the proportions of population parameters that are within two-standard-errors distance from the corresponding estimated parameters. In each plot, the horizontal line at 0.95 gives the 95% normal-distribution benchmark.

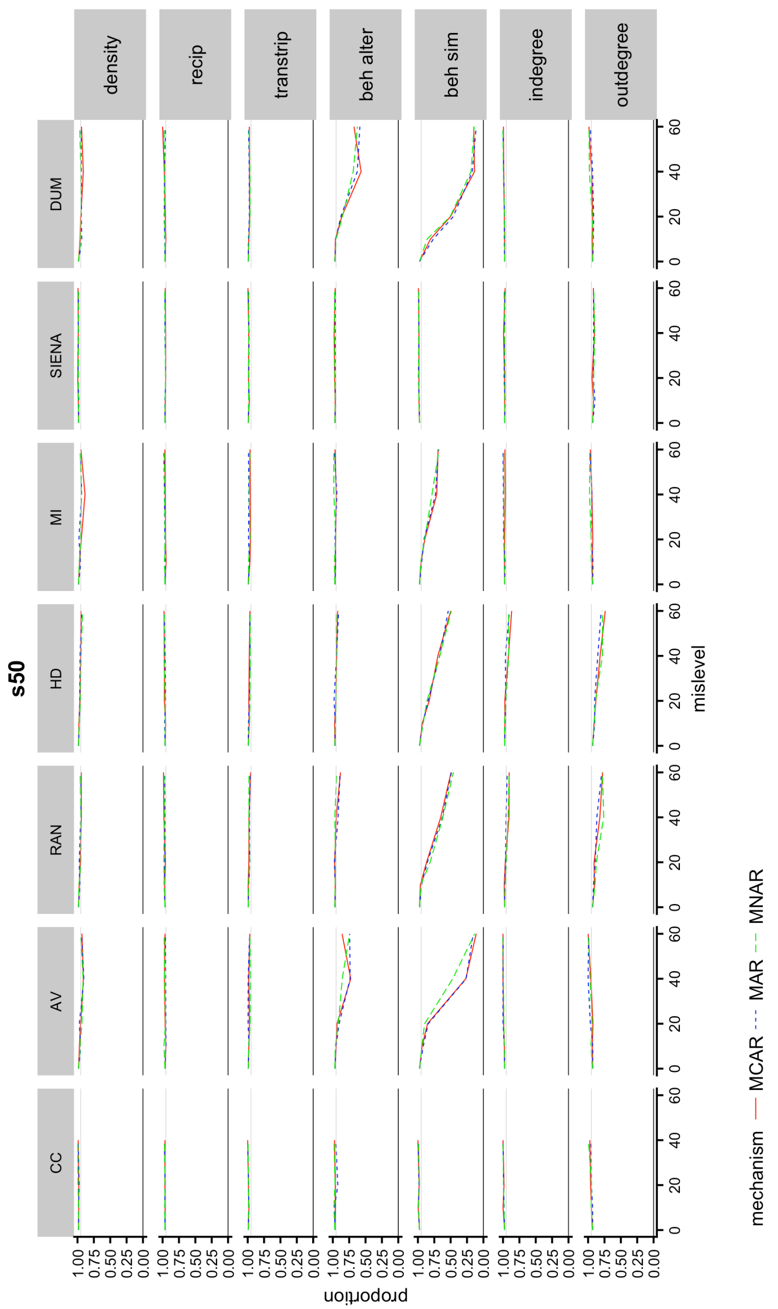


Figure 2.4a: Data set s50. Proportion of runs with difference between population parameter and estimated parameter smaller than two standard errors.

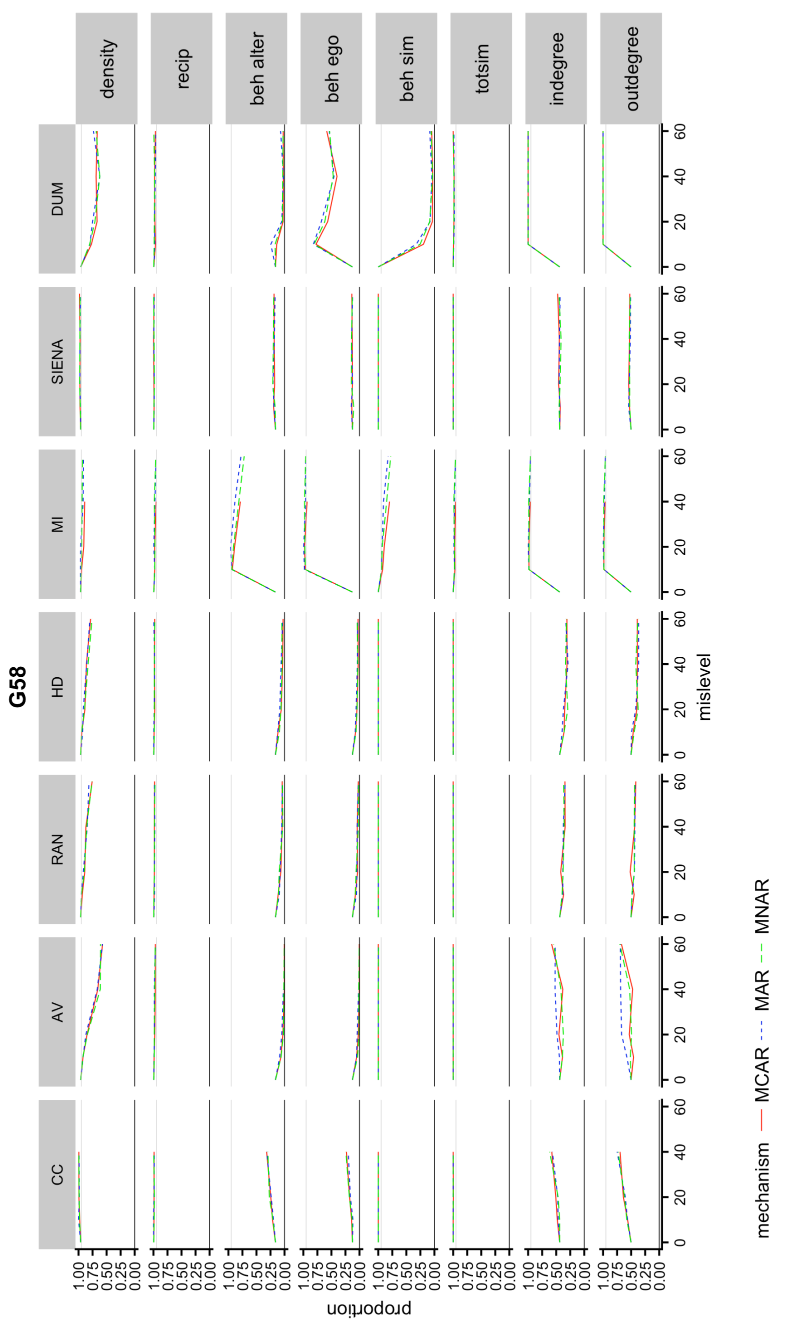


Figure 2.4b: Data set G58. Proportion of runs with difference between population parameter and estimated parameter smaller than two standard errors.

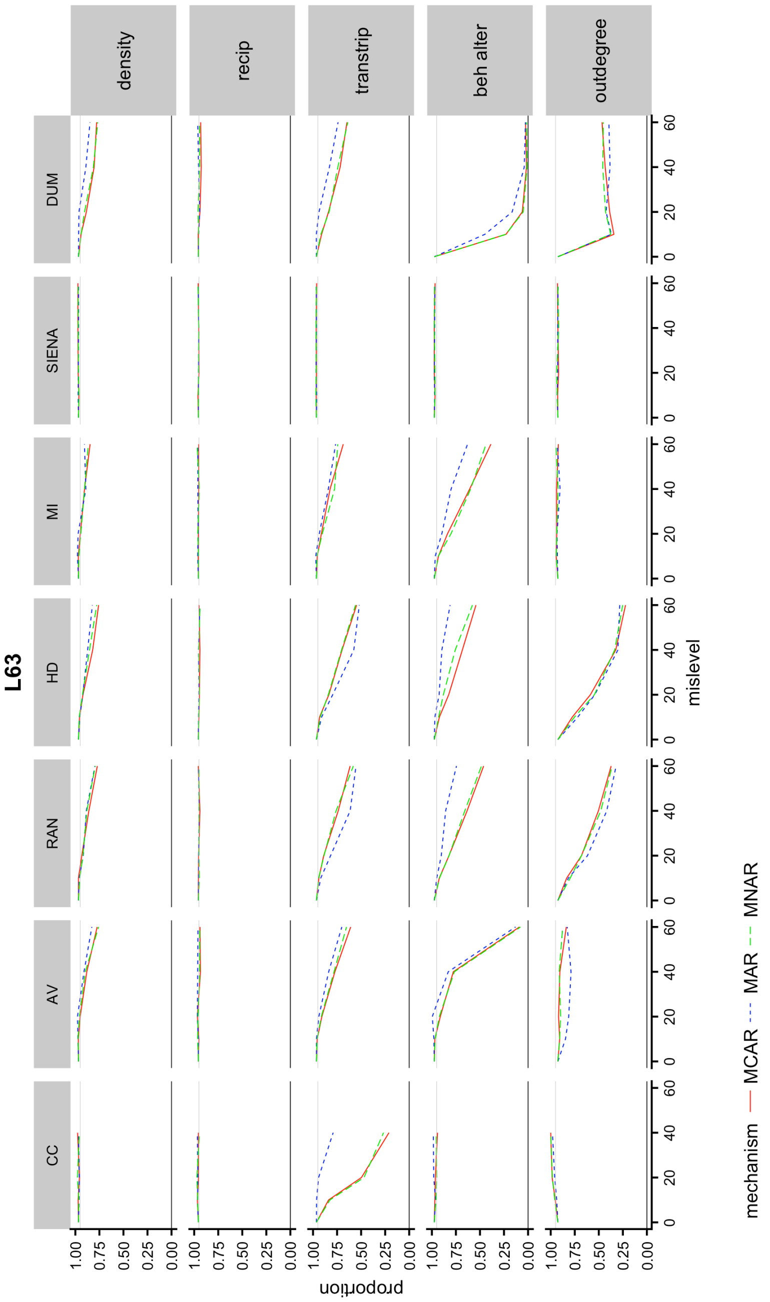


Figure 2.4c: Data set L63. Proportion of runs with difference between population parameter and estimated parameter smaller than two standard errors.

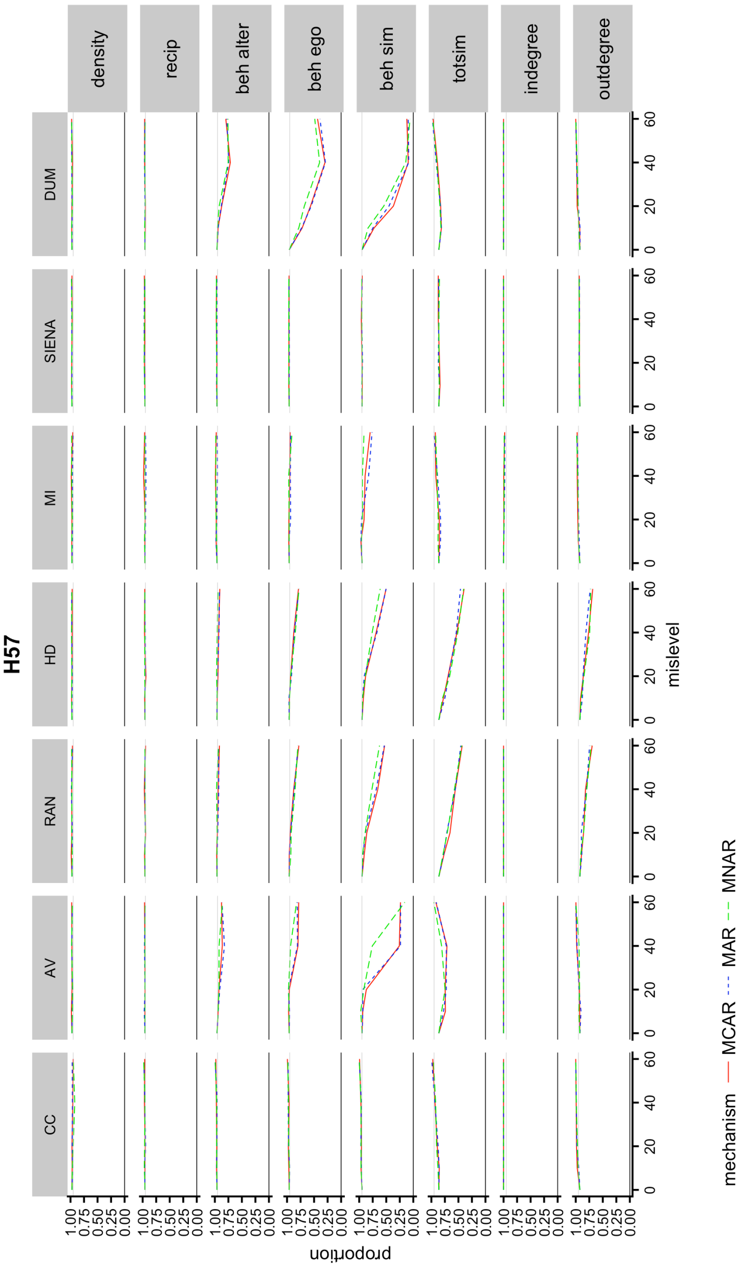


Figure 2.4d: Data set H57. Proportion of runs with difference between population parameter and estimated parameter smaller than two standard errors

The first observation is that there is hardly a difference between the three missingness mechanisms. Inspection of the missing data methods shows that in most cases CC leads to 95% of the population parameters within the expected boundary, although it should be noted that for high percentages missing (60%), the proportions could not be calculated in three of the four data sets (due to low numbers of convergent model runs). Only the L63 transitive triplets parameter, and the G58 behavior alter and ego effects, indegree, and outdegree parameters show an unexpected low proportion of smaller than 2 SE deviations. For the G58 data, these parameters show similar poor results for all other methods as well.

In general, the imputation methods perform similar or worse than CC, especially for higher levels of missing data. The single imputations AV, RAN, and HD give similar results (again RAN and HD are almost identical in their patterns) and are not able to give acceptable parameter coverage for high levels of missing data. Multiple imputation can only do a little better, indicating that the number of imputations (m = 5) is probably too low. In the L63 data, MI clearly outperforms the single imputation for parameter coverage of the transitive triples and outdegree effects and is slightly better for other effects. MI also clearly outperforms CC, AV, RAN, and HD in the G58 and H57 data sets.

The outcomes of SIENA are always at the .95 level, except for a number of effects in the G58 data set. The dummy method is on a number of individual cases on the 0.95 level, but often clearly much lower (for some parameters in all data sets, e.g., s50 behavior alter and behavior sim, or L63 all parameters but reciprocity). This is not surprising as the dummy effect prevents development of the behavior between waves, and so hampers effects related to behavior.

There is no clear indication that one parameter is experiencing more coverage problems than others. All parameters show poor results in some conditions. For example, indegree and outdegree show satisfactorily results in the s50 and H57 data sets, poor results for most methods in the G58 data set, and mixed results in the L63 data set. Overall, the conclusion is that SIENA outperforms other methods.

There are two notable effects of type of data set. First, the L63 data shows more variation in coverage than the other data sets, with low coverage levels for high missingness levels. Only for the SIENA method coverage is stable and at the desired level. Second, the G58 data shows extremely low coverage for some behavior effects (alter, ego, indegree, outdegree), for all methods. These effects were already nonsignificant in the base model (in the sense that the estimated value is smaller than two times the standard error), and the simulations show wildly varying results. Multiple imputation can partly compensate for this by taking into account the between-imputations variance.

2.6 Discussion

Missing data is a challenge for network researchers. While much research has focused on the effect of missing actors, we addressed the influence of missing actor behavior in longitudinal network studies. In particular we focused on strategies to deal with missing behavior data in SAOMs. These strategies are based on general principles to deal with missing data and can be categorized as complete cases only, imputation-based, and model-based methods. We have used three criteria to evaluate these strategies: estimation convergence, relative parameter bias, and coverage. We argue that relative parameter bias is the most important of these three criteria, as it reflects the accuracy of the parameter estimates. Coverage describes the proportion of two-standard-errors intervals around the estimated parameter that contain the original parameter (true parameter of the base model which generated the simulated data). We have to realize that the distribution of the parameter estimates is unknown, which implies that a priori we cannot expect 95% of the estimated intervals to contain the true parameter. Despite this caveat, the proportion found is an indication of the spread and stability of outcomes. Therefore, we consider coverage the second criteria to apply. Thirdly, convergence is an indication of correct model specification. Poor convergence means that the data set contains not enough information to estimate the model parameters properly. This might be an indication the chosen strategy leads to a too strong loss of information as we have witnessed for the complete cases strategy in the simulation, or to an imputation that represents the missing information incompletely or imperfectly.

Regarding the relative parameter bias, the results show that the methods based on single imputation are roughly comparable. Multiple imputation sometimes outperforms the single imputations but performs worse in other cases. In most cases, the default SIENA procedure shows the smallest bias and the SIENA dummy method shows strongest parameter bias. These latter results show that the dummy method is too restrictive in allowing change between consecutive waves, as missing actors are not allowed to make changes, thereby biasing parameter estimates. The default SIENA procedure is more flexible and missing actors do influence the co-evolution process, which leads to better results. The default SIENA procedure is more a model-based approach to deal with missing data, in that it estimates the missing values in the course of parameter estimation (i.e., in simulating the co-evolution process) and missing actors do have an indirect influence on parameter estimates. However, contrary to the dummy approach or the imputation-based strategies, the final estimation is based only on the observed cases. This is shown to lead to better results (i.e., smaller biases in parameter estimates).

Single imputations often show a poor parameter coverage, especially for high levels of missingness and for parameters related to (the missing) behavior. Multiple imputation often, but not always, outperforms single imputation. This also shows that the number of imputations used in the simulations (m = 5) is not large enough. The SIENA dummy method often gives coverage results below the 0.95 level, and gives in general similar results as imputation, and in some cases even worse. For the default SIENA method, however, in almost all combinations of data set and effect parameter, 95% of the two-standard-errors intervals around the estimated parameters contain the original parameter, making it the best performing procedure with respect to coverage.

The single donor-based imputation methods (RAN and HD) often see an increase of convergent runs for higher levels of missingness. This suggests information is inserted that benefits model estimation, that is, there are enough changes between consecutive waves to result in some converged solution. This solution, however, often is biased and coverage is poor. Mean imputation and especially multiple imputation give poorer results with respect to convergence. The latter result may be due to large variation between imputations, indicating that there are large differences between imputation runs, which do not allow for stable estimation of SAOMs. The SIENA methods perform better, where SIENA with the dummy option leads to convergence problems with higher levels of missingness, but the default SIENA method shows rather strong convergence performance, even for high levels of missingness.

We observed only a limited influence of the missingness mechanisms MCAR, MAR (probability of missingness proportional to outdegree), and MNAR (probability of missingness proportional to behavior). This suggests that the performance of each treatment strategy is mostly unaffected by the used missingness mechanisms. There was also a small effect of the data set used, especially on the coverage criterion, but there were no methods that performed substantially better in one data set than another.

Taking all three criteria into consideration, we recommend the default SIENA procedure as the optimal strategy currently available to deal with missing behavior data. First, it leads to the smallest average parameter bias. Secondly, for almost all combinations of effect parameter and data set we investigated, 95% of the two-standard-errors intervals around the estimated parameters contain the original parameter. And thirdly, it has the best convergence performance, which besides being an indication of operational strength, indicates that other methods are less capable of dealing with the loss of information due to the missing behavior data.

The study has a number of limitations. First, is the use of real-life data sets instead of simulated data. As it is impossible to draw clear conclusions about the effect of data characteristics on the performance of the missing data procedures, the potential influence of the characteristics has to be explored further. For example, closure effects are more likely to be affected in low-density networks than in high-density networks because the impact of missing data well be felt more severely. This holds in particular for friendship networks.

Although the explored data sets differed in terms of network characteristics like density, type of ties (friendship/advice) and behavior variables, we have not been able to establish a relation between these characteristics and their impact on the three evaluation criteria we applied.

Secondly, one likely reason for the worse performance of the imputation methods, might be their neglect of the influence of network structure. To deal with missing ties in cross-sectional network studies, Krause (2019) and Krause, Huisman, & Snijders (2018) proposed a multiple imputation based on Bayesian ERGMS, which uses the information contained in the network structure. Applying this approach to missing behavior data might lead to improved performance because better use is made of the information contained in the data set.

3 Do social capital and personality breed personal initiative? A Longitudinal Actor-Based study Among International Students

Abstract

Personal initiative, or proactive work behavior that overcomes barriers to achieve a goal, is key to many important individual or organization level outcomes. Its antecedents, in particular its interplay with personality and personal social networks, are little understood. According to the independent main effects model, personality (openness to experience and conscientiousness) and personal networks (structural autonomy) complement each other as triggers of personal initiative. The network mediation model predicts personality to impact personal initiative indirectly through its effect on personal networks. And according to the network outcome model, personality affects personal initiative, which in turn shapes personal networks. Four waves of sociometric data were collected in two newly established cohorts of international students (n = 42 and n = 47). Stochastic actor-oriented modelling provides partial support for the independent main effects model, suggesting that students scoring high on conscientiousness have a stronger tendency towards personal initiative. Implications for future research are discussed.

3.1 Introduction

Personal initiative is a trait desired by many, and is believed to be a condition for being successful in personal, social and professional settings. For example, entrepreneurship and innovation are often among the criteria to evaluate a manager's performance (Kuratko et al., 2005). Personal initiative is proactive work behavior that overcomes barriers to achieve a goal (Frese & Fay, 2001), with 'proactive' referring to a long-term focus and initiative before one is forced to act (Parker, Bindl, & Strauss, 2010). The concept captures the idea that individuals are able to identify or to create new opportunities and to exploit these opportunities. Personal initiative is related to many concepts, like agency (Emirbayer & Mische, 1998), (corporate) entrepreneurship (Ma & Tan, 2006; Ren & Guo, 2011), creativity and innovation (Mainemelis, 2010), learning (Gašević, Zouaq, & Janzen, 2013; Hwang, Kessler, & Francesco, 2004), pro-active behavior (Fuller & Marler, 2009; Parker, Bindl, & Strauss, 2010), and organizational citizenship (Caza, 2012).

Given its manifold consequences for individuals and organizations, a key question is what triggers personal initiative. The major perspectives addressing this question point to two different sets of antecedents. Personality theories claim that stable personality traits are associated with personal initiative (Fay & Frese, 2001; Frese & Gielnik, 2014; Hogan, 2005). For example, two meta-analytical studies found entrepreneurial intention associated with proactive personality (Fuller & Marler, 2009) and four dimensions (openness, conscientiousness, extraversion and neuroticism) of the Five Factor Model of personality (Zhao, Seibert, & Lumpkin, 2010). Fay and Frese (2001) report personal initiative to be associated with the need for achievement, extraversion, and conscientiousness. In a study among 183 employees of a financial services firm, proactive personality was found to be positively associated with the Five Factor Model (Major, Turner, & Fletcher, 2006).

Evidence from social network research suggests that the structure and content of an individual's web of personal relationships is an important antecedent of personal initiative. For example, business school alumni were found to build and use networks to pursue initiatives (Thompson, 2005), strong ties with entrepreneurial peers incite students to take the step to entrepreneurship after graduating (Kacperczyk, 2013), and managers spanning structural holes are more likely to successfully propose new ideas (Burt, 2004).

Both approaches have identified important antecedents, and a potential conclusion could be that both personality and social networks affect personal initiative independently from each other. The present study argues that current explanations based on this *independent main effect model* remain incomplete unless they disentangle the complex causal interplay between personality, social networks, and personal initiative. If both personality differences and network structure are antecedents of personal initiative, the question arises to what degree their effects on personal initiative are independent of each other (Balkundi, Kilduff, & Harrison, 2011; Burt, 2012). More specifically, two other possible mechanisms require closer scrutiny. First, personality may affect personal initiative indirectly, through its impact on personal social networks (*network mediation model)*. For example, individuals with an entrepreneurial personality have been found to occupy brokerage positions in the informal networks of organizations (Burt, Jannotta, & Mahoney, 1998; Burt, 2012). The same holds for high self-monitors, though the effect sizes of this trait are low, as a recent meta-analysis has shown (Fang et al., 2015). Second, personality may indeed have a direct effect on personal initiative, which in turn affects the structure of someone's personal network (*network outcome model).*

The present study aims to disentangle these three mechanisms. The key question is: to what degree personal initiative is either the product or the driver of an individual's personal network, while accounting for personality differences? Stochastic actor-oriented models (Snijders, van de Bunt, & Steglich, 2010; Veenstra & Steglich, 2012) are applied to analyze four waves of longitudinal sociometric data of a newly created group of international students. The study is replicated using a second dataset. The next section outlines the theoretical framework and derives testable hypotheses. This is followed by sections on the research design, results, and a discussion and conclusion.

3.2 Theoretical background

3.2.1. Personality as an antecedent of personal initiative

A first perspective to understand personal initiative is to look at personality traits. Personality traits can be described as complex psycho-physiological structures that cause individual behavior (Brandstätter, 2011). Though there is some discussion if personality traits are stable throughout one's life (Specht, Egloff, & Schmukle, 2011), it is commonly accepted that they are stable during relatively longer time periods and able to explain variation in individual behavior (Hogan, 2005). According to the Five-Factor Model (McCrae & Costa, 1999), human personality can be exhaustively described by five personality traits: Openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism. Of these five traits, openness to experience and conscientiousness are particularly conducive to personal initiative (Parker & Collins, 2010; Parker, Bindl, & Strauss, 2010).

Individuals *open to experience* are intellectually curious, have an interest in unusual thought processes, are more creative, willing to try new things, are not afraid of uncertainty, seek out new ideas, and have a preference for variety of experiences (McCrae & John, 1992). Their broad and multifaceted interests make them aware of many new opportunities. Together with their willingness to try new things and preference for variety (Zhao, Seibert, & Lumpkin, 2010) individuals scoring high on openness to experience are likely to show a high level of personal initiative.

Conscientious individuals are organized, dependable, prefer planned behavior, and show self-discipline (McCrae & John, 1992). Their sense of duty and aim for achievement are strong drives to take action when considered necessary. Therefore, individuals who score high on conscientiousness are likely to show a high level of personal initiative.

Empirical studies provide evidence of a positive relationship between these two personality traits and personal initiative (Parker & Collins, 2010; Parker, Bindl, & Strauss, 2010) and entrepreneurial intention, as shown in a meta-analysis (Zhao, Seibert, & Lumpkin, 2010). In sum, individuals high in conscientiousness and openness are likely to exhibit higher levels of personal initiative compared to individuals scoring low on these personality traits. This leads to the following hypothesis:

> *Hypothesis 1 (independent personality effect model): The higher an individual's (a) conscientiousness or (b) openness to experience, the higher the level of personal initiative.*

3.2.2. Personal networks as an antecedent of personal initiative

Structural Hole Theory (Burt, 1992) argues that individuals in brokerage positions – which allow them to connect individuals or groups that are otherwise unconnected – show more entrepreneurial behavior than individuals lacking this kind of network structure. Due to the large number of diverse contacts, such brokers have early access to and control of information, as well as more opportunities to mobilize support, leading to higher levels of personal initiative as well as improved performance. The opposite holds for individuals lacking brokerage opportunities because they find themselves in dense networks, in which their contacts are directly or indirectly connected (Burt, 2000). They lack access to new and alternative information or sources of support. Such network structures reflect a high degree of constraint, and leave little room to exploit structural holes, which limits opportunities for personal initiative. A high level of constraint also implies embeddedness in a dense network. In such a dense network, closure mechanisms like conformity to group values become important, which in turn also may lead to a reduced personal initiative.

There is some empirical evidence for these claims. For example, a study among students showed that network brokers have more ideas and more valued ideas (Burt, 2012). A study among a group of managers in an American electronics company showed that brokerage was associated to variety in thinking and new ideas (Burt, 2004). Similarly, in a study among research scientists, Perry-Smith (2006) found that weak ties support divergent and autonomous thinking, which in turn leads to individual creativity. Summarizing this reasoning, an individual's personal initiative increases to the degree that this individual's personal network is characterized by structural autonomy as opposed to structural constraint. This leads to the following hypothesis:

> *Hypothesis 2 (Independent network effect model): The higher an individual's structural autonomy, the higher this individual's level of personal initiative.*

3.2.3. Personality as antecedent of network opportunities

Though the personality perspective and the social network perspective often assume the other perspective constant, there is reason to combine them in one framework because research suggests that personality differences shape the structure of personal networks. A study of individuals who created multiple characters in an online virtual world indicates that individuals tend to recreate similar kind of networks. Those who created closed networks in one role, did the same in other roles, and those who build networks rich in structural holes in one role, also tend to build such networks in other roles (Burt, 2012). Other research suggests that self-monitors are more likely to occupy central positions in social networks (Mehra, Kilduff, & Brass, 2001; Sasovova et al., 2010).

Individuals with a high openness to experience have a wide variety of interests and a desire for new original experiences (Fang et al., 2015; McCrae & John, 1992). Because they tend to be different from others, they resist pressures to similarity and network closure (Baer, 2010; Landis, 2016). They are more likely to form ties with otherwise unconnected individuals from disparate social circles, thereby a network rich in structural holes instead of network closure (Landis, 2016).

Conscientiousness has been found to be the most stable indicator of job performance across occupational groups in several meta studies (Hogan 2005). Conscientious individuals are hardworking, competent, and dependable, and therefore often considered attractive partners (McCrae & John, 1992). These characteristics also lead to a more effective interaction with others (Barrick, Mount, & Judge, 2001), resulting in more intense network relations. Because they are primarily valued for their qualities, also individuals from different social circles may select them which result in conscientious individuals selected in brokerage positions. This leads to hypothesis three:

> *Hypothesis 3 (Network mediation model): The higher an individual's (a) conscientiousness or (b) openness to experience, the higher this person's level of structural autonomy.*

3.2.4 Personal Initiative as an Antecedent of Personal Network Structure

Though previous research focused mainly on how network structures influence personal initiative, the reverse may also hold. For example, a study into the networking-motivations of students found that they pursue the creation of new contacts with the aim to increase their social capital (Villar & Albertín, 2010). Another study (Hwang, Kessler, & Francesco, 2004) found that an individualistic versus collectivistic background of students influenced their attitude towards networking behavior; students with an individualistic orientation were more inclined to rely on themselves instead of on others. As a result, they showed a higher level of initiative with regards to networking.

Individuals scoring high on personal initiative also take initiatives before they are forced to act (Parker, Bindl, & Strauss, 2010), suggesting that they proactively create new opportunities through building more heterogeneous personal networks rich in structural holes (Burt, 2004). Findings of a study among 867 students in Barcelona are in line with this argument: students with more heterogeneous relations were more successful than students with less diverse relations (Daza, 2016). This leads to the final hypothesis:

> *Hypothesis 4 (Network outcome model): The higher the level of an individual's personal initiative, the higher this person's level of structural autonomy.*

3.3 Research design and data

3.3.1 Sample and Data Collection

A four-wave sociometric panel study was conducted in 2012 and 2013 among a cohort of 47 students at a Dutch University of Applied Sciences (dataset 1). The sample consists of students enrolled in two international masters' programs (coded S and L). Due to a shared common core, students of both programs worked closely together in the first three months and therefore the whole group was considered as one network. The boundaries of the group were clear and interaction with students outside these programs was on average much lower than inside the group. The students had a diverse international background. With few exceptions, all students arrived at the beginning of the academic year and didn't know each other before the start of their study. One year later the data collection was replicated with a second cohort of 42 new students (dataset 2). In this replication study the items in the questionnaire were identical to the original study. Table 3.1 summarizes descriptive information on the samples.

Table 3.1 Description of sample.

	Dataset 1	Dataset 2
Proportion of students in program S	0.64	0.66
Proportion of male students	0.25	0.29
Proportion of Asian students	0.80	0.90

Data were collected in four waves. For dataset 1, data were collected in weeks 1, 5, 13, and 21 after the start of the program. For dataset 2, data were collected in weeks 2, 6, 13, and 20. The period between the first two waves is shorter because we expected a faster development of the networks in the first weeks. Hardcopies of the questionnaire were distributed and filled out during lectures. Absent students were asked by email to fill out the questionnaire. Participation was not related to credits or any other incentive. Complete name rosters were used for the network questions. It was explained to the participants that in order to ensure confidentiality, their names would be replaced by numerical codes during the analysis phase. All students (47 in dataset 1 and 42 in dataset 2) participated in at least one wave. In dataset 1, three students left the program between waves 2 and 3. In dataset 2, a total of five students left, two just before wave 2, and three between waves 2 and 3. On top of these students leaving, the non-response in the first dataset was 2, 2, 7, and 4 students, and 4, 0, 5, and 4 students in dataset 2, respectively, leading to partial scores for these students.

3.3.2 Measures

Personal initiative is measured using the seven-item scale of Frese et al. (1997) on self-reported initiative (SRI). Answer categories represent a five-point Likert scale, ranging from low to high on taking initiative. Values of Cronbach's alpha were between 0.70 and 0.84, indicating sufficient reliability of this scale.

Two types of personal networks were collected. For the *friendship network*, participants were asked to describe their relation with fellow students (0 = don't know this student, 1 = neutral, 2 = friendly, and 3 = friendship). For the *advice network*, participants were asked to describe how often they asked their fellow students for help or support during the past three weeks. This could be for both study and personal matters (0 = never asked for help, 1 = 1 or 2 times, 3 = 3 or 4 times, and 4 = about daily). All network items were dichotomized with 0 representing the answer 0 (don't know student/never asked for help) and 1 representing an answer of 1 or higher (at least neutral relationship/some advice asked).

Structural autonomy of each actor was measured with the constraint index C_i that describes the extent to which a network consists of redundant contacts (Burt 2000). Network constraint measures if a student's network consists of unconnected clusters of relations, or if it is a cohesive group in which alters are connected among themselves, leading to many redundant contacts. A high value for constraint means there is less opportunity to broker and control information and resources between clusters of relations. For each actor i, the constraint is the sum of direct and indirect relations with all other actors j in the network: $C_i = \sum_j c_{ij}$ where $c_{ij} = \left(p_{ij} + \sum_q p_{iq}\, p_{qj}\right)^2\ for\ q \neq i, j$ with $p_{ij} = \frac{z_{ij}}{\sum_q z_{iq}}$ and z_{ij} expressing the relation between i and j (adjacency matrix). The dyadic constraint c_{ij} measures the degree to which actor *j* constrains actor *i*. The first component of c_{ij} measures the time and energy spend by *i* to reach *j*. The second component measures how *j* is tied to other contacts of *i*. When an actor *i* invests times and energy in a relation with actor *j* who is also tied to many other contacts of *j* the dyadic constraint c_{ij} will be high and *i* will not bridge structural holes. A low dyadic constraint c_{ij} will be found when actors *j* don't have many ties to other contacts of *i*. C_i is measured on a scale from 0 to 1. A low value indicates that the actor spans more structural holes and is less constrained by his network. The constraint index is negatively associated with structural autonomy. If structural holes are considered sources of social capital, then C_i should be negatively related to performance or personal initiative. However, if closure is considered a source of social capital, then the relation should be positive. A constraint measure was calculated for both the friendship and the advice network.

Personality traits (openness to experience and conscientiousness) were measured using the NEO Five Factor Inventory test (Costa & McCrae, 1992), a self-reported measure with 12 items per dimension. These items are answered on a five-point Likert scale with higher scores indicating higher levels of openness or conscientiousness. Values of Cronbach's alpha for openness were 0.43 and 0.47, and for conscientiousness 0.74 and 0.67, respectively. For openness, these values are low and indicate a limited reliability of this scale.

Controls. The *study program* was coded 0 for students in program S and 1 for students in program L. *Gender* was coded 0 for female and 1 for male students. *Region* was coded 0 for Asian and 1 for non-Asian students.

Table 3.2 summarizes descriptive information on these variables.

Table 3.2 Attribute values of sample (standard deviations in parentheses)

	Dataset 1		Dataset 2	
Variable	Average	Cronbach's alpha	Average	Cronbach's alpha
Openness	3.27 (1.23)	0.43	3.18 (0.36)	0.47
Conscientiousness	3.90 (1.15)	0.74	3.64 (0.40)	0.67
personal initiative wave 1	3.61 (0.52)	0.76	3.80 (0.56)	0.71
personal initiative wave 2	3.61 (0.45)	0.71	3.79 (0.59)	0.84
personal initiative wave 3	3.60 (0.52)	0.81	3.63 (0.57)	0.81
personal initiative wave 4	3.48 (0.37)	0.70	3.81 (0.57)	0.84

3.3.3 Analytical Strategy

A stochastic actor-oriented model for the co-evolution of network and behavior (Steglich, Snijders, & Pearson, 2010) was used. It assumes that network structures and behavior evolve and interact continuously in small unobserved micro steps between the observations of the network and behavior obtained in waves according to a panel design. By simulating sequences of the micro steps, the models simulate the co-evolution of network structure and behavior. In each micro step an actor can decide to change either one network tie (initiate a new or dissolve an existing tie), to change his or her behavior, or do nothing. Conditional upon wave 1, the micro steps leading towards subsequent waves are simulated repeatedly until simulated network states for the following waves have been achieved that resemble actual observations. In this manner, the parameters of the specified effects can be estimated. The R package RSiena 4.0, version 1.1-304 (Ripley et al., 2016) was used.

Two categories of dynamic effects are estimated. *Selection dynamics* represent the development of the network due to structural network effects and the influence of behavior on the network. *Behavior dynamics* represent the development of behavior due to structural shape effects and the influence of the network.

For each data set two different models were estimated, a friendship model and an advice model. These models represent the interaction between either friendship or advice relations on the one hand and personal initiative on the other hand. They were used to estimate the hypotheses together with several structural network effects (density, reciprocity, transitivity, 3-cycles, and betweenness) and structural shape effects (linear and quadratic; Steglich, Snijders & Pearson, 2010). The linear shape effect represents the effect of high or low scores on behavior and the quadratic effect represents a feedback of behavior. A positive quadratic effect parameter indicates self-enforcing behavior, while a negative parameter indicates a self-correcting effect. Next to these standard structural effects, we also controlled for the possible influence of indegree popularity and the effect personal initiative might have on the network by testing for ego, alter and similarity effects. Huisman & Snijders' (2003) procedure for composition change was applied to deal with students who entered or left the program during the study. The network constraint index C_i cannot be calculated inside the RSiena package, therefore it was calculated separately for each wave. This implies that the constraint index is treated as an external covariate. Due to SIENA's co-evolutionary approach, it can still be used simultaneously as a dependent and an explanatory variable. Note that because the constraint variable does not vary between the waves, the effect of constraint is based on the observed values of the last wave.

Estimated models were checked for convergence by calculating *t*-ratios (Ripley et al., 2016). For convergence of individual parameters, the *t*-ratios should be smaller than 0.10 and the *t*-ratio for overall convergence should be smaller than 0.25. Further, the quality of the models was evaluated by the goodness of fit (GOF) of the model with respect to three auxiliary statistics: The indegree, the outdegree, and the IWB distributions (Ripley et al., 2016). For this test, the estimated model is used to create a number of simulated outcomes for the cumulative indegree frequency, the cumulative outdegree frequency, and the cumulative IWB frequency. These simulated outcomes are compared to the actual cumulative frequencies, using the Mahalanobis distance.

3.4 Results

3.4.1 Descriptives

Table 3.3 summarizes the main descriptives of both networks. Density of the networks increases strongly in the beginning, and becomes more stable later on. The Jaccard index, calculated as the fraction of stable ties compared to the sum of stable, new and terminated ties, tests if there is enough stability in the datasets between two waves. Preferably Jaccard values should be higher than 0.3, though for strong growing networks a value above 0.2 is still acceptable (Snijders, van de Bunt, & Steglich, 2010). In the first dataset we found a Jaccard value of 0.21 between the first and second wave, but given the strong growth of the network density from 0.10 to 0.31, this is acceptable. All other Jaccard values are between 0.55 and 0.73, indicating enough stability for our analysis.

To assess if there is any association between personal initiative (personal initiative) and social network characteristics, Moran's I, a network autocorrelation coefficient, was calculated (Veenstra et al., 2013). For these calculations, we used the adjacency matrices as distance matrices. The results indicate that there are only weak relations between network position and personal initiative.

Table 3.3 Descriptive network statistics

	Friendship network				Advice network			
Wave	1	2	3	4	1	2	3	4
Data set 1								
Density	0.10	0.33	0.48	0.46	0.09	0.25	0.33	0.33
Average degree	4.56	15.38	22.27	21.33	4.04	11.64	15.27	15.38
Number of ties	205	692	824	853	182	524	565	615
Missing fraction	0.04	0.04	0.21	0.15				
Jaccard index		0.21	0.62	0.73		0.25	0.56	0.71
Moran's I	0.021	-0.025	0.007	-0.062	0.020	–0.017	0.027	-0.062
Data set 2								
Density	0.23	0.29	0.35	0.35	0.23	0.32	0.46	0.47
Average degree	9.61	12.05	14.47	14.51	9.34	13.10	18.81	19.15
Number of ties	365	482	463	478	355	524	602	632
Missing fraction	0.10	0.05	0.24	0.21				
Jaccard index		0.55	0.60	0.69		0.52	0.63	0.74
Moran's I	0.013	–0.033	–0.032	0.017	0.010	–0.018	–0.004	–0.020

3.4.2 Results

The estimation results for the models (excluding time dummies) are presented in table 3.4. The results of the complete models including time dummies and results for time heterogeneity and goodness-of-fit tests are presented in the supplementary materials section (Appendix to Chapter 3). Adding time dummies was found necessary, due to time heterogeneity in behavior data between the two waves (Lospinoso et al., 2011).

Table 3.4 Model estimation, parameters and standard errors

			Advice dataset 1	Friendship dataset 1	Advice dataset 2	Friendship dataset 2
		Network dynamics				
1		Constant advice rate (period 1)	15.06 (1.65)	21.25 (2.15)	10.85 (1.06)	9.10 (0.93)
2		Constant advice rate (period 2)	11.05 (0.98)	10.41 (1.03)	10.30 (1.09)	12.75 (1.86)
3		Constant advice rate (period 3)	6.39 (0.61)	7.26 (0.84)	11.68 (1.28)	9.20 (1.12)
4		Outdegree (density)	1.35 (0.50)	0.64 (0.43)	0.53 (0.50)	1.76 (0.59)
5		Reciprocity	1.27 (0.16)	1.32 (0.15)	0.85 (0.14)	1.07 (0.16)
6		Transitive triplets	0.26 (0.02)	0.24 (0.02)	0.13 (0.04)	0.13 (0.02)
7		3-cycles	-0.23 (0.03)	-0.20 (0.03)	-0.08 (0.04)	-0.11 (0.03)
8		Betweenness	-0.21 (0.04)	-0.13 (0.03)	-0.18 (0.06)	-0.26 (0.04)
9		Indegree - popularity	-0.13 (0.02)	-0.11 (0.02)	-0.08 (0.02)	-0.10 (0.03)
10		Outdegree - activity (sqrt)			0.14 (0.17)	
11		Personal initiative alter	0.06 (0.09)	-0.06 (0.06)	0.07 (0.06)	-0.03 (0.09)
12		Personal initiative ego	-0.12 (0.14)	0.11 (0.31)	0.20 (0.11)	0.31 (0.11)
13		Personal initiative similarity	-0.39 (0.83)	-0.48 (0.73)	-1.94 (0.72)	0.09 (0.96)
		Behavior personal initiative dynamics				
14		Rate personal initiative (period 1)	2.06 (0.67)	1.98 (0.68)	3.20 (1.13)	3.02 (1.12)
15		Rate personal initiative (period 2)	3.28 (1.61)	3.84 (3.43)	4.45 (2.33)	4.43 (2.26)
16		Rate personal initiative (period 3)	6.84 (6.86)	7.12 (9.47)	2.29 (0.84)	2.34 (0.88)
17		Personal initiative linear shape	0.02 (0.11)	0.01 (0.09)	0.08 (0.10)	0.12 (0.11)
18		Personal initiative quadratic shape	-0.41 (0.08)	-0.38 (0.08)	-0.23 (0.06)	-0.23 (0.07)
19	H1b	Personal initiative: effect from openness	-0.03 (0.34)	-0.05 (0.33)	-0.51 (0.31)	-0.60 (0.37)
20	H1a	Personal initiative: effect from conscien	0.71 (0.28)	0.69 (0.27)	0.93 (0.34)	0.98 (0.36)
21		Personal initiative: effect from gender	-0.24 (0.25)	-0.22 (0.26)	0.20 (0.22)	0.22 (0.23)
22		Personal initiative: effect from program	0.02 (0.21)	0.04 (0.19)	-0.05 (0.21)	-0.03 (0.21)
23		Personal initiative: effect from nationalit	0.36 (0.28)	0.38 (0.28)	0.24 (0.39)	0.21 (0.40)
24	H2	Personal initiative: effect from constr.	0.12 (0.17)	0.14 (0.14)	-0.06 (0.14)	-0.12 (0.13)
		Behavior constraint dynamics				
25		Rate constraint (period 1)	2.42 (0.39)	2.77 (0.49)	2.42 (0.39)	1.91 (0.60)
26		Rate constraint (period 2)	1.15 (0.34)	2.95 (1.05)	1.15 (0.34)	2.78 (1.10)
27		Rate constraint (period 3)	0.73 (0.27)	0.88 (0.32)	0.73 (0.27)	1.12 (0.39)
28		Constraint linear shape	-2.11 (1.93)		-2.11 (1.93)	
29		Constraint quadratic shape	-1.30 (1.21)		-1.30 (1.21)	
30	H3b	Constraint: effect from openness	-0.24 (1.93)	0.46 (0.49)	-0.24 (1.93)	-0.60 (0.38)
31	H3a	Constraint: effect from conscientiousness	0.95 (1.64)	0.29 (0.43)	0.95 (1.64)	0.35 (0.39)
32	H4	Constraint: effect from personal initiative	1.21 (1.85)	-0.18 (0.30)	1.21 (1.85)	-0.07 (0.16)

We found partial support for the claim that personality traits affect self-rated initiative (H1). Whereas the effect of conscientiousness is positive and significant in both datasets, as predicted by H1a, no significant effect was found for openness to experience, leading us to reject H1b. No evidence was found for the remaining hypotheses. There is no significant effect of structural autonomy on personal initiative (H2), of personality on structural autonomy (H3), or of personal initiative on structural autonomy (H4). This leads us to reject both the network mediation and the network outcome model. Results across both datasets are largely consistent, pointing to the robustness of our findings. Overall, the findings lend partial support only to the independent main effects model: personality, in particular conscientiousness, increases personal initiative, but the structure of personal networks, in particular structural autonomy, doesn't.

3.5 Discussion and conclusion

In one of the first sociometric field studies of the co-evolution of networks, personality, and personal imitative, we found limited evidence for a systematic interrelation. At least in the two cohorts of newly formed networks of students at a Dutch University of Applied Sciences, someone's brokerage position in the friendship or advice network does not trigger higher levels of initiative, nor does personal initiative result in different types of personal networks. We also did not find that openness to experience boosts personal initiative. What we *did* find is that conscientious students show more personal initiative. The overall conclusion is that goal orientation explains personal initiative, but that the relation between network constraint and personality and personal initiative is minimal. This finding is in line with earlier research (Parker & Collins, 2010; Parker, Bindl, & Strauss, 2010). It points to the importance of goal-orientations as a trigger for personal initiative. These results support earlier more general calls to pay closer attention to personality differences in organizational settings (Barrick & Ryan, 2004), but also suggest that more in-depth research is needed with regard to the link between individual differences and social networks (Day & Kilduff, 2003).

We conclude with some reflections on potential reasons for the non-significant results. First, the low reliability of the psychometric scale measuring the personality trait *openness to experience* in our study reflects findings in previous studies that suggest the construct actually reflects more than one latent dimension (Connelly, Ones, & Chernyshenko, 2014; Woo et al., 2014). Future studies may explore to what degree refined measures tapping into, for example, cultural and intellectual openness (DeYoung, Quilty, & Peterson, 2007), relate to personal initiative and social networking.

Second, the absence of any systematic co-variation between the structure of advice and friendship networks on the one hand, and personal initiative on the other hand is at odds with previous studies showing that social networks affect a large variety of individual behavior. One possible explanation might be related to the specific nature of our study population, consisting of two newly established cohorts of international students. Developing much personal initiative may not be among the primary concerns of young adults during this phase of their studies, and in such a setting. This may be different for newly hired professionals working in for-profit settings, for whom both personal initiative and social capital become pivotal tools to perform their tasks well and receive good evaluations from their bosses. A recent meta-analysis (Fang et al., 2015) points into this direction. It shows that brokerage only works in settings in which information is crucial for performance, for example for managers in knowledge intense industries like the banking sector.

Another context condition may be group size. The effectiveness of brokerage increases with the number of disconnected groups. Our two study populations were relatively small (n = 42 and n = 47). With each of the two cohorts being further divided into two subgroups, brokerage hardly ever involved bridging otherwise disconnected groups. This may limit the relative benefits accruing to an individual broker.

Finally, discussions with individual students revealed that many of them perceived the group structure as static and were reluctant to approach students outside their own clique. Though the observed dynamics in the networks partially contradict these perceptions, these perceptions are nevertheless likely to affect behavior. Hence, the absence of a systematic link between personal initiative and network structure may be due to the fact that many students perceive the network as a collection of static cliques, which in turn may decrease the expected success and benefits of building new brokerage ties.

In sum, our findings imply that the interrelation between networks, personality and behavior might be more complex than our current theories seem to suggest. In order to disentangle the various underlying mechanisms, longitudinal sociometric research carried out in a variety of institutional and organizational settings is essential. Our study is a step in this direction.

Appendix to Chapter 3: Supplementary materials

This appendix contains per estimated model the specification of the full model plus the results for tests on overall convergence, time heterogeneity and Goodness of Fit (Lospinoso et al., 2011).

Table S1. Full model estimation Dataset 1 Advice

	Effect	Parameter and SE.
1	Constant advice rate (period 1)	15.06 (1.65)
2	Constant advice rate (period 2)	11.05 (0.98)
3	Constant advice rate (period 3)	6.39 (0.61)
4	Outdegree (density)	1.35 (0.50)
5	Reciprocity	1.27 (0.16)
6	Transitive triplets	0.26 (0.02)
7	3-cycles	–0.23 (0.03)
8	Betweenness	–0.21 (0.04)
9	Indegree - popularity	–0.13 (0.02)
10	Personal initiative alter	0.06 (0.09)
11	Personal initiative ego	–0.12 (0.14)
12	Personal initiative similarity	–0.39 (0.83)
13	Dummy2:advice ego	0 (NA)
14	Dummy3:advice ego	–0.89 (0.91)
15	Dummy2:advice ego x transitive triplets	–0.16 (0.05)
16	Dummy3:advice ego x transitive triplets	–0.30 (0.05)
17	Int. Dummy2:advice ego x 3-cycles	0.22 (0.06)
18	Int. Dummy3:advice ego x 3-cycles	0.25 (0.07)
19	Int. Dummy3:advice ego x betweenness	0.11 (0.07)
20	Dummy3:advice ego x indegree - popularity	0.09 (0.04)
21	Int. Dummy3:advice ego x personal initiative alter	0.12 (0.24)
22	Int. Personal initiative ego x dummy2:advice ego	–0.25 (0.22)
23	Int. Personal initiative ego x dummy3:advice ego	0.48 (0.32)
24	Rate personal initiative (period 1)	2.06 (0.67)
25	Rate personal initiative (period 2)	3.28 (1.61)
26	Rate personal initiative (period 3)	6.84 (6.86)
27	Personal initiative linear shape	0.02 (0.11)
28	Personal initiative quadratic shape	–0.41 (0.08)
29	Personal initiative: effect from openness	–0.03 (0.34)
30	Personal initiative: effect from conscien	0.71 (0.28)
31	Personal initiative: effect from gender	–0.24 (0.25)
32	Personal initiative: effect from program	0.02 (0.21)
33	Personal initiative: effect from natio	0.36 (0.28)
34	Personal initiative: effect from constraint.a	0.12 (0.17)
35	Personal initiative: effect from constraint.a x Dummy2:personal initiative: effect from Dummy2:personal initiative	0.44 (0.44)
36	Personal initiative: effect from constraint.a x Dummy3:personal initiative: effect from Dummy3:personal initiative	–0.12 (0.34)
37	Dummy2:personal initiative: effect from Dummy2:personal initiative	0 (NA)
38	Dummy3:personal initiative: effect from Dummy3:personal initiative	0 (NA)
39	Rate constraint.a (period 1)	2.42 (0.39)
40	Rate constraint.a (period 2)	1.15 (0.34)
41	Rate constraint.a (period 3)	0.73 (0.27)
42	Constraint.a linear shape	–2.11 (1.93)
43	Constraint.a quadratic shape	–1.30 (1.21)
44	Constraint.a: effect from openness	–0.24 (1.93)
45	Constraint.a: effect from conscien	0.95 (1.64)
46	Constraint.a: effect from personal initiative	1.21 (1.85)

The *t*-ratio for overall convergence = 0.18, well below the standard 0.25 limit, indicating a good convergence. There is no evidence of time heterogeneity, $\chi^2(30) = 30.5$ ($p = 0.26$).

Goodness-of-fit tests for behavior (PI), outdegree and indegree show *p*-values of 0.24, 0.12 and 0.00 respectively. The cumulative boxplots show the distribution of the observed value compared to the boxplots of the simulated values. It can be seen that overall the observed values fall well inside the band-width, except for low values of indegree. The reason might be that due to the start-up of the networks in wave 1, the frequency of low indegrees is rather high, and difficult to replicate in a simulation and therefore explaining the low *p*-value. Therefore, we have confidence that the estimated model specification reflects the underlying network and behavior dynamics.

Figure S1. GOF Dataset 1 Advice

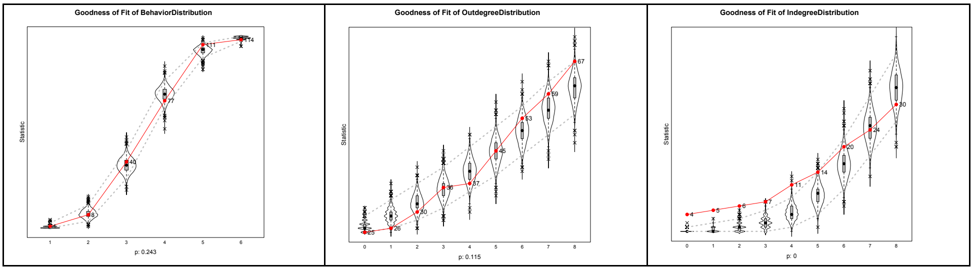


Table S2. Full model estimation Dataset 1 Friendship

	Effect	Parameter and SE.
1	Constant friendship rate (period 1)	21.25 (2.15)
2	Constant friendship rate (period 2)	10.41 (1.03)
3	Constant friendship rate (period 3)	7.26 (0.84)
4	Outdegree (density)	0.64 (0.43)
5	Reciprocity	1.32 (0.15)
6	Transitive triplets	0.24 (0.02)
7	3-cycles	–0.20 (0.03)
8	Betweenness	–0.13 (0.03)
9	Indegree - popularity	–0.11 (0.02)
10	PI alter	–0.06 (0.06)
11	PI ego	0.11 (0.31)
12	PI similarity	–0.48 (0.73)
13	Dummy2:friendship ego	0 (NA)
14	Dummy3:friendship ego	0.24 (0.54)
15	Int. Dummy2:friendship ego x reciprocity	–0.09 (0.29)
16	Int. Dummy3:friendship ego x reciprocity	–0.53 (0.34)
17	Dummy2:friendship ego x transitive triplets	–0.13 (0.04)
18	Dummy3:friendship ego x transitive triplets	–0.13 (0.05)
19	Int. Dummy2:friendship ego x 3-cycles	0.17 (0.07)
20	Int. Dummy3:friendship ego x 3-cycles	0.10 (0.08)
21	Dummy2:friendship ego x indegree - popularity	0.04 (0.02)
22	Dummy3:friendship ego x indegree - popularity	0.03 (0.04)
23	Int. PI ego x Dummy2:friendship ego	–0.46 (0.25)
24	Int. PI ego x Dummy3:friendship ego	1.02 (0.88)
25	Int. Dummy2:friendship ego x PI similarity	–2.86 (1.70)
26	Rate PI (period 1)	1.98 (0.68)
27	Rate PI (period 2)	3.84 (3.43)
28	Rate PI (period 3)	7.12 (9.47)
29	PI linear shape	0.01 (0.09)
30	PI quadratic shape	–0.38 (0.08)
31	PI: effect from openness	–0.05 (0.33)
32	PI: effect from conscien	0.69 (0.27)
33	PI: effect from gender	–0.22 (0.26)
34	PI: effect from program	0.04 (0.19)
35	PI: effect from natio	0.38 (0.28)
36	PI: effect from constraint.f	0.14 (0.14)
37	Rate constraint.f (period 1)	2.77 (0.49)
38	Rate constraint.f (period 2)	2.95 (1.05)
39	Rate constraint.f (period 3)	0.88 (0.32)
40	Constraint.f: effect from openness	0.46 (0.49)
41	Constraint.f: effect from conscien	0.29 (0.43)
42	Constraint.f: effect from PI	–0.18 (0.30)

The t-ratio for overall convergence = 0.17, well below the standard 0.25 limit, indicating a good convergence. There is no evidence of time heterogeneity, $\chi^2(28) = 27.8$ ($p = 0.48$). Goodness-of-fit tests for behavior (PI), outdegree and indegree show p-values of 0.27, 0.40 and 0.00 respectively. The cumulative boxplots show the distribution of the observed value compared to the boxplots of the simulated values. It can be seen that overall the observed values fall well inside the band-width, except for low values of indegree. The reason might be that due to the start-up of the networks in wave 1, the frequency of low indegrees is rather high, and difficult to replicate in a simulation and therefore explaining the low p-value. Therefore we have confidence that the estimated model specification reflects the underlying network and behavior dynamics.

Figure S2. GOF Dataset 1 Friendship

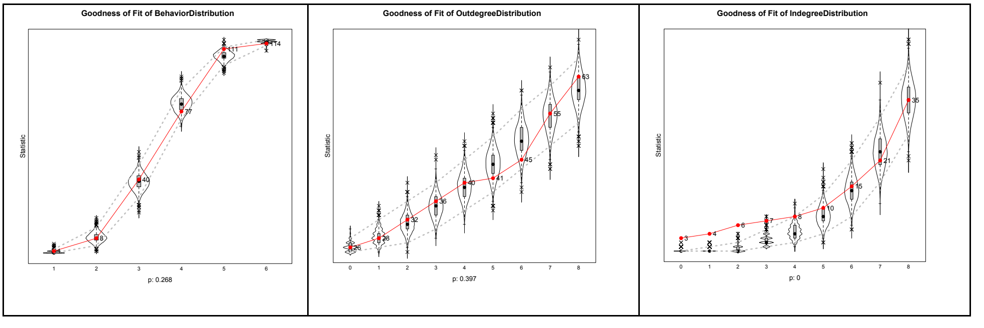


Table S3. Full model estimation Dataset 2 Advice

	Effect	Parameter and SE
1	Constant advice rate (period 1)	10.85 (1.06)
2	Constant advice rate (period 2)	10.30 (1.09)
3	Constant advice rate (period 3)	11.68 (1.28)
4	Outdegree (density)	0.53 (0.50)
5	Reciprocity	0.85 (0.14)
6	Transitive triplets	0.13 (0.04)
7	3-cycles	–0.08 (0.04)
8	Betweenness	–0.18 (0.06)
9	Indegree - popularity	–0.08 (0.02)
10	Outdegree - activity (sqrt)	0.14 (0.17)
11	PI alter	0.07 (0.06)
12	PI ego	0.20 (0.11)
13	PI similarity	–1.94 (0.72)
14	Dummy2:advice ego	–1.19 (0.95)
15	Dummy3:advice ego	0 (NA)
16	Int. Dummy2:advice ego x reciprocity	0.18 (0.38)
17	Int. Dummy3:advice ego x reciprocity	0.07 (0.32)
18	Dummy2:advice ego x transitive triplets	0.01 (0.04)
19	Dummy3:advice ego x transitive triplets	–0.09 (0.03)
20	Int. Dummy2:advice ego x 3-cycles	0.01 (0.07)
21	Int. Dummy3:advice ego x 3-cycles	0.01 (0.06)
22	Int. Dummy2:advice ego x betweenness	0.19 (0.06)
23	Int. Dummy3:advice ego x betweenness	0.15 (0.04)
24	Dummy2:advice ego x indegree - popularity	–0.02 (0.04)
25	Dummy3:advice ego x indegree - popularity	–0.01 (0.02)
26	Int. Dummy3:advice ego x pi alter	–0.17 (0.11)
27	Int. Pi ego x dummy2:advice ego	0.34 (0.26)
28	Int. Pi ego x dummy3:advice ego	0.30 (0.18)
29	Rate PI (period 1)	3.20 (1.13)
30	Rate PI (period 2)	4.45 (2.33)
31	Rate PI (period 3)	2.29 (0.84)
32	PI linear shape	0.08 (0.10)
33	PI quadratic shape	–0.23 (0.06)
34	PI: effect from openness	–0.51 (0.31)
35	PI: effect from conscien	0.93 (0.34)
36	PI: effect from gender	0.20 (0.22)
37	PI: effect from program	–0.05 (0.21)
38	PI: effect from natio	0.24 (0.39)
39	PI: effect from constraint.a	–0.06 (0.14)
40	Rate constraint.a (period 1)	1.54 (0.49)
41	Rate constraint.a (period 2)	2.94 (0.68)
42	Rate constraint.a (period 3)	1.27 (0.61)
43	Constraint.a linear shape	–0.48 (0.30)
44	Constraint.a quadratic shape	–0.37 (0.21)
45	Constraint.a: effect from openness	0.25 (0.63)
46	Constraint.a: effect from conscien	0.62 (0.71)
47	Constraint.a: effect from PI	–0.09 (0.30)

The t-ratio for overall convergence = 0.17, well below the standard 0.25 limit, indicating a good convergence. There is no evidence of time heterogeneity, $\chi^2(28) = 41.6$ ($p = 0.048$). Goodness-of-fit tests for behavior (PI), outdegree and indegree show p-values of 0.02, 0.82 and 0.05 respectively. The cumulative boxplots show the distribution of the observed value compared to the boxplots of the simulated values. It can be seen that overall the observed values fall well inside the band-width, except for values 0 for indegree. The reason might be that due to the start-up of the networks in wave 1, the frequency of zero degrees is rather high, and difficult to replicate in a simulation and therefore explaining the low p-value. Therefore we have confidence that the estimated model specification reflects the underlying network and behavior dynamics.

Figure S3. GOF Dataset 2 Advice

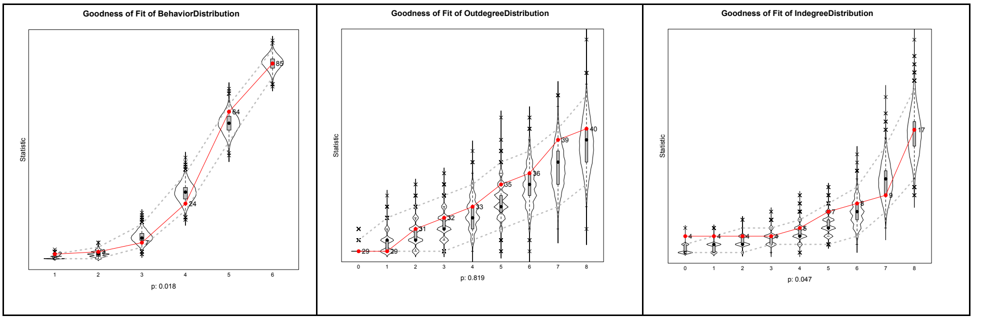


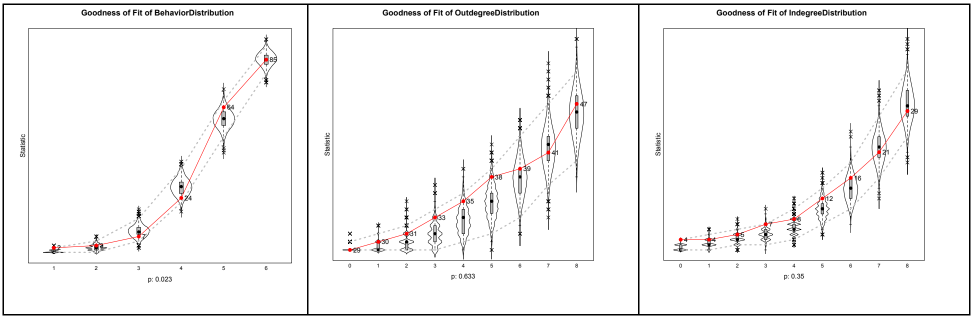
Table S4. Full model estimation Dataset 2 Friendship

	Effect	Parameter and SE.
1	Constant friendship rate (period 1)	9.10 (0.93)
2	Constant friendship rate (period 2)	12.75 (1.86)
3	Constant friendship rate (period 3)	9.20 (1.12)
4	Outdegree (density)	1.76 (0.59)
5	Reciprocity	1.07 (0.16)
6	Transitive triplets	0.13 (0.02)
7	3-cycles	–0.11 (0.03)
8	Betweenness	–0.26 (0.04)
9	Indegree - popularity	–0.10 (0.03)
10	PI alter	–0.03 (0.09)
11	PI ego	0.31 (0.11)
12	PI similarity	0.09 (0.96)
13	Dummy2:friendship ego	–2.06 (0.63)
14	Dummy3:friendship ego	–2.02 (1.33)
15	Int. Dummy2:friendship ego x reciprocity	0.06 (0.29)
16	Int. Dummy3:friendship ego x reciprocity	0.78 (0.43)
17	Dummy3:friendship ego x transitive triplets	–0.03 (0.03)
18	Int. Dummy2:friendship ego x betweenness	0.35 (0.09)
19	Int. Dummy3:friendship ego x betweenness	0.34 (0.11)
20	Dummy3:friendship ego x indegree - popularity	0.00 (0.05)
21	Int. Dummy3:friendship ego x pi alter	–0.61 (0.25)
22	Int. Dummy2:friendship ego x pi similarity	–2.33 (2.22)
23	Int. Dummy3:friendship ego x PI similarity	4.07 (2.27)
24	Rate PI (period 1)	3.02 (1.12)
25	Rate PI (period 2)	4.43 (2.26)
26	Rate PI (period 3)	2.34 (0.88)
27	PI linear shape	0.12 (0.11)
28	PI quadratic shape	–0.23 (0.07)
29	PI: effect from openness	–0.60 (0.37)
30	PI: effect from conscien	0.98 (0.36)
31	PI: effect from gender	0.22 (0.23)
32	PI: effect from program	–0.03 (0.21)
33	PI: effect from natio	0.21 (0.40)
34	PI: effect from constraint.f	–0.12 (0.13)
35	Rate constraint.f (period 1)	1.91 (0.60)
36	Rate constraint.f (period 2)	2.78 (1.10)
37	Rate constraint.f (period 3)	1.12 (0.39)
38	Constraint.f: effect from openness	–0.60 (0.38)
39	Constraint.f: effect from conscien	0.35 (0.39)
40	Constraint.f: effect from PI	–0.07 (0.16)

The *t*-ratio for overall convergence = 0.15, well below the standard 0.25 limit, indicating a good convergence. There is no evidence of time heterogeneity, $\chi^2(29) = 40.0$ ($p = 0.083$). Goodness-of-fit tests for behavior (PI), outdegree and indegree show *p*-values of 0.023, 0.63

and 0.35 respectively. The cumulative boxplots show the distribution of the observed value compared to the boxplots of the simulated values. It can be seen that overall the observed values fall well inside the band-width, except for low values of indegree. Therefore we have confidence that the estimated model specification reflects the underlying network and behavior dynamics.

Figure S4. GOF Dataset 2 Friendship



4 Middle manager autonomy and innovative work behavior; The effect of informal networks, spatial distance and organizational complexity

Abstract

A middle manager's autonomy is considered a key factor to explain middle manager's innovative work behavior (IWB). Because many middle managers work in large and multi-site organizations with complex governance structures, we argue that next to formal autonomy based on job design, current conceptualizations of middle managers' autonomy should be extended to include a potential wider scope of autonomy. At the individual level, the social network of a middle manager may constrain or enhance a middle manager's autonomy. At the organization level, two conditions affecting autonomy so far have received relatively little attention: the formal and the spatial structure of the organization. This is particularly problematic given that many middle managers work in large multi-site organizations with complex governance structures. This study investigates to what degree four dimensions of middle manager autonomy jointly affect middle managers' innovative work behavior: job design, personal network structure, distance to the head-office, and the structure of the formal organization.

We conducted a longitudinal field study in a multi-national firm that manages 75 leisure parks (franchised, managed, or owned). Using stochastic actor oriented modeling, we modeled to what degree informal networks and job autonomy affect variations in the innovative work behavior of 110 middle managers.

The study revealed no systematic association between innovative work behavior and autonomy based on job design, personal network structure, distance to the head office, or the degree of formal organizational constraint. Our findings suggest that at least in this particular organization, autonomy may not be an important precondition for IWB. We believe this may be caused by two characteristics of the particular case, the relative high network density, and the obfuscating influence of other factors.

4.1 Introduction

OECD (2018, p. 20) defines innovation as "*a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)*". Middle managers' innovative work behavior contributes significantly to an organization's innovation. Innovative Work Behavior (IWB) is intentional behavior that introduces new ideas in order to improve products or processes with the explicit aim to benefit the organization. IWB differs from creativity and the development of new ideas, because it also includes the implementation of new ideas (de Jong & den Hartog, 2010; Ramamoorthy et al., 2005).

The importance of middle managers' role in innovation is well described (Burgess, 2013, Hornsby, Kuratko, & Zahra, 2002; Kuratko 2017). They contribute to an organization's strategy (Floyd & Wooldridge, 1997; Floyd, Schmid, & Wooldridge, 2008) and facilitate entrepreneurial action (Kuratko et al., 2005). Their central position enables them to assemble information about internal strengths and weaknesses and to become familiar with market developments and the competition. Being linking pins between top management and operations enables them to feed top management with relevant strategic information and plans for innovations, and to identify and provide access to the resources needed for successful innovations (Hornsby, Kuratko, & Zahra, 2002; Nonaka & Takeuchi, 1995). The IWB of middle managers is therefore considered to be key to the success of companies. Consequently, understanding why some middle managers excel in IWB, whereas others lag behind is high on the agenda of scholars and practitioners alike. For a comprehensive review of IWB we refer to (Anderson, Potocnik, & Zhou, 2014).

Autonomy, that is, a middle manager's discretion to make independent decisions regarding his or her work, is since long considered as one of the key enablers and triggers of IWB (Foss, Lyngsie, & Zahra, 2015; Hornsby, Kuratko, & Zahra, 2002). The present study builds on this insight, but argues that current conceptualizations of autonomy should be extended to include a potential wider scope of autonomy. More specifically, we posit that middle manager autonomy rests on four key pillars: job design, the structure of the formal organization, the structure of the informal organization, and the spatial distance to its headquarters. Whereas quite some insights are available on the job design-IWB link, far less is known about the other three bases of middle manager autonomy.

The present paper makes three distinct contributions to current scholarship on middle managers' IWB. Synthesizing the different IWB studies on job design, informal networks, and organizational governance, we first introduce a refined multi-dimensional conceptualization of a key theoretical construct, middle manager autonomy.

Second, this study is among the first to assess how four dimensions of autonomy jointly affect IWB in a longitudinal field study of a real-life multi-national firm, which manages 75 leisure parks, sizeable proportions of which consist of franchises, and managed parks. In a multi-method research study, we used a longitudinal sociometric research design to model to what degree informal networks and job autonomy affect variations in the IWB of 110 middle managers. 50 of them work at headquarters, the rest are park managers. This is supplemented with structured interviews of seven managers to interpret the results of this sociometric research.

Third, shifting the focus to individual level changes in IWB through time, our study pioneers into the hitherto understudied longitudinal co-evolution between innovative behavior and intra-organizational social networks. Until now, research into middle managers' social network is limited to a small number of cross-sectional studies (for an overview see Cohen & Nair, 2017). Stochastic actor oriented models (SAOM; Snijders, van de Bunt, & Steglich, 2010; Snijders, 2017) allows to disentangle to what degree informal constraints in the personal social network of middle managers affect and are affected by IWB.

The remainder of this paper is organized as follows. The theoretical background and hypotheses are sketched in the next section. This is followed by an outline of the research design and a section on results. We conclude with a discussion of the implications of our findings.

4.2 Theoretical Background

Current explanations of IWB focus on antecedents at three levels of analysis, one capturing individual characteristics, the other two representing organizational or job design features. At the level of the individual, personality (e.g., conscientiousness and openness to experience), goal orientation (pro-activeness), values (conformity value), strategic knowledge, and affective commitment (Anderson Potocnick, & Zhou, 2014; Jafri, 2010) were found to be important predictors. At the level of job design, a key condition fostering innovative behavior is a middle manager's decision-making autonomy (Hornsby, Kuratko, & Zahra, 2002). Finally, addressing the level of organizational design, decentralized governance structures were found to increase opportunity discovery and realization (Foss, Lyngsie, & Zahra, 2015). According to these studies, a middle manager's independence from organizational or job requirements is among the major preconditions for engaging in innovative thinking and behaviors. Hence, middle managers' IWB is expected to flourish in organizational environments designed to keep formal restrictions imposed on middle managers' decision making to a minimum, and to enhance their ability to operate autonomously.

Whereas this multi-level perspective yielded important insights, the picture emerging from current research remains incomplete because it neglects the multidimensional nature of autonomy. The present study addresses this gap. It posits that assessing the impact of autonomy on IWB requires a more refined conceptualization of autonomy at the three levels of analysis. Four different bases of autonomy need to be considered when modeling IWB. First, the link between IWB and autonomy based on a middle manager's job design has been well studied (Foss, Lyngsie, & Zahra, 2015; Hornsby, Kuratko, & Zahra, 2002). It reflects formal rights and responsibilities as agreed in the manager's contract or job descriptions, and defining what falls within his or her decision space.

Second, at the individual level, a middle manager's autonomy can also be affected by informal pressures and conventions as they are usually conveyed through the personal social network. For example, a large body of research has shown that dense, close-knit social network structures tend to stifle individual creativity and innovative behavior, whereas conformity pressures are far less strong in loose-knit structures and brokerage positions (Perry-Smith & Mannucci, 2017; Soda, Stea, & Pedersen, 2017; Burt, 2004).

And third, at the organization level, two conditions affecting autonomy so far have received relatively little attention: the formal and the spatial structure of the organization. This is particularly problematic given that many middle managers work in large multi-site organizations with complex governance structures. First, such organizations are often characterized by networked governance structures like franchising, joint ventures, or strategic alliances (Podolny & Page, 1998). In such networked organizations, operations are intertwined between units that formally belong to different legal entities, resulting in opposing interests of stakeholders (Detlefsen & Glodz, 2013; Hodari, Turner, & Sturman, 2017; Turner & Guilding, 2010, 2013). These different interests often lead to more regulations and constraints, as well as to a close monitoring of operations by stakeholders. Both factors are likely to decrease a middle manager's scope for IWB. Second, multi-site organizations are often geographically dispersed (Turner & Pennington, 2015), with the result that many sites are spatially separated from each other and from the head office (Chang & Harrington, 2002). In an extensive study of the strategy making process in four multinational companies, Regnér (2003) found that strategy making in the periphery of an organization is generally more inductive and less formal than at the center and is more exploratory by nature. This suggests that next to job autonomy, social network structure, and the structure of the formal organization, a middle managers' spatial distance to the center of their organization is a fourth structural factor that may influence IWB.

The main objective of the present study is to understand how variations in middle managers' IWB can be explained by the interplay between these four conditions affecting their autonomy: their job design, the structure of their informal network and of their formal organization, and the spatial distance to their head office. Previous scholarship has treated them separately, rather than in combination (Boyett & Currie, 2004; Glaser, Fourne, & Elfring, 2015; Hodari, Turner, & Sturman, 2017; Regnér, 2003; Turner & Pennington, 2015).

4.2.1 Autonomy Based on Job Design

Job autonomy is not a direct cause of IWB but it gives managers the freedom to make choices, which is also known as managerial discretion. Carpenter and Golden (1997, p. 187) define managerial discretion as "*executives' ability to affect important organizational* *outcomes*". Managerial discretion emphasizes freedom of choice, the capacity to evaluate situations and to make choices to realize the goals of their company (de Rond & Thietart, 2007). Managerial discretion may lead to increased performance as middle managers are given the opportunity to be innovative (Hutzschenreuter & Kleindienst, 2013).

Several studies have indeed shown that a middle manager's IWB is strongly influenced by the freedom they have to make decisions. A variety of different mechanisms contributes to this effect. Job autonomy fosters opportunities to discover new opportunities (Foss, Lyngsie & Zahra, 2015), it stimulates risk taking and proactivity (Miller, Kets de Vries, & Toulouse, 1982), contributes to an entrepreneurial culture (Hornsby, Kuratko, & Zahra, 2002), motivates managers (Hagedoorn & Hesen, 2007), and increases their commitment to the organization (Yan, Chong, & Mak, 2010). This leads to hypothesis 1:

> *Hypothesis 1 (Job autonomy): The higher a middle manager's job autonomy, the higher a middle manager's Innovative Work Behavior.*

4.2.2 Autonomy Based on the Structure of the Informal Network

According to Burt's structural holes theory, individuals in brokerage positions derive benefits from being connected to individuals who are not (yet) connected to each other. This structural autonomy gives them early access to a wider range of information and support for implementing new ideas. Brokers can exploit the resulting information advantage for their own benefit (Burt, 1992, 2000). They are exposed to more perspectives, which influences individuals' cognitive structures and may lead to new knowledge combinations (Perry-Smith & Mannucci, 2017; Perry-Smith & Shalley, 2003). Conversely, managers who lack structural holes and are locked into dense personal networks miss access to new and alternative information. Combined with the conformity pressures resulting from close-knit social structures (Burt, 1992), their personal networks become a liability for their IWB, as illustrated by a study in French franchise chains (El Akremy, Mignonac, & Perrigot, 2011), where a strong positive correlation between social cohesion among franchisees and conformity with chain standards was found. Hypothesis 2 summarizes the structural autonomy effect:

> *Hypothesis 2 (Social network): The higher a middle manager's structural autonomy, the higher a middle manager's Innovative Work Behavior.*

4.2.3 Autonomy Based on the Structure of the Formal Organization

Different governance structures such as franchising, joint ventures, management contracts, or strategic alliances have led to organizations that no longer resemble traditional unitary organizations (Turner & Pennington, 2015), but are better described as networked organizations. As an illustration, Box 4.1 describes the different stakeholders a hotel manager has to deal with when seeking approval for an investment plan for a rather simple upgrade of the breakfast area. The example shows that a seemingly standard unitary organization like a hotel is in reality composed of a combination of different stakeholders with different interests.

In the hotel industry it is common that hotel chains follow asset-light strategies in which asset ownership and management are split. In such settings, each individual hotel in a hotel chain consists of a cooperation between two or more participating companies, like an investor who owns the real estate, an asset management company managing the real estate, a hotel management company managing the hotel operations, and a franchiser who is responsible for brand standards as well as marketing and sales (Ivanova, Ivanov, & Magini, 2016). Hotel chains operating several types of hotels, like corporate managed hotels, franchised hotels, and hotels under a management contract (Ivanova, Ivanov, & Magini, 2016) represent a type of networked organization that is quite common in the hospitality industry, and it is also the focus of the present study. A middle manager's scope for IWB depends on the business model of the hotel in such a chain.

Box 4.1 A hotel as a networked organization.

The General Manager of an upscale hotel considers changing the breakfast area into a restaurant concept matching the character of an International DeLuxe branded hotel. From a financial perspective a rather straightforward case. In her proposal, she has to deal with the following stakeholders:

1. The owner of the property, a real estate investment fund (REIT).
2. The foreign based real estate development company who leases the property from this REIT and operates it as a hotel. All employees are employed by this company.
3. The asset management company, who manages the assets on behalf of the owner. The main duties of the asset management company are: Property planning & development, risk evaluation, operational analysis & review, and property repositioning analysis.
4. The management company who manages the hotel on behalf of an international hotel chain. This means that the hotel chain acts as franchisor, but in addition effectively manages the property and supports it with a variety of services and systems. The general manager in this case is employed by this international hotel chain.

In case she decides not to develop the restaurant herself, she may rent it out to a third party, or alternatively join a franchise organization specialized in upscale restaurant concepts. Both alternatives would further add an influential stakeholder to the hotel as networked organization.

Regarding this investment decision, the stakeholders have different interests. The owner and the asset management company focus on a long-term return on investment. For the hotel chain upholding brand standards is important to maintain brand integrity.

In a *corporate managed hotel*, the hotel chain owns or leases the real estate, but is fully in control of the operations in the hotel. A managed hotel resembles the traditional unitary organization in which the middle manager reports to the top management.

In case of *franchising*, the hotel chain is the franchisor, and primarily acts as supplier of brand standards and as a distribution channel, while the franchisee manages the hotel. The middle manager responsible for the hotel is typically employed by the franchisee who owns the company. The chain organization aims to keep up brand standards, which specify in detail how to operate the hotel. These brand standards may severely limit a middle manager's autonomy (Martin, 2017). In addition, the interests of the owner/franchisee also need to be served, possibly leading to additional constraints. For example, in a study among hotel managers in the Aberdeen area, Martin (2017) found that in comparison to hotel managers in owned hotels, hotel managers in franchised hotels suffered from reduced decision-making autonomy because they were strongly focused on complying with the brand standards. And in a study among chain hotels, Turner and Guilding (2013) found that owners often focused on short term profits, making it difficult for middle managers to keep up with the brand standards of the chain.

Hotels operating under a *management contract* are managed by a hotel management company (which may or may not belong to the hotel chain) on behalf of the owner. The middle manager is accountable to both the owner and the hotel management company. In most cases owners and management companies have conflicting interests. Hotel management companies are often focused on increasing revenues because their fee is revenue based, and they have a strategic interest to maintain the value of their brand. Hotel owners are more interested in short term profits and asset value (Hodari, Turner, & Sturman, 2017; Turner & Guilding, 2013). These differences limit a middle manager's autonomy and decision-making scope. In addition, these divergent roles often lead to detailed contracts and extensive monitoring by the owner, which further limits middle management's autonomy (Hodari, Turner, & Sturman, 2017).

The present study investigated a hotel chain that operates three different types of leisure parks: managed parks, parks under a management contract, and franchised parks, which together represent three different types of networked organizations. Settings with different types of parks provide a strong research case to investigate the influence of park type on middle managers' IWB, as recently shown by Turner and Pennington (2015). Hypothesis 3 summarizes the effect of park type on IWB:

> *Hypothesis 3 (Park type): The higher the constraint caused by type of park, the lower a middle manager's Innovative Work Behavior: Innovative Work Behavior will be highest in managed parks, and lowest in franchised parks.*

4.2.4 Autonomy Based on Spatial Distance

The fourth factor affecting a middle manager's IWB is spatial distance to the headquarter (Ducruet & Beauguitte, 2014; Illenberger, Nagel, & Flötteröd, 2013). Middle managers are often found in large multi-site organizations where a middle manager can be a site or subsidiary manager. Working in different, physically distant sites may affect middle manager autonomy in at least three ways.

First, being dispersed over different sites reduces the opportunities for middle managers to have daily informal face-to-face interactions with each other or with the head office. Despite extensive communication facilities, distance often complicates coordination, communication, and monitoring (Boschma, 2005; Ducruet & Beauguitte, 2014; Hutzschenreuter, Kleindienst, & Lange, 2016). As a consequence, peer pressure and informal control is likely to be weaker, which should translate distal locations providing more autonomy for the local middle manager.

Second, distance can affect autonomy and IWB through increased diversity (Ambos & Håkanson, 2014). Middle managers in different sites are exposed to specific local situations, products and processes that may lead to new ideas and trigger them to innovate. For example, previous research showed that subsidiary managers in remote sites tend to contact a variety of local sources to solve puzzles or acquire necessary knowledge, often without involvement or knowledge of a head office (Tippmann, Scott, & Mangematin, 2014)

Third, conditions at a distal location often differ substantially from the conditions near the head office. Though corporate policies may be meant to benefit all subsidiaries, they often do not necessarily match with the requirements of the local conditions in the periphery of the organization, as a result of which they may not be feasible there (Boyett & Currie, 2004). This forces middle managers to become innovative and adapt corporate policies to local conditions. Their intimate knowledge of local market conditions and contexts helps local managers to adapt corporate policies to local requirements (Morosini, Shane, & Singh, 1998).

In sum, higher distance to the head office may lead to situations in which middle managers are forced to adapt corporate policies, are exposed to new practices, and face less direct control. Hence, a higher distance to an organization's head office may lead to a higher level of middle managers' IWB.

Several studies indeed have already found a positive association between distance to the head office and innovative behavior. In a case study of an international telecom company, Boyett and Currie (2004) show that local managers deviate from corporate strategies in order to adapt to local market conditions. And in an extensive study of the strategy making process in four multinational companies, Regnér (2003) found that while strategy at the center is often more deductive and based on formal analysis and planning, strategy making in the periphery of an organization is generally more inductive and externally oriented, often including exploratory activities like trial and error and experiments when deviating from formal corporate policies. This leads to the following fourth hypothesis:

> *Hypothesis 4 (Spatial distance): The larger the spatial distance of a middle manager's location to the organization's headquarter, the higher a middle manager's Innovative Work Behavior.*

4.3 Research Method

4.3.1 Population and data collection

To test the hypotheses, we collected data on the innovative behavior and performance of middle managers in a subsidiary of an internationally listed company. The subsidiary, *A Leisure Company (ALC),* operates seventy-five leisure and holiday parks in Europe. The park managers together with the senior managers at ALC's head office constitute the group of middle managers in our study. The parks are either managed, operated under a management contract, or franchised (Turner, Hodari, & Blal, 2016).

In the case of managed parks, the assets are in most cases owned by a separate owner (usually an investment company) and then leased to or rented by ALC. This means ALC has full discretion to operate these parks as they see fit, and the park manager manages the park on behalf of ALC. Employees are employed by ALC and the park manager is a pivot between head office and operational staff.

In parks operated under a management contract, the assets are owned by a separate party, who also operates the park and employs the employees. The owning company has contracted ALC to manage he park on behalf of the owner and the park manager is therefore employed by ALC. This means that the park manager has to serve the interests of both ALC and the park owner.

In a franchised park, the owner (franchisee) also manages the park, which means that all employees, including the park manager, are employed by the franchisee. ALC only operates as franchisor, that is, it delivers at least the brand standards and access to the corporate sales and distribution channel. Depending on the contract, additional services as HR, accounting, or facility management may also be provided. The park manager is employed by the franchisee, but depending on the franchise conditions, ALC exerts a strong influence on decision making.

The data collection was carried out in two steps. It started with document analysis to reconstruct key elements of the organization's history. This was followed by exploratory semi-structured interviews with seven different managers (three management parks, one management contract park, one franchise park, and two managers working at an office). The objective of these interviews was to become familiar with the organization, to explore what factors might be of relevance to the IWB of middle managers, and to evaluate the outcomes of the longitudinal study. The interviewees were asked to describe their park or department, to give examples of their innovative behavior, and to elaborate on factors that might influence IWB, in particular the autonomy of managers, the IWB of peer managers and the support (or lack of) of the central departments. They were also asked to describe their motives for IWB and how these motives relate to the existing rules, routines, and practices in the organization. The interviews were fully transcribed. Transcript summary sheets were used to capture answers about the influence of the corporate organization on middle managers' IWB. In a next step, these answers were interpreted and related to the different hypotheses. A summary of these results can be found in appendix 4.1 of this chapter.

The second part of the research consisted of a longitudinal sociometric panel study among the complete management team. This panel study consisted of two waves (October 2013 and May 2014), using online questionnaires. Complete name rosters were used for the network questions. It was explained to the participants that in order to ensure confidentiality, their names would be replaced by encrypted identifiers before the analysis phase. The whole management team of the organization, consisting of seventy-five park managers plus sixty office managers, was involved in this panel study. The group of office-managers consisted of board members, area managers and managers of staff departments. In this way, all management levels between corporate and operational levels were included, effectively including all middle managers in the study. Table 4.1 summarizes descriptive information on the samples.

Table 4.1 Descriptives of the population and sample.

	wave 1	wave 2
Parks managed	17	17
Parks under management contract	5	5
Parks franchised	52	53
Total parks	74	75
Park managers	69	73
Managers office	59	58
Total managers	128	131
Response	104	70
Managers new/exit		9/6
Parks new/exit		2/1
Managers first time participating in survey		18

Changes in the composition of the sample are common in longitudinal field studies. As can be seen from Table 4.1, the number of management positions varies around 130 and has been occupied by 137 (128+9) managers during this period. 122 managers started filling out a questionnaire at least once and 110 managers filled out a questionnaire completely at least once. Comments received by email or telephone indicated that reasons for non-completion or not responding were the length of the questionnaire, an aversion to answer items in which names of colleagues are mentioned, or because being to new or too unfamiliar with the organization.

4.3.2 Measures

Innovative Work Behavior is measured using a six-item scale developed by Scott and Bruce (1994), also used by, for instance, Carmeli and Spreitzer (2009). Examples of items are: *"I seek out new technologies, processes, techniques, and/or product ideas at work.", "I promote and champion ideas to others at work."*, and *"I investigate and secure funds needed to implement new ideas."* Cronbach's alpha values for IWB (6 items; α = 0.87 and 0.92, for waves 1 and 2, resp.) are good. Average scores for IWB are 4.06 and 4.08, which are rather high, with standard deviations 0.54 and 0.61 resp. and range 2.67 to 5.00 for both waves. These statistics indicate that the majority of the managers considers themselves to be innovative.

Job Autonomy is measured using a five-item scale developed by Hage and Aiken (1967) and validated by Dewar, Whetten, and Boje (1980). The scale is used by, for instance, Jansen, Den Bosch, and Volberda (2006) to measure centralization of decision making. Examples of items are "*A person who wants to make his own decisions would be quickly discouraged*."

and “*Even small matters have to be referred to someone higher up for a final decision.*” Values of Cronbach’s alpha for Job autonomy (5 items; α = 0.81 and 0.76, for waves 1 and 2, resp.) are satisfactory. The average scores for job autonomy are 2.40 and 2.37 with standard deviations 0.86 and 0.79 and range from 1.0 to 4.4 in wave 1 and 1.0 to 4.8 in wave 2. This indicates that managers perceive their autonomy as rather average, but with enough diversity in the sample to explore further relations.

Network Constraint was used to measure a middle manager’s structural autonomy, and was determined per wave as the extent to which the advice network of managers consists of redundant contacts (Burt, 2000). Network constraint measures if a manager’s advice network consists of unconnected clusters of relations, or if it is a cohesive group in which alters are connected among themselves, leading to many redundant contacts. A high value for constraint means there is less opportunity to broker and control information and resources between clusters of relations. Constraint was calculated for each individual manager *i* as the sum of direct and indirect relations with all other managers *j* in the network: $C_i = \sum_j c_{ij}$ where $c_{ij} = \left(p_{ij} + \sum_q p_{iq}\, p_{qj}\right)^2 \; for\ q \neq i, j$ with $p_{ij} = \frac{z_{ij}}{\sum_q z_{iq}}$ and z_{ij} expressing the advice-relation between *i* and *j* (advice matrix). The dyadic constraint c_{ij} measures the degree to which actor *j* constrains actor *i*. The first component of c_{ij} measures the time and energy spend by *i* to reach *j*. The second component measures how *j* is tied to other contacts of *i*. When an actor *i* invests times and energy in a relation with actor *j* who is also tied to many other contacts of *j* the dyadic constraint c_{ij} will be high and *i* will not bridge structural holes. A low dyadic constraint c_{ij} will be found when actors *j* don’t have many ties to other contacts of *i*. C_i is measured on a scale from 0 to 1. A value close to 0 means the manager is less constrained by his personal network. The average constraint is 0.11 with a standard deviation of 0.15. The network constraint index C_i cannot be calculated inside the RSiena package, therefore it was calculated separately for each wave. This implies that the constraint index is treated as an external covariate. Due to SIENA’s co-evolutionary approach, it can still be used simultaneously as a dependent and an explanatory variable. Note that because the constraint variable does not vary between the waves, the effect of constraint is based on the observed values of the first wave only. The advice networks were elicited using complete name rosters. Participants were asked to answer the following question: “*Which of the following colleagues have you approached in the past six months for advice or information?*“. Answer categories (forced choice) were “*Not approached in the past six months*” or “*Yes, approached in the past six months”.*

Spatial Distance. The logarithm of the distance in kilometers from the park to the head office. To calculate the distance, the actual addresses were converted into GPS-coordinates using the site http://www.gpsvisualizer.com/geocoder/. Using the R-package *fossil*, (version 0.3.7, Vavrek, 2012) these GPS-coordinates were used to calculate the Euclidean distances between parks and head office. The Euclidean distance was converted to its logarithm to remove skewness. The average (non-logarithmic) distance is 169 km with standard deviation 2013, minimum 0, and maximum 1,114 km.

There is no existing measure for the influence of the structure of the formal organization, and therefore we used *park type* as a proxy measure for the level of constraint due to the structure of the formal organization. This proxy is constructed using an ordinal scale: “1” for managers working at the head office, “2” for park managers that manage a managed park, “3” for managers that manage a management contract park, and “4” for managers that manage a franchised park. Higher values reflect higher levels of formal constraint on the middle manager. Managers at a management park only have to deal with an owner who is committed to a long-term lease or rent contract. At a management contract park, the owner operates the park, and therefore is more likely to exercise influence to operate the park according to his or her interests. In a franchise park, the park manager is even more obliged to take the interests of the franchisee into consideration as the manager is formally employed by the franchisee. The park type of each manager was based on a list of parks (offices) with the names of the park manager and the type of each park, provided by ALC.

Table 4.2 summarizes descriptive information on the variables.

Table 4.2 Description of attribute variables.

	Mean (SD)		Cronbach’s alpha		Moran’s *I*	
	W1	W2	W1	W2	W1	W2
Innovative work behavior	4.06 (0.54)	4.08 (0.61)	0.87	0.92	-0.01	0.01
Autonomy	2.40 (0.86)	2.37 (0.79)	0.81	0.76	-0.03	0.00
Network constraint	0.11 (0.15)					
Distance (km) to Head Office	169 (2013)					

4.3.3 Analytical Strategy

A longitudinal dataset containing networks cannot be analyzed with standard statistical techniques due to the high interdependence of network observations. Therefore, we analyzed the data using a stochastic actor oriented model (SAOM; Kalish, 2019; Snijders, van de Bunt, & Steglich, 2010; Snijders, 2017). In a SAOM, both network structure and actor behavior (IWB) are jointly dependent variables while at the same time influencing each other. This co-evolution of network and behavior enables us to analyze the interdependence between network dynamics and behavior dynamics.

In a SAOM two categories of parameters can be distinguished. Selection effects to model the dynamics and development of the network, and influence effects to model the development of the behavior variable (IWB). In the SAOM we estimated, the dynamics of the network depends on two subcategories of effects: network effects derived from the network structure and actor attribute effects based on characteristics of the actors. The development of the behavior (IWB) similarly depends on these two subcategories of effects. The following two sections describes the effects we included in our SAOM.

Network or selection dynamics

Social networks tend to be governed by a number of self-organizing principles, which means that network dynamics are to a certain extent affected by the existing network structure. In a SAOM these effects have to be included to ensure a proper and convergent model estimation. Therefore, we controlled for a number of these effects. *Outdegree* is the basic tendency to have ties, in our case, to ask for advice. *Reciprocity* is the tendency of relations to be returned. If A asks B for advice, this increases the probability of B asking A for advice. *3-cycles* reflect generalized reciprocity in triadic relations: if A asks B for advice, and B goes to C for advice, then it is more likely that C will go to A for advice. *Indegree popularity* is the tendency for actors with high indegrees to receive more advice requests. It means that popular actors are likely to become even more popular. *Outdegree activity* models the effect that managers who are used to ask for advice, are more comfortable to do so and as a consequence are more likely to approach other managers for advice. The *indegree activity* effect models the tendency of managers who receive many advice requests, to approach others more often for advice.

Next to these network effects, the characteristics of the managers may also influence the development of the network structure. *IWB alter* describes the influence of a manager's level of IWB on the probability of being approached for advice. *IWB ego* describes the influence of a manager's level of IWB on the probability of approaching others for advice. *IWB similarity* describes the tendency to approach other managers who have a similar level of IWB. In other words, innovative managers tend to approach innovative managers and the less innovative managers prefer to approach other less innovative managers. *IWB indegree popularity* is comparable to the already mentioned indegree popularity. The difference is that the probability to attract new ties now no longer depends on the number of incoming ties, but on the level of IWB of the existing advice-seekers. A manager becomes interesting to approach, not when many others do so, but when this manager is already being approached by the innovative managers.

Behavior or influence dynamics

The influence effects in a SAOM are used to analyze how IWB is influenced by a combination of network structures and other characteristics of the managers. In particular, we considered the following two network effects. *Indegree* represents the influence of the number of incoming advice request on IWB. It can be interpreted as a manager receiving many calls for advice, by receiving the advice requests becomes well informed about recent developments and issues, which in turn increases the capability of this managers to become innovative. *Outdegree* represents the influence of asking for advice on innovation, the more advice is asked, the more innovative this manager will become due to the information collected. Finally, we included in our SAOM the effects from other attributes on behavior to test our hypotheses. These other attributes are *Job Autonomy, Network Constraint, Distance to the Head Office,* and *Park Type.*

For the estimation, the R package RSiena 4.0, version 1.2-12 (Ripley et al., 2018) was used. Joining and leaving actors (managers) were treated according to Huisman and Snijders' (2003) procedure for composition change. Missing data on the behavioral variables were treated with the hybrid imputation procedure, which is default in the SIENA software and according to Zandberg and Huisman (2019) the optimal strategy to deal with missing data.

After estimating the parameters, the validity of the model was assessed, using two criteria (Ripley et al., 2018). First, the convergence of the estimation procedure was checked by calculating *t*-ratios. For convergence of individual parameters, the *t*-ratios should be smaller than 0.10 and the *t*-ratio for overall convergence should be smaller than 0.25. Second, the quality of the SAOM was evaluated by assessing the goodness of fit (GOF) of the model with respect to three auxiliary statistics: The indegree, the outdegree, and the IWB distributions. For this test, the estimated model is used to create a number of simulated outcomes for the cumulative indegree frequency, the cumulative outdegree frequency, and the cumulative IWB frequency. These simulated outcomes are compared to the actual cumulative frequencies, using the Mahalanobis distance.

4.4 Results

4.4.1 Descriptives

Table 4.3 summarizes the main descriptives of the network at waves 1 and 2. The Jaccard index, calculated as the fraction of stable ties compared to the sum of stable, new and terminated ties, tests if there is enough stability in the datasets between two waves (Snijders, van de Bunt, & Steglich, 2010). If there is not enough stability, the SIENA method may not be suitable for the data set. The Jaccard index for the change between wave 1 and wave 2 is 0.66, much larger than the common minimum of 0.3, and therefore we conclude there is enough stability to proceed with estimation. Density, the number of ties as fraction of potential ties, is 0.31 and 0.35, for waves 1 and 2, respectively. This means the network is very dense and it is common to approach peers with requests for advice and information and it suggests a high level of cooperation and trust.

Table 4.3 Descriptive network statistics.

	Wave 1	Wave 2
Number of ties	3203	2638
Density	0.31	0.35
Average degree	33.61	38.33
Missing fraction	0.13	0.37
Jaccard index		0.66

The fraction of missing ties is 0.13 in wave 1 and 0.37 in wave 2. The level of missingness in wave 2 is high, but due to the hybrid imputation method used to deal with this missingness, this is not affecting the conclusions. This hybrid imputation procedure is integrated in the estimation procedure of the SAOM, which is explained in more detail in section 2.2 of this thesis. We used the method of moments procedure to estimate the parameters of the model. In this estimation procedure, missing ties in wave 1 are replaced by the value 0, assuming there is no relation between the two actors. A SAOM assumes that the change between two consecutive observations can be modeled as a sequence of small steps, and uses a simulation to model this process. The simulation of this process is based on all variables, including the imputed variables. The calculation of the estimated parameters is only based on the observed values, the missing tie variables are excluded from this calculation. In this way, missing ties do not have a direct influence on the estimated parameters, but still play a role in the simulated co-evolution of network and behavior and therefore have only an indirect influence on the non-missing parts of the network. Therefore, the method of moments is rather robust, even with a larger level of missingness of ties in wave 2.

4.4.2 Estimation results

The estimation results of the SAOM are presented in Table 4.4. Before we discuss individual parameters, we will first discuss the overall characteristics of the model.

Table 4.4 Co-evolution of IWB and Advice network over time.

	Parameter Estimate (SE)	Convergence *t*-ratio
Selection dynamics		
Network effects		
Rate parameter	20.98 (1.72)	0.03
Outdegree	1.04 (1.34)	0.03
Reciprocity	2.01 (0.35)	0.03
Cyclic ties	0.10 (0.02)	0.03
Indegree popularity	-0.02 (0.02)	0.03
Outdegree activity	0.05 (0.02)	0.02
Indegree activity	-0.15 (0.08)	0.02
Individual attribute effects		
IWB alter	-0.11 (0.19)	-0.01
IWB ego	0.44 (0.29)	0.00
IWB similarity	-0.21 (0.43)	-0.05
IWB indegree popularity	-0.24 (0.07)	0.01
Influence dynamics		
Network effects		
Rate parameter	1.51 (0.46)	-0.02
Shape effect	-0.07 (1.00)	0.01
Indegree	0.01 (0.05)	0.00
Outdegree	-0.01 (0.02)	-0.01
Individual attribute effects		
Autonomy	0.04 (0.25)	-0.05
Network constraint	-0.80 (2.59)	0.01
Park type	-0.08 (0.29)	0.04
Distance to Head Office	-0.10 (0.21)	0.02

The t-ratio for overall convergence of all parameters = 0.16.
The Mahalanobis distances for the goodness-of-fit tests for behavior (IWB), outdegree, and indegree are 3.43 ($p = 0.49$), 22.4 ($p = 0.09$), and 15.3 ($p = 0.14$).

The *t*-ratio for individual convergence of parameters are all below the 0.10 standard. In addition, the overall convergence (0.16) is well below the standard 0.25 limit, therefore we conclude that convergence levels are acceptable.

Goodness-of-fit tests for behavior (IWB), outdegree and indegree give Mahalanobis distances of 3.43 ($p = 0.49$), 22.4 ($p = 0.09$), and 15.3 ($p = 0.14$). The p-values are all greater than 0.05, which means that we cannot reject the null hypothesis that there is no difference between the observed and simulated distributions of the three auxiliary statistics. Therefore, we may be confident that the estimated model represents a good fit of the true network and behavior dynamics.

Since the variable Park Type is based on an ordinal scale with four values, treating it as an interval scale in the analysis rests on the strong and untested assumption of equal "distances" between the four levels. In order to check the robustness of our findings, we reran the analysis using three dummy variables for the managers who do not work at the head office: a dummy for managers of a managed park, a dummy for managers of management contract parks and a third dummy for managers of franchised parks. The outcomes remain the same: there is still no significant effect of Park Type on Innovative Work Behavior. Other outcomes are also unchanged. Details of this estimation can be found in appendix 4.2. of this chapter.

In the first part of Table 4.4, the selection dynamics due to network effects and actor attribute effects are presented. The second part lists the effects that influence IWB. Two parameters for standard network effects are not significant: Outdegree (1.04, SE = 1.34) and Indegree popularity (-0.02, SE = 0.02). The following parameters for standard network effects are significant: Reciprocity (2.01, SE = 0.35), Cyclic ties (0.10, SE = 0.02), Outdegree activity (0.05, SE = 0.02), and Indegree activity (-0.15, SE = 0.08). We conclude that the effects of the advice network are comparable to the effects of many other networks. The individual attribute alter effect has a non-significant parameter (-0.11, SE = 0.19), indicating that a middle manager's IWB is no reason to approach this middle manager for advice. Similarly, the non-significance of the IWB ego effect (0.44, SE = 0.29) means that a middle manager's level of IWB has no influence on asking advice. The non-significant IWB-similarity effect (-0.21, SE = 0.43) means that there is no evidence of middle managers preferring to approach middle managers with a similar level of IWB. The significant but negative parameter for IWB indegree popularity (-0.24, SE = 0.07) suggests that there is a barrier to approach popular middle managers.

Finally, we will discuss the findings for the four hypotheses. Since none of the hypothesized effects were significant, we will immediately contextualize the presentation of the findings with background information obtained through the qualitative interviews, in order to explore potential reasons for these non-significant effects.

The parameter for job autonomy, Hypothesis 1, is not significant (0.04, SE = 0.25). In a response to the question about autonomy, Manager 1 explained the ambiguous setting in which middle managers were expected to simultaneously be both entrepreneurial and to comply with the extensive corporate regulations. Manager 2 answered that non-compliance with corporate policies or not meeting prescribed targets often had no visible consequence (e.g., in terms of criticism). These answers indicate that middle managers perceived their setting as ambiguous, without clear guidance and strong support for innovative behavior**.** This pattern mirrors earlier research in which explicit and unambivalent support from top management was found to be a crucial success factor for middle managers to be entrepreneurial (Kuratko, et al., 2005). Since interviewees suggest this support is largely absent in ALC, this may at least partly explain why we see no clear influence of job autonomy on middle managers' IWB. This implies that middle manager IWB depends strongly on their ability to deal with such ambiguity caused by a lack of top management's support. In sum, the perceived ambiguity could be a reason why we see no clear influence of job autonomy on middle managers' IWB, and finding no support for Hypothesis 1.

The parameter for network constraint, Hypothesis 2, is also not significant (-0.80, SE = 2.59). Asked about the autonomy middle managers experienced to innovate, Manager 4 answered that there was some space for initiative, but to be successful, it was crucial to connect to the right people in the organization. Through previous positions he had a wide variety of contacts within the organization, and he extensively used these contacts to organize support when necessary. Manager 2 answered that through a prolonged period he had witnessed a very strong trend towards centralization. He had no problem with that, but stressed the need for middle managers to be strongly involved in developing these corporate policies. Both answers indicate that in order to be successful innovators, middle managers need a network that supports them. Rather than constraining IWB, having many contacts and a dense personal network may also benefit their IWB. A high network density means that information is almost equally available to all managers. This might be a reason why we found no significant outcomes for Hypothesis 2, the influence of structural autonomy (network constraint) on IWB.

The parameter for park type, Hypothesis 3, was also not significant (-0.08, SE = 0.29). Managers 1 and 3 explained additional complexities involved in franchising. First the role of the franchisee, who in some cases is very supportive of an entrepreneurial middle manager, but in other cases gives very strict instructions that strongly limit the middle managers' IWB. A second factor is the level of support activities that are outsourced to the franchisor. In a franchising cooperation at a minimum the branding has to be outsourced to the franchisor. In addition to branding, there is an option to outsource other functions, like sales, HR, and finance to the franchisor. As a result, different levels of franchising are possible. Both middle managers explained that a low level of outsourcing to the franchisor, combined with a supportive franchisee, strongly enabled a middle manager to be entrepreneurial and innovative. This implies that the details of the contract and the attitude of the franchisee might temper the outcomes. The limited influence of park type and the rejection of Hypothesis 3 could be related to this.

The parameter for distance to the head office, Hypothesis 4, was also not significant (-0.10, SE = 0.21). Managers 1 and 3 emphasized the tension between local and central rules. Manager 1 explained how local laws and culture complicated the implementation of corporate policies. Similarly, Manager 3 mentioned the tension between local and central purchasing. Central purchasing prevented him from purchasing locally that might be beneficial for either selling local produce or increasing involvement in local networks.

4.5 Discussion and Conclusion

This longitudinal sociometric study in a complex multi-site networked organization investigated to what degree four dimensions of middle manager autonomy jointly affect their innovative work behavior. Stochastic actor-oriented modeling revealed no systematic association between innovative work behavior and autonomy based on job design, personal network structure, distance to the head-office, or the degree of formal organizational constraint. Our findings suggest that at least in this particular organization, autonomy may not be an important precondition for IWB. We believe this may be caused by two characteristics of the particular case, the relative high network density, and the obfuscating influence of other factors.

Network density is quite high (0.31 in wave 1 and 0.35 in wave 2), with managers having on average 34 and 38 ties. Such high densities leave hardly any possibility for bridging structural holes and for benefiting from a brokerage position, as earlier research has shown: actors benefit most from bridging structural holes when collaboration in the network is low (Soda, Stea, & Pedersen, 2019), and the value of bridging relationships decreases with the 'age' of the ties (Baum, McEvily, & Rowly, 2012). The high density in our case suggests that middle managers cooperate extensively, and that collaboration in the network is high. And many managers have been working many years for ALC. This may result in a collaborative culture (which is supported by the interviews) and a reduced value of bridging.

Second, the objective of this study was to investigate if a further differentiation of the autonomy concept would improve our insights into middle managers' IWB. The managers' reflections on the non-significant results suggest that there is no straightforward direct link between autonomy and IWB in this organization and that a broader set of context conditions need to be considered. Top management's support for IWB and franchisees both seem to play a key moderating role. Furthermore, many other small factors that might influence middle managers' IWB were mentioned during the interviews. Examples are a manager's personal background (e.g., being raised in an entrepreneurial family), prior experience in a different organization, support or resistance of department heads, attitude of local stakeholders, etc. This suggests that the combined influence of all these micro-factors may obfuscate the influence of autonomy.

Our findings put into perspective the strong emphasis that autonomy plays in previous research as one of the main triggers of IWB. Not only could our study not replicate earlier findings related to autonomy based on job design, it also did not find evidence for the autonomy-innovativeness link using a broader conceptualization of autonomy incorporating constraints resulting from the formal management of the organization, the informal social network of the middle manager, and the spatial distance to the headquarter.

Appendix 4.1 Summary of relevant interview segments

Manager	Relevant interview segment.	Interpretation.
	H1 autonomy	
M1	Within the organization there are many unclarities. A park manager is compelled to implement corporate policies, but also responsible for realizing targets. Park managers have to act as entrepreneurs while being bound to all sorts of rules at the same moment.	This ambiguous situation causes a situation in which a middle managers may flip between entrepreneurial or more rule observing behavior. This is strongly influenced by the middle manager's ability to operate in such ambiguous settings or his autonomy.
M2	Not sticking to regulations or meeting targets is often without consequences, leading to opaque situations.	Ambiguity in the organization, no clear support for innovative behavior.
	H2 Influence social network	
M2	In the past a park manager had lots of freedom, but more and more the central organization becomes more guiding. This is good because we need uniformity as an organization. It means that a park manager has to engage in this process of central policy formulating to exercise influence.	For a park manager it is critical to network internally, in particular within the office. This suggest an IWB-enabling role of relations.
M4	Though there is limited space for personal initiatives, it is important to address the right people and get their support. (In his previous roles he had to cooperate a lot with managers from the head office or other parks and therefore knows many people).	It is important to network within the organization and in particular the head office. Having many relations is not constraining but enabling.
	H3 Influence of networked organization	
M1	The managers of franchise park have to deal with park owners while management and management contract parks are in a different situation. The exact contract can also	an increase of powerful stakeholders leads to less autonomy for middle managers

	hamper implementation of corporate policies.	
M1	Franchise parks do have the option to cap their franchising to some core modules. This gives them freedom to for example purchase locally or to cooperate with other partners.	As a result, a park manager of a franchised park may have more discretion, but it can also result in more and constraining influence of the franchise owners.
M3	Has much freedom to act without ALC' permission because as franchise park it has only a light franchise agreement with ALC.	
M3	The main responsibility is towards the franchisee. This manager is blessed with a strong franchisee board that supports her and gives room for entrepreneurship.	
M3	To her, corporate account managers have no hierarchical authority, but contrary are supposed to deliver value for money.	Instead of being constrained by a central organization, the central organization is an advantage and support. Of course, under the condition that you manage the park well and you are supported by a strong franchisee board.
M3	Other franchise parks are often run by a franchisee board that constrains the park manager.	Between franchise parks there is much difference between owners who don or do not support the park manager in entrepreneurship.
	H4 influence of spatial distance	
M1	There is a tension between corporate policies and local rules. For example, parks abroad have to deal with laws and cultural differences that make implementation of corporate policies complicated.	distance is a stimulus to deviate from corporate policies.
M7	There is tension between local versus central purchasing.	Which implies less space for IWB.

Appendix 4.2 Alternative model specification using dummy variables for park type

Co-evolution of IWB and Advice network over time using dummy variables for park type

	Parameter Estimate (SE)	Convergence t-ratio
Selection dynamics		
Network effects		
Rate parameter	20.96 (1.89)	0.05
Outdegree	0.96 (1.23)	0.06
Reciprocity	2.01 (0.22)	0.06
Cyclic ties	0.10 (0.03)	0.06
Indegree popularity	–0.02 (0.02)	0.06
Outdegree activity	0.05 (0.02)	0.06
Indegree activity	–0.15 (0.08)	0.06
Individual attribute effects		
IWB alter	–0.10 (0.15)	–0.01
IWB ego	0.44 (0.27)	–0.02
IWB similarity	–0.18 (0.45)	–0.02
IWB indegree popularity	–0.24 (0.07)	–0.02
Influence dynamics		
Network effects		
Rate parameter	1.52 (0.42)	0.04
Shape effect	–0.04 (0.78)	–0.05
Indegree	0.01 (0.04)	–0.05
Outdegree	–0.01 (0.02)	–0.06
Individual attribute effects		
Autonomy	0.04 (0.23)	0.00
Network constraint	–0.74 (1.68)	–0.01
Distance to Head Office	–0.10 (0.25)	–0.02
Effect from managed park	–0.04 (0,60)	–0.02
Effect from management contract park	0.16 (0.88)	–0.00
Effect from franchised park	–0.33 (0.84)	–0.00

The t-ratio for overall convergence of all parameters = 0.11.
The Mahalanobis distances for the goodness-of-fit tests for behavior (IWB), outdegree, and indegree are 3.38 (p = 0.49), 23.4 (p = 0.09), and 13.1 (p = 0.18).

5 Public managers’ networking and innovative work behavior: The importance of career incentives

This chapter has previously been published as Zandberg, T. & Morales, F.N. (2019). Public managers’ networking and innovative work behavior, the importance of career incentives. *International Review of Administrative Science,* 85(2), 286–303.

Abstract

From theories on middle managers’ entrepreneurship in private organizations, it is known that the structural network position of middle managers influences their innovative work behavior. Our study investigates if in a governmental setting the intra-organizational networking behavior of public managers has a similar positive influence on innovative work behavior. Because networking mechanisms may depend on the particular context and organizational norms, we also investigate the influence of networking motivations. According to social network research in private enterprises, social network links can be used to advance individual careers. According to public management and Public Service Motivation theories, public managers have a collective orientation aimed at producing public goods. Therefore, we investigate if next to intraorganizational networking an individual career motive or a collective motivation for networking explains innovative work behavior. In a case study on public managers of a municipality in Mexico City we find a strong influence of networking on innovative work behavior. We also find support for additional influences of individual career motives, but no evidence for collective motivations.

5.1 Introduction

This study seeks to contribute to the literature on public managers’ innovative behavior by looking at intraorganizational managerial networking. Public managers are the linking pin between political appointees and bureaucratic operatives. They play an important role in daily operation, including duties such as monitoring the provision of services and meeting policy and budgetary deadlines. Attention for public managers’ behavior and their role in policymaking and public service provision increased in recent years mainly as consequence of the rise and institutionalization of the New Public Management movement (Boston, 2011). Although public managers have been portrayed traditionally as an obstacle to change (Huy, 2001), New Public Management and other contemporary administrative reforms build on the assumption that managers do play a crucial role in the strategic process of governmental organizations (Boston, 2011; Osborne & Gaebler, 1992). In addition, a number of contributions in the public administration literature have developed the notion that managerial behavior is crucial to organizational performance (e.g., Altman, 1979; Döring, Downe, & Martin, 2015). In particular, public managers can play a central role in promoting organizational responsiveness, innovation and policy renewal (Chen, Berman & Wang, 2017; Vigoda, 2002).

Networking and networks are important antecedents of organizational performance in the public sector (Peters et al., 2017; Randma-Liiv, Uudelepp, & Sarapuu, 2015; Torenvlied et al., 2012). Managerial networking, that is, the frequency of contacts that managers maintain with other actors (Wolff & Moser, 2009), seems to have a positive effect on performance by increasing access to support and resources (Meier & O'Toole, 2001). This echoes findings in the (private) managerial literature, where networking has been associated positively with organizational survival, and increased output. Specifically, networking has been associated with performance via innovativeness: networking improves access to resources, support, ideas and information, which in turn potentiate innovation and overall performance (Pappas & Wooldridge, 2007).

There are several ways in which public managers can make use of the social capital contained in their social networks. Previous studies in the public administration literature have focused by and large on understanding (organizational) performance, and have studied mainly processes of interorganizational networking (i.e., networking in interorganizational networks between managers and actors in the organizational environment). The core idea of these studies is that managers act as boundary spanners between the external environment and the internal organization. This boundary-spanning mechanism drives the relation between networking and performance. One simplifying assumption of this approach is an unitary actor perspective of the organization. This assumption leads to a limited interpretation of networking, and neglects possible effects of *intraorganizational* networking (i.e., networking among managers and other actors within the organization). To relax this assumption, we need to study intraorganizational networking, and how this allows public managers to mobilize resources and information that enable innovation (Burt, Kilduff & Tasselli, 2013).

From this perspective, the relation between managerial networking and innovative behavior implies that public managers are active intraorganizational networkers. However, such a relation does not occur in isolation. Because public managers have limited resources, they have to decide if and to what extent they maintain social ties and networks in the organization. That is, in order to understand the importance of (intraorganizational) networking in enabling innovative behavior, we also need to consider the specific motivations that drive public managers. While early research on social networks suggested a strong positive influence of brokerage on innovation (Burt, 2004) and career opportunities (Burt, 2000), more recent research shows that these relations may be specific for particular contexts. A meta-analysis of Fang et al. (2015), found less support for the influence of brokerage. According to this study, brokerage mechanisms are typical for organizations where timely access to and control of information are crucial for individual success. This is not a surprise as brokerage is typically based on the assumption of the 'apt individual' (Moran, 2005).

However, institutional characteristics of the public organization may also be associated with managerial motivations to network. Previous research found that public managers place higher value than their private counterparts on political rewards and loyalty, which may indicate a higher propensity to maintain social ties in public organizations (see e.g., Crewson, 1997; Grindle, 2012; Rainey, 1983; Rainey & Bozeman, 2000).

Although these relations cannot be attributed solely to institutional differences between the public and the private sector or to cultural differences, available evidence does suggest that the relation between networking and behavioral outcomes (such as innovative work behavior) needs to be studied in relation to particular motivations of public managers. This study contributes to close this gap by theorizing on the effect of managerial networking in the public organization as well as public managers' motivations to network (particularly, teamwork-related motivation and individual career incentives). We then test our ideas using data from a sample of public managers from a municipality in Mexico City. The statistical analysis allows for testing the relative significance of networking and managerial motives on different roles of innovative behavior.

The remainder of this chapter is structured as follows. The first section presents the theoretical argument. Section two introduces the empirical study. The third section presents the results of the statistical analysis, and the fourth section the conclusions.

5.2 Theoretical background

5.2.1 Managerial networking

In public management research two sorts of networks are studied: Collaborative and managerial networks. Collaborative network studies consider the whole network as the unit of analysis and analyze the relation between network characteristics and performance. A major result coming from this type of studies is that high coordination often results in improved performance due to increased stability and cohesion (Akkerman, Torenvlied, & Schalk, 2012). Managerial network studies focus on the individual actor and define networking as the contact frequency of relations that (high-ranking) managers maintain with other managers (Wolff & Moser, 2009).

There are two major types of mechanisms that explain the relation between managerial networking and performance. The first one was proposed by academics in the Kennedy

School of Public Management. It stresses the importance of external resources. According to this argument, support from politicians, the public and other stakeholders is crucial for the performance of public managers (Moore, 1995). For example, Moynihan and Pandey (2005) found that political support positively influences performance of public sector managers. Studies by Meier and O'Toole (2003, 2008) in Texas school districts showed that external networking can be used to reduce uncertainty, exploit resources in external networks, and it has a stabilizing buffer function in case of external shocks.

A second type of mechanism is related to internal managerial networking of public managers. Recent research (van den Bekerom, Torenvlied & Akkerman, 2016) shows that 'downward' networking, that is, maintaining frequent contact with subordinates and work teams, is particularly important in mitigating the negative impact of external shocks on performance. It is assumed that downward networking increases coordination, consensus around strategic decisions, and may lead to new ideas to deal with external shocks. This finding is similar to a meta-analysis of 37 studies on team performance by Balkundi and Harrison (2006). These authors found that leadership centrality in a team had a positive influence on team performance. Downward networking and a central position of a manager in a team improve coordination and increase interpersonal trust and group cohesion, and foster organizational learning. As a result, innovation and performance can increase.

5.2.2 Public managers' innovative work behavior

The previous section described how the managerial networking of public managers may be a determinant of performance in public administration. While the benefits of interorganizational networking rely strongly on access to external support and resources, the benefits of intraorganizational networking rely also strongly on innovations such as creating flexibility, generating new ideas, and promoting alternative use of resources (van den Bekerom, Torenvlied & Akkerman, 2016). We define innovation broadly, as a process that can involve changes in four areas: Products, processes, markets served, and the organization (OECD, 2005, p 46). Public managers play a crucial role in this process. Managers are not merely implementers of strategies, but also actively contribute to and shape the strategies of superiors and elected officials. Because public managers occupy a linking position between political principals and operatives, they can be compared to middle managers in private organizations. Similar to middle managers, public managers are not involved in daily operations but are responsible for operations and performance of subunits (Floyd, Schmid, & Wooldridge, 2008). Middle management theory suggests that middle managers' networking influences their strategic involvement—a variable closely connected to innovative work behavior of middle managers (Hornbsy, Kuratko & Zahra, 2002). Similarly, public managers can use their networks as a source of information and as a source of support and a means to coordinate operations (Burt, 2004; Fang et al. 2015; Mehra et al., 2006).

The contribution of public managers towards innovation can be diverse and depends on their strategic role (Floyd & Wooldridge, 1997). These strategic roles can be described using two dimensions. First, involvement can be upward or downward oriented. Second, it can be divergent or integrative. The first dimension refers to the direction of strategic involvement. The second refers to the nature of the role. Crossing these dimensions results in four different roles, which are helpful to categorize innovative involvement of public managers (see Figure 5.1). First, managers may champion new initiatives, which refer to the introduction and presentation of comprehensive strategic plans to upper management or political principals. Second, managers synthesize information, thus evaluating and communicating information upwards in the organizational hierarchy. Third, managers implement strategies and policies. Finally, managers facilitate adaptability by fostering flexible organizational arrangements that increase adaptability and readiness to change.

	Upward influence	Downward influence
Divergent thinking	*Championing alternative*	*Facilitating adaptability*
Integrative thinking	*Synthesizing information*	*Implementing deliberate strategy*

Figure 5.1 Middle managers' strategic roles
From: Floyd & Wooldridge (1997: 467)

The first two roles (championing and synthesizing) are upward-oriented and strongly depend on new proposals and strategically relevant information. Rapid and precise knowledge of environmental developments is necessary to formulate new plans or to brief superiors with relevant information. The two other roles (implementing and facilitating) are downward-oriented (cf. van den Bekerom, Torenvlied, & Akkerman, 2016). Next to passing through relevant information, these roles specifically rely on a manager's ability to galvanize internal support and to coordinate teams closely. When this is done successfully, a team or subunit is better prepared for change and to deal with external shocks.

Intraorganizational networking can be an important reason for public managers to succeed in these different roles. First, networking increases access to resources and information. This results in better data, more knowledge and increased support. Resources and information obtained through networking can be used upward for championing new initiatives or for synthesizing information towards higher echelons, as well as downward in preparing public employees for change and the implementation of policy. Managers in boundary spanning positions are supposed to have better and faster access to fresh information and have been found to exert more strategic influence than others (Floyd & Wooldridge, 1997). Increased access to information can also be used downward to inform operatives about external contingencies, threats and trends. This information can either be used to improve alignment of deliberate strategies to the actual situation, or to improve adaptability to change. That is, intraorganizational networking can increase managerial innovative involvement, as is formulated in the following hypothesis:

> *Hypothesis 1 (Networking): A higher level of a public manager's intraorganizational networking leads to an increase of his innovative behavior.*

5.2.3 Public managers' motivations

We hypothesized that public managers are active networkers and that their networking can have an important effect on the performance of their departments. We assume that public managers are goal-directed and, as a consequence, next to networking these goals influence their innovative behavior. To understand the mechanisms behind this influence, we refer to social production function theory (Ormel et al., 1997). Located within rational choice theory social production function theory claims that people produce their own well-being by striving towards two general goals: Social approval and physical well-being. These general goals are supposed to consist of instrumental goals. While these general goals are universal, the instrumental goals differ for individuals and, depending on individual constraints, may be substituted for each other. Networking in the public agency can be seen as a means to achieve such instrumental goals. Since several instrumental goals can be identified, it may be argued that several motivations for networking can be identified, with each motivation leading to differentiated forms of innovative behavior. To define these instrumental goals, two characteristic goals/motivations can be identified in the literature that seem particularly important to disentangle this puzzle.

The first one originates from public management theory and public service motivation research, and assumes that public managers aim to create public value and meet organizational and policy objectives (Le Grand, 2003; Moore, 1995). That is, public managers are driven by the goal to meet collective objectives and comply with public sector expectations. Moreover, organizational norms (such as 'being a team player') have been identified in the literature as important antecedents for compliance and performance (Barker, 1993; Rainey, 2003; Tung-Mou & Maxwell, 2011). Managers who are motivated by the creation of public value through commitment to organizational goals and norms are, consequently, more likely to also be active in innovation. Furthering these goals requires coordination between departments, teams, and individuals, as well as creating an enabling environment for team members to perform optimally. Intraorganizational networking is instrumental to this because it facilitates obtaining critical resources to implement policy and to improve team performance. Therefore it may be assumed that public managers who understand that networking is important to achieve these collective goals, are also more successful innovators. This leads to the hypothesis:

> *Hypothesis 2 (Collective goals): Higher salience of collective goals is related to a higher level of innovative behavior.*

A second reason for public managers to engage in networking can be found in networking theory (Forret & Dougherty, 2001, Wolff & Moser, 2009). In terms of social production function theory, a successful career is instrumental to physical well-being. Networking Theory suggests that intraorganizational networking may be instrumental to individuals' career goals. Whereas public management theory assumes that goals are normative and exogenous to the individual, networking theory relies on the assumption that individuals' behavior is driven by individual gain-goals. Networking results from "*individuals' attempts to develop and maintain relationships with others who have the potential to assist them in their work or career*" (Forret & Dougherty, 2004: 420). Research shows that networking can be used to predict career success and salary increases (Forret & Dougherty, 2004; Wolff & Moser, 2009). Intraorganizational networking and maintaining a large network also contribute to the perception that an individual is valued by her principals (Porter & Woo, 2015). A successful career dependent on loyalty and the frequency of relations is connected to informal networks (Lomnitz, 1990). Informal relations can facilitate and secure career opportunities because they function as an asset that secures information and resources for the manager herself.

But networking is not the only manner to advance a career. It may be assumed that those public managers motivated by career goals will engage with higher probability in innovation, to the extent that innovative behavior is deemed instrumental in improving managers' chances of maintaining or increasing career opportunities in the public service:

> *Hypothesis 3 (Individual career goals): Higher salience of career goals is related to a higher level of innovative behavior.*

5.3 Research method

5.3.1 Background and setting

We used survey data from n = 64 public managers of the Milpa Alta municipality in Mexico City. Data were collected in June 2012. Managers received a personal invitation to participate in the study and respond to an online questionnaire (response rate = 69%). Public managers from all departments of the municipality were included in the study (administration, government and law enforcement, public works and urban development, urban services, economic development, social development, and ecology and environment).

Milpa Alta is a semirural community and the least populated of Mexico City's 16 boroughs. It has the lowest gross domestic product and human development index score of Mexico City (although it is way above national average). Milpa Alta government lacks an established civil service system, which is not uncommon in Mexico and other developing nations (Grindle, 2012). This means that managerial positions are often appointed using discretionary and political criteria and not necessarily or exclusively professional merit. This characteristic is important to our study because it implies that we can directly compare collective versus career motivations (because career development is related to public managers' behavior and not determined by an institutionalized career system). Also, the fact that all managers are concentrated in a single location facilitates comparison of individuals' intraorganizational networking.

5.3.2 Measures

The four dependent variables that represent innovative behavior, *championing new alternatives*, *synthesizing information*, *implementing strategies* and *facilitating adaptability*, are each measured using five Likert scale items (1 = strongly disagree, 5= strongly agree). Examples are "*communicate and sell top management initiatives"* (implementing), "*propose new programs to top management"* (championing), "*assess and communicate business level implications of new information to top management"* (synthesizing). A complete description of the items can be found in (Floyd & Wooldridge, 1996) which is based on (Floyd & Wooldridge, 1992). Cronbach's alpha values for these four scales vary between 0.75 and 0.81, indicating that the scales, which were originally developed for use in American private companies, are also reliable measures in the Mexican case.

In the public management literature, it is common to define networking as the frequency of contacts that managers maintain with other actors (van den Bekerom, Torenvlied & Akkerman, 2016). We measured *networking* by the amount of personal contact a public manager has with coworkers inside his department, compared to his peers (0 = much less, 4 = much more).

To measure the influence of network motives on innovative behavior, we asked two questions. For the *career motivation* we asked if knowing people is important to develop a career and to measure the *collective motivation* we asked whether being a team player was crucial for success (0 = strongly disagree, 4= strongly agree).

We controlled for a number of other factors that might be of influence. A common explanation for the innovative behavior of middle managers is their *autonomy*. Greater autonomy is supposed to result in more strategic involvement. We measured managerial autonomy with a single item by asking how much autonomy public managers have regarding daily activities on a five-level Likert scale (0 = no autonomy, 4 = much autonomy). *Centralization of decision-making* is a second measure to check whether there is room for public managers to operate, and measured with a single item on a five-level Likert scale (0 = very centralized, 4 = very decentralized). Besides these specific variables, we also controlled for *gender* (0 = male, 1 = female), *educational attainment* (2 = secondary school, 3 = high school 4 = bachelor's degree, 5 = master's degree, 6 = doctoral degree) and *hierarchical position* (0=head of unit, 1 = deputy director, 2 = director, 3 = director general). Descriptive statistics of the variables can be found in Table 5.1.

Table 5.1 Sample descriptives (*n* = 64)

	Cronbach's alpha	range	Rean	SD
Championing	0.77	1-5	3.34	0.10
Synthesizing	0.81	1-5	3.66	0.10
Implementing	0.76	1-5	3,48	0.10
Facilitating	0.75	1-5	2.89	0.11
Networking		0-4	2.84	0.96
Being a team player		0-4	3.38	0.88
Career motive		0-4	2.08	1.40
Managerial autonomy		0-4	2.15	0.97
Centralization of decision-making		0-4	1.52	1.05
Gender		0-1	0.21	
Education		2-6	3.82	0.69
Hierarchical position		0-3	0.95	0.80

A potential risk of self-reported measures are systematic measurement errors due to common method variance (CMV). As a result, correlations may be inflated or attenuated, in either case possibly leading to wrong conclusions. (Podsakoff et al., 2003; Conway & Lance, 2010; Favero & Bullock, 2015). Despite this risk, we consider self-reports appropriate for our study. A number of our variables (networking, collective motivation, career motive) focus on the opinion or motivation of participants. Variation in these variables reflects subjective judgments of participants and is not necessarily a source of measurement error (Favero & Bullock, 2015). Innovative behavior is sometimes measured by counting the number of successful innovations. However, such a measure only reflects a part of innovative behavior. Innovative behavior starts with an assessment of new developments or information and a decision how to respond. Next a plan can be presented, information may be passed through or nothing is done. The evaluations that underlie these decisions are only known to the middle managers themselves. Neither top managers, nor lower level managers are fully aware of middle managers assessment or innovative behavior and therefore we choose for self-reports to measure middle managers' innovative behavior.

To reduce the risk of common method bias, a personal invitation for an online survey was sent to all participants. In this way we could guarantee full anonymity to participants and assure that supervisors or peers had no access to the answers. The invitation was also used to explain that there were no right or wrong answers and that participants were free to express their own opinion. One objective of this explanation was to reduce the risk of socially desirable answers.

We also tested the results for evidence of CMV. Several tests to detect CMV are described in the literature, many of which do have theoretical drawbacks or limited efficacy. In a simulation study, Richardson, Simmering, and Sturman (2009) have investigated the characteristics of three tests in different settings. Their findings are that the CFA-marker technique (confirmatory factor analysis; Williams, Hartman, & Cavazotte, 2010) is the only test that works reasonably to detect CMV. This CFA-marker technique uses a latent marker variable to represent measurement effects. This marker variable shares measurement characteristics with the substantive variables but is otherwise uncorrelated. Testing for common method bias can be done by comparing the fit of two similar models, one with and one without influence of the marker on the correlation between the variables of interest. We have carried out this test for each of the four dependent variables, using the R-package Lavaan. The pairwise comparison of these models using chi-square difference tests leads to chi-square values ranging from 1.86 to 5.66, with six degrees of freedom. These values are smaller than the 0.05 chi-square critical value (12.59), meaning we find no evidence for the influence of common method bias on the correlation of variables we have researched. More details about this test can be found in the appendix to this chapter.

5.4 Results

Because the four innovative roles are clearly distinct (Floyd & Wooldridge, 1997), we estimated a different model for each role. To investigate the three hypotheses, we carried out a linear regression analysis. The results of the analysis can be found in Table 5.2.

Table 5.2 Regression outcomes for different dependent variables

	Championing	Facilitating	Synthesizing	Implementing
(Intercept)	0.47 (0.99)	0.25 (0.98)	0.61 (1.02)	1.56 (1.01)
Networking	0.36 (0.13)**	0.44 (0.13)**	0.42 (0.13)**	0.34 (0.13)*
Team motive	0.10 (0.11)	0.07 (0.11)	0.18 (0.11)	-0.01 (0.11)
Career motive	0.18 (0.08)*	0.19 (0.08)*	0.18 (0.08)*	0.09 (0.08)
Managerial Autonomy	0.12 (0.12)	-0.10 (0.12)	0.17 (0.13)	-0.05 (0.13)
Centralization of departmental decision making	0.01 (0.09)	0.00 (0.09)	-0.04 (0.1)	0.01 (0.09)
Gender	0.10 (0.23)	-0.08 (0.23)	-0.01 (0.24)	0.00 (0.24)
Education	0.18 (0.14)	0.20 (0.14)	0.11 (0.14)	0.16 (0.14)
Organizational position	0.16 (0.10)	0.14 (0.10)	0.07 (0.10)	0.30 (0.10)**
R^2	0.26	0.34	0.25	0.29
Durbin-watson	1.86	2.28	2.23	1.96
VIF-min	1.07	1.07	1.07	1.07
VIF-max	1.37	1.37	1.37	1.37
Shapiro-wilks Significance	0.35	0.86	0.21	0.61

Standard deviations n parentheses.
* = 0.05 and ** = 0.01 significance.

To justify the use of linear regression analysis, we tested common assumptions of linear regression. The Durbin-Watson test for autocorrelation in the residuals varies between 1.86 and 2.28, indicating that there is almost no autocorrelation. To test for collinearity, the Variance Inflation Factors (VIF) were calculated for estimated coefficients. These factors are all close to one and smaller than five, hence it can be concluded that there are no indications of collinearity. To test for the normality of residuals, Q-Q plots were visually inspected and showed no anomalies. Above this, Shapiro-Wilks statistics for testing of normality were calculated. The p values of these statistics are all well above 0.05 and there is no reason to doubt the assumption that residuals are normal distributed.

The championing, facilitating and synthesizing roles show similar results and appear to be comparable. In all models there is a highly significant and positive result for networking, varying between 0.34 and 0.44 (unstandardized). This clearly supports hypothesis 1. In all four models we could not find any significant influence of a teamwork motivation on innovative behavior. However, in the championing, facilitating, and synthesizing models, we found a clear influence of career motivations with a parameter around 0.18. In the implementing model we found no evidence of career motives affecting implementing behavior. The control variables showed no influence, apart from the organizational level positively influencing implementing behavior. This suggests that managers occupying higher positions are more involved in implementing strategies than lower-positioned managers.

5.5 Discussion

Our first hypothesis states that intraorganizational networking of a public manager leads to an increase of innovative behavior. Existing research on public managers' networking has shown the value of managerial networking for organizational performance by securing access to external resources and by improving internal coordination and consensus (Torenvlied et al., 2012). Managerial networking of public managers is considered particularly useful in dealing with external turbulence and problems (van den Bekerom, Torenvlied & Akkerman, 2016). However, the specific question whether managerial networking leads to increased innovative behavior (and thus induce increased performance), to the best of our knowledge, has never been researched in governmental settings.

Research on middle management in for-profit organizations has already shown that intraorganizational networking specifically can contribute to innovative behavior and so can contribute to increased performance (Pappas & Wooldridge, 2007). Our findings on hypothesis one clearly indicate that also in a public organization the networking behavior of public managers contributes to increased innovative behavior. One implication of this finding is that theories of middle managers' innovative behavior and strategic involvement that are developed in Western private companies (Floyd, Schmid, & Wooldridge, 2008), can be extended to a public management setting in a developing country. Though further research is necessary, it suggests that other causal mechanisms related to middle management may also be informative in public settings as well.

The second and third hypotheses of our study explore the motivations behind public managers' networking and their effect as additional factors on innovative behavior. We reject the hypothesis that a collective motive influences innovative behavior. However, in our case study we found evidence supporting the hypothesis that career-driven motivations for networking do influence (three of the four) innovative roles. Only for the implementing role we found no evidence of influence of career-driven networking motivation. It has to be noted that the implementing role is different from the other three roles in being oriented at a rather straightforward implementation of top management's strategies. The other three roles—championing new initiatives, synthesizing information and facilitating adaptability—all involve own initiative, as well as clear judgment.

An explanation for these results might be the politico-administrative specifics of our case. As mentioned above, in Milpa Alta managerial positions are often appointed based on discretionary criteria. As a result, managers' behavior may not necessarily be primarily aimed at meeting public goals or the successful implementation of policies, but instead may be mainly motivated by furthering individual career opportunities. This does not discard more normative public service ideas, which claim that public managers strive for higher collective goals in order to create public value, but rather supplements them by stressing the importance of career incentives in the absence of institutions that reduce public officials' career uncertainty.

The previous also suggests that a certain hierarchy of motivations may be at play. A primary goal is the public manager's career goal. Only after this goal is secured and a reasonable career perspective is guaranteed, other higher order goals such as creating public value or being a team player can become salient in inducing innovative behaviors. Studies on bureaucracies in the public sector (Evans & Rauch, 1999; Rauch, 2001) show that offering civil servants rewarding and long-term careers leads to increased corporate coherence, a long-term focus on public goals and reduced likelihood of unethical behavior. If such a career perspective is not offered, individual motives and interests become more prevalent. This shows that in both social network analysis and in public management, the specific context influences the relative importance of individual versus collective goals. In our case there is no long-term career perspective for public managers and not a strong collective orientation. This supports our findings that a career motive is more influential than a collective motive in explaining public managers' innovative behavior.

The career motive for networking correlates with three of the four innovative roles, championing new initiatives, synthesizing information, and facilitating adaptability. It does not correlate with the fourth innovative role, implementing deliberate strategies. Rather unexpectedly we found that hierarchical position positively influences this role. Though one significant outcome in a small sample is always a reason for caution, these results seem to support our previous discussion. Higher-ranked public managers already have achieved a successful career, so this motive becomes less important for them. They also have higher power to execute plans; therefore, it is plausible that higher-ranking public managers can more often than lower-ranking managers take on the implementation of policies and innovations.

Clearly, additional research is needed to disentangle some of issues mentioned above. However, our data and results do suggest that intraorganizational networking and motivations arising from the institutional characteristics of the public organization may be important in explaining public managers' innovative behavior. Results also imply that the relation between networking and performance may run, in the case of some public organizations, through innovative behaviors and the relative importance of career incentives.

Appendix 5.1 Questionnaire items

The scales for measuring innovative work behavior roles are from Floyd and Wooldridge (1996) and are slightly adapted from the original publication (Floyd & Wooldridge, 1992). Additionally, we used the following items:

1. In comparison to your coworkers in the department how much personal contact do you have with coworkers from your own department? (0 = much less, 4 = much more)?
2. Being a team player is considered crucial for the success of the department. (0 = strongly disagree, 4 = strongly agree)?
3. “Who knows you and whom you know” is an important factor to develop a career in this department. (0 = strongly disagree, 4 = strongly agree)?
4. Regarding daily activities, how much autonomy do middle managers have? (0 = no autonomy, 4 = much autonomy)?
5. How centralized is the decision-making process in your department? (0 = very centralized, 4 = very decentralized)?
6. What is your gender? (0 = male,1 = female)?
7. In which year were you born?
8. What is your last finished educational level? (2 = secondary school, 3 = high school 4 = bachelor’s degree, 5 = master’s degree, 6 = doctoral degree)?
9. What is your hierarchical level in the organization? (0 = Head of unit, 1 = Deputy director, 2 = Director, 3 = Director General)?

Appendix 5.2 CFA-marker tests for common method variance

In this appendix we describe the results of the CFA-marker test for common method variance. A detailed description of the test procedure can be found in (Williams, Hartman, & Cavazotte, 2010). As marker we selected the variable *change as source of trouble*, a self-reported variable based upon three items (Continuous changes in public policy priorities are an important source of trouble; Lack of personnel continuity [turnover] is a source of trouble; Continuous changes in the leadership of the organization are an important source of trouble). Theoretically this marker is not likely to be correlated to either of the substantive variables and observed correlations are also low.

The CFA-marker technique requires the specification of five different latent variable models. The models were estimated with the R-package lavaan version 0.6-3. In the first (CFA) model, loadings from the marker indicators on the marker variable are estimated, as well as correlations between marker variable and all substantive variables. Loadings from the marker variable to the substantive indicators are fixed to zero. For the single-item constructs (networking, being a team player, and career motive) we artificially inserted latent variables for these constructs that were loaded on their single item with a coefficient fixed to 1.

In the second (Baseline) model the substantive variables are still correlated to each other, but the marker variable is orthogonal. The loadings from the marker indicator on the marker variable and the unstandardized error variances of the marker are fixed to the estimates obtained from the CFA model. This Baseline model serves as a reference for further model specifications.

The third Method-C (Constrained) model is similar to the Baseline model, but has additional factor loadings from the marker variable to the indicators of the substantive factors. These loadings are constrained to be equal. A comparison of the Method-C model to the Baseline model provides a test of the assumption that the marker has equal effects on the substantive indicators. Table 5.3 shows for the several models Chi-squares ranging from 21.78 to 27.81 with df = 4, all exceeding the 0.05 critical value of 9.49. Hence the null-hypothesis of equal loadings influence on all indicators is rejected for all models.

Table 5.3 CFA-marker method comparison tests

	χ^2				df	χ^2 -0.05 critical value
	Champ	Fac	Syn	Imp		
Baseline vs. Method-C	25.95	27.81	21.78	26.93	4	9.49
Method-C vs. Method-U	29.71	26.46	28.70	16.91	7	14.07
Method-C/U vs. Method-R	1.86	5.00	5.66	3.95	6	12.59

The fourth Method-U (Unconstrained) model is similar to the Method-C model, the difference is that the loadings of the marker on the substantive indicators are no longer constrained to be equal. Comparing the Method-U model to the Method-C model tests the assumption that the marker factor has unequal loadings on the substantive indicators. In the four models we find Chi-squares ranging from 16.91 to 29.71 with 7 degrees of freedom all exceeding the 0.05 Chi-square critical value of 14.07, and we conclude that the Method-U model performs best in modeling marker variance.

The fifth and final Method-R (Restricted) model is identical to Method-C or Method-U models, but now the correlations between the substantive variables are fixed to their values from the baseline model. A comparison of the Method-R to the Method-U model, provides a test for method bias between the substantive variables that is due to the marker. As can be seen from table 5.3, the Chi-squares range from 1.86 to 5.66, df = 6, and are all smaller than the critical value of 12.59, and therefore provide no support for the assumption of method bias.

6 Conclusion

The four studies in this dissertation address the overall question why some middle managers exhibit more innovative work behavior than others. One study is methodological in nature and investigates strategies to handle a frequently occurring problem in longitudinal social network studies in real life organizations: How to deal with missing attribute data? The other three chapters are empirical studies that explore different sets of conditions that may play a role in innovative work behavior of middle managers: (1) Do middle managers have sufficient autonomy to innovate? (2) Do middle managers possess the necessary personal characteristics to be innovative? (3) Does the social network facilitate or constrain middle managers' innovative behavior? The empirical studies are set in three different contexts, students at a business school who will likely become middle managers in the near future, an international multi-site company with a complex organizational structure that operates over a hundred leisure parks, and a municipality in Mexico City. This concluding chapter summarizes the main findings and discusses implications for future research.

Study 1 Methods to deal with missing data

Longitudinal social network data sets based on real-world organization studies often contain missing data. Up until now, relatively little is known how to address this problem, and in particular research into the impact of missing attribute data (behavior or other individual characteristics) in longitudinal network data is scarce. In the first study, several methods to deal with missing behavior data for stochastic actor-oriented models were investigated. Stochastic actor-oriented models are designed to analyze the co-evolution of network relations and individual attributes. In a simulation study based on four real-life datasets, we used three criteria to compare seven alternative methods to deal with missing behavior data: model convergence, parameter bias, and parameter coverage. The default method in the RSiena software (Ripley et al., 2017) was found to outperform the alternative methods. This simulation study provided an important methodological foundation for correctly interpreting the findings of the three substantive chapters in this dissertation. More specifically, since we did not find significant influences of social network on innovative behavior in these substantive chapters, this study on missing data shows that it is highly unlikely that missing data have caused this insignificance.

Study 2 The business school, students as future managers

Study 2 used data from two cohorts of international students in a Dutch business school to investigate the first two research questions: The influence of social networks and personal characteristics on innovative work behavior. The dependent variable in this study was *personal initiative*, which was used as proxy of innovative work behavior. Table 6.1 summarizes the hypotheses, Figure 6.1 visualizes the underlying conceptual model.

Table 6.1. Hypotheses for the business school case (2 cohorts of 42 and 47 students)

Hypothesis	Outcome
H1 Independent personality effect model The higher an individual's (a) conscientiousness or (b) openness to experience, the higher the level of personal initiative.	Yes (H1a)
H2 Independent network effect model The higher an individual's structural autonomy, the higher this individual's level of personal initiative.	No
H3 Network mediation model The higher an individual's (a) conscientiousness or (b) openness to experience, the higher this person's level of structural autonomy.	No
H4 Network outcome model The higher the level of an individual's personal initiative, the higher this person's level of structural autonomy.	No

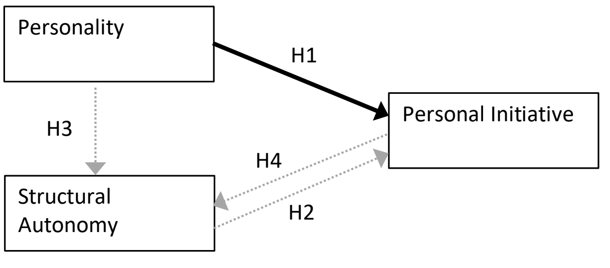


Figure 6.1 Conceptual model of the business school students' case. A bold line indicates an accepted hypothesis, while a dotted line means the hypothesis is rejected.

Of the four hypotheses, significant results were obtained only for H1a: Personality (conscientiousness) positively influences personal initiative. No evidence was found for significant influence of the social network (friendship) on personal initiative, neither did we observe that social network position was influenced by personality or personal initiative. In our discussion we described that some specific network characteristics as well as the context of the network may have led to these outcomes.

First, group size might be relevant. The effectiveness of brokerage increases with the number of disconnected groups. The sample sizes of both studies were relatively small (*n* = 42 and *n* = 47) and with each of the two cohorts being further divided into two subgroups, brokerage hardly ever involved bridging otherwise disconnected groups. This may limit the relative benefits accruing to an individual broker.

A second possible explanation is that developing personal initiative may not be the primary goal of young students and therefore a network position is not seen as a means to increase personal initiative. The latter explanation would be in line with the findings of a meta-analysis (Fang et al., 2015), according to which brokerage only works in settings in which early access to information is crucial for performance, for example, for managers in knowledge intense industries like the banking sector.

Study 3 A public-listed international Leisure Company

Study 3 analyzed longitudinal sociometric data from a complex international multi-site networked organization. It investigated to what degree four dimensions of middle manager autonomy jointly affect middle managers' innovative work behavior: Job design, personal network structure, distance to the head office, and the degree of formal organizational constraint. Table 6.2 summarizes the hypotheses, Figure 6.2 visualizes the underlying conceptual model.

Table 6.2 Hypotheses for the leisure company case (110 middle managers).

Hypothesis	Outcome
H1 Job Autonomy The higher a middle manager's job autonomy, the higher a middle manager's innovative work behavior.	No
H2 Social network The higher a middle manager's structural autonomy, the higher a middle manager's innovative work behavior.	No
H3 Park Type The higher the constraint caused by type of park, the lower a middle manager's innovative work behavior: innovative work behavior will be highest in managed parks, and lowest in franchised parks.	No
H4 Spatial distance The larger the spatial distance of a middle manager's location to the organization's headquarter, the higher a middle manager's innovative work behavior.	No

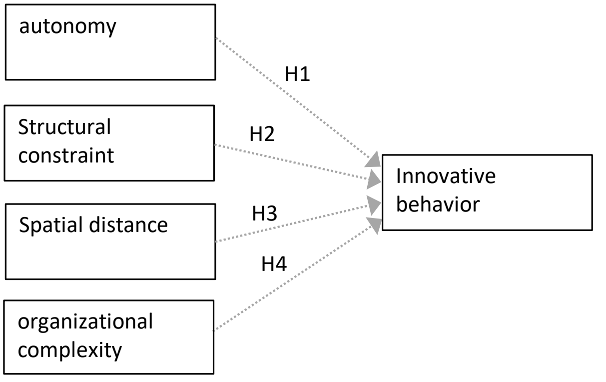


Figure 6.2 Conceptual model of Leisure Company case. A bold line indicates an accepted hypothesis, while a dotted line means the hypothesis is rejected.

We found no significant effects, which suggests that at least in this organization there is no systematic association between autonomy and innovative work behavior of middle managers. The following factors might explain the absence of significant results. First, according to in-depth interviews with some middle managers, a wide variety of factors such as tenure, prior experience, or local differences affect middle managers' innovative behavior. It seems these factors may obfuscate the potential impact of the social network. This suggests that just as in the case of the students, context is an important factor for the influence of social network.

Second, the networks are characterized by a high density, with managers having on average 36 peers (out of 110) to which they turn for advice. This high density may be due to the fact that many middle managers have been with the firm for many years and know each other very well. As a result of this strongly collaborative pattern, there may be hardly any opportunity to benefit from bridging structural holes, as earlier research has shown, actors benefit most from bridging structural holes when collaboration in the network is low (Soda, Stea, & Pedersen, 2019), and the value of bridging relationships decreases with the age of the ties (Baum, McEvily, & Rowly, 2012).

A third factor is the fuzzy boundary of the network. Organizational boundaries have become fluid and middle managers have probably more contacts outside than inside their organization. This makes it difficult to ascribe behavioral changes to changes in the internal middle manager network.

Study 4 Mexico City municipality

Study 4 used a cross-sectional survey among 64 managers of a Mexican municipality in order to investigate to what degree managerial networking, individual career motivation, and collective public orientation leads to increased innovative behavior in a public setting. Table 6.3 summarizes the hypotheses, Figure 6.3 visualizes the underlying conceptual model.

Table 6.3 Hypothesis in Mexican City case (64 middle managers).

Hypothesis	Outcome
H1 Networking A higher level of a public manager's intra-organizational networking leads to an increase of his innovative behavior.	Yes
H2 Collective goals Higher salience of collective goals is related to a higher level of innovative behavior.	No
H3 Individual career goals Higher salience of career goals is related to a higher level of innovative behavior.	Yes

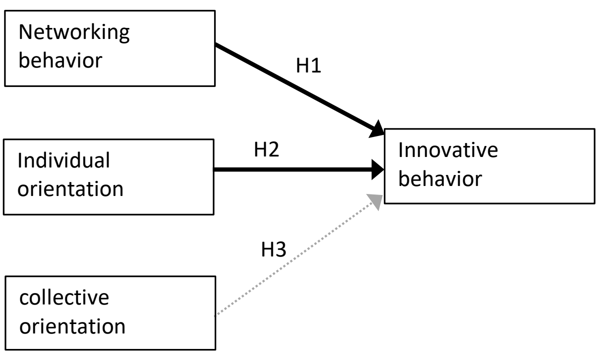


Figure 6.3 Conceptual model of Mexican municipality case. A bold line indicates an accepted hypothesis, while a dotted line means the hypothesis is rejected.

We found significant influence of networking behavior on innovative work behavior and support for additional influences of individual career motives, but no evidence for collective motivations. The outcomes may be explained by the specific context, in which managerial positions are often filled on discretionary and political criteria instead of professional merit, and job security is absent. As a result, the individual career motive to secure job positions or career is highly relevant for middle managers.

The findings also suggest there is a similar contextual influence of individual versus collective orientation in public sector studies and in social network studies. Studies on bureaucracies in the public sector (Evans & Rauch, 1999; Rauch, 2001) show that offering civil servants rewarding and long-term careers leads to increased corporate coherence (higher and middle management sharing the vision, mission and goals of the organization) and a long-term focus on public goals. If, like in our study, such a career perspective is not offered, individual motives and interests become more prevalent. Similarly, in social-network theory, the brokerage mechanism is an individualistic mechanism, while the cohesion mechanism has a collective orientation based upon the embeddedness of the individual in the group. Brokerage is often found in organizations in which early access to new information is crucial, like in financial companies (Fang et al., 2015), whereas cohesion is more important in high commitment organizations (Xiao & Tsui, 2007). In the Mexican municipality under investigation, there is no secure long-term career perspective for middle managers and not a strong collective orientation. Middle managers appear to be mainly motivated by their own benefit when aiming for high performance and use networking to achieve this goal. This suggests that the prevailing individual orientation is related to a positive influence of networking behavior on performance.

Final conclusions

Summing up, the following answers can be given to the three questions formulated in the introductory chapter.

The first question addresses the potential influence of social network position on innovative work behavior. Our results do not show any relation between the level of network constraint in a personal network, and innovative work behavior. A reason may be that a potential influence of social network position is obfuscated by other factors. Our findings support earlier research that brokerage mechanisms work well in in an individual culture, but less in a collective and collaborative culture.

The second question addresses individual characteristics. Our findings suggest that personal characteristics play a role in understanding innovative work behavior. In particular personality (conscientiousness) and goal orientation (career focus) influence the level of innovative work behavior.

The third question focusses on the concept of autonomy. It is commonly assumed that a certain level of autonomy in job design is a necessary condition for a middle manager to be innovative. We expanded this concept of autonomy to investigate if it would lead to increased understanding of innovative work behavior, but found no evidence.

In addition, the problem of missing behavior data in longitudinal network studies was researched. The findings suggest that SIENA's default method to deal with missing data outperforms other methods.

The studies in this dissertation show that explaining innovative work behavior of middle managers may be more complex than previous research would suggest. Unlike earlier studies (Kuratko et al., 2005), we did not find a relation between a variety of autonomy dimensions and innovative work behavior. Neither did we find a systematic association between network position and innovative work behavior. The only dimension that was found to significantly increase innovative work behavior are personal characteristics: personality (conscientiousness) and an individual motive for networking.

Our analysis of missing data suggests that the estimates of effect parameters in stochastic actor-oriented models were not systematically influenced by data availability. This suggests that the absence of significant network effects in our three studies may not be due to missing data. Instead, it may be the specific characteristics of the networks under investigation which may prohibit the exploitation of structural holes: Opaque network boundaries, high network density, and small network sizes.

In the case of international students, social networks were dense and cohesive, and bridging positions had little added value for their performance. In the case of the leisure company, the high number and age of ties reflect a dense pattern of collaboration and suggest that brokerage is less important for performance. Here too, early access to new information is also not necessarily crucial for performance. In the case of the Mexican municipality, a strong individual goal orientation suggests that cohesion and collaboration are less important, and networking serves mainly to realize personal goals. Middle managers appear to be mainly motivated by their own benefit when aiming for high performance and use networking to achieve this goal. This suggests that a prevalence of individual goal orientation is related to a positive influence of networking behavior on performance and that a collective and collaborative culture will reduce a potential constraining effect of network position on performance and innovative behavior.

These findings support claims in the social-network literature that organizational context conditions influence the relevance of brokerage mechanisms. In a meta-analysis based on 138 samples, Fang et al. (2015) concluded that much of the evidence supporting the claims related to brokerage mechanisms comes from companies for which timely access and control of information is a crucial success factor. As Baum, McEvily, and Rowley (2012) show, exploiting brokerage positions works well with young ties in rapidly changing environments where novelty and uniqueness quickly lose their value. However, once ties have grown older, closure mechanisms become stronger.

The final question of the thesis, based upon the relatively unexplored application of longitudinal network analysis on organizational behavior, was how useful or suitable network analysis is for research in organizational behavior. Though it is obvious that this research is inadequate to answer this question in a conclusive manner, at least some cautious remarks can be made, including some suggestions for further research. This final reflection can be split into empirical and theoretical considerations

Starting with the empirical considerations, we observed that missingness in data not necessarily leads to problems in stochastic actor oriented modelling. It must be stressed this does not imply that researchers can go easy on data collection in network studies. Contrary, sociometric studies demand a collection of all data in a network, including network relations and relevant attributes. The data collection is further complicated by the non-anonymous character of the data collection and the need for repeated sampling in longitudinal studies. As has been experienced in this research, even with the full support of the organization, it will often be difficult to realize complete sampling in organizational studies.

What we did witness is that the influence of network position on innovative behavior is obfuscated by other factors. This seems surprising at first, as social-network literature in general has delivered a strong case about the relation or co-evolution between network position and behavior in general. Perhaps this strength might be the reason we didn't find a relation between network position and innovative behavior. Behavior consists of a multitude of elements that are not necessarily correlated with each other. A network position will then never be able to explain all these elements of behavior and perhaps only those behavioral elements that are important to the person are potentially related to network position. This might explain the lack of significance we found. This suggests that factors other than network position might be more relevant to innovative work behavior.

Related to this is the problem of opaque boundaries (Cohen & Nair, 2017). Network studies are based on stable groups with a clear boundary. It is clear who belongs to a group and who doesn't. In many cases this works fine in, for example, classrooms or socially isolated groups. However, in real life firms, identifying a group is not always straightforward. Cooperation partners, joint ventures, investors, preferred suppliers are just a few examples of partner organizations that are closely integrated in operations and individual members of such organizations are likely to exert influences similar to network effects. Similarly, within an organization a network of peers like middle managers discards network effects coming from other organizational layers like supervisors or top management (Gould & Fernandez, 1989; Shi, Markoczy, & Dess, 2009).

Taken together, the difficulties in collecting the data, a myriad of other factors that might obfuscate network influences and difficulties in defining relevant network boundaries together create substantial empirical challenges in applying network analysis in management research.

Besides these empirical issues, there are also some theoretical considerations regarding the suitability of social network analysis for management research in general and middle manager's innovative work behavior in particular.

In the thesis, network effects are based on the brokerage principle in which a personal network is seen as an enabling or constraining factor. We've seen that this competitive brokerage mechanism does not work in the studies because collaboration is a strong feature in the organizational culture. This is supported by research of, for example, Soda, Stea, and Pedersen (2019), who in an empirical study found that actors benefit most from bridging structural holes when collaboration in the network is low, while in a closed network, collaboration will positively influence creativity. An alternative to the brokerage mechanism is to focus on indegree effects as for example Fang et al. (2015) and Wong and Boh (2014) did. This might be a recommendation for further research.

Brokerage is purely structure-oriented and among others based on the rather strong assumption that all relations are identical and that all individual actors are equally able to take advantage of their network position (Moran, 2005). Such a strong assumption is in line with the graph-theoretical foundations of network analysis (Wasserman & Faust, 1994). Obviously, relations are not identical and hence will also differ in conveying influence. Little is known how such diversity in tie-strength might be of influence.

Taken together, the results of this thesis suggest that applying social network analysis to organizational behavior is less straightforward than sometimes expected. Not all challenges can be solved, for example the problem with data collection or boundary identification are difficult to solve. Further research is needed into alternative brokerage mechanisms, the influence of context, and in methods that take heterogenous tie-strength into consideration.

Summary

This thesis focuses on the question why some middle managers are more innovative than others. To answer this question, several theoretical explanations for innovative behavior in general have been explored. In particular, this thesis focuses on the following three drivers of innovative behavior: The enabling or constraining influence of middle managers' social network position, the personal characteristics of middle managers, and the discretionary space or autonomy of middle managers to innovate.

It is increasingly recognized that middle managers play a crucial role in innovation. They are not only responsible for supporting top management in drafting and executing corporate strategies, but also for providing input for new strategies. Middle managers are familiar with market developments and contribute to an organization's success by pioneering new initiatives and responding to changes in an organization's environment. At the same time, the role of middle managers has become more complex. Delayering of organizations, combined with the increased information available to top management, has resulted in increased control of top management over middle managers, reduced middle managers' scope to make decisions in general, and reduced their ability to realize innovations. Organizational structures have become increasingly complex, creating an opaque environment for middle managers and making it more complicated for middle managers to operate. It is in this complex and difficult setting, in which middle managers are increasingly held responsible for realizing innovations, that three factors that might drive middle managers' innovative work behavior are researched.

These factors originate in three different perspectives, a sociological perspective, an individual or personality perspective, and an organizational perspective. The first (sociological) factor is related to the core role of middle managers: Processing and conveying information. Due to their central and pivotal position in the organization, middle managers have a strong insight in both operational and corporate developments. In addition, they maintain intense relations with an extensive set of peers and external partners. This suggests that the competence of a middle manager to exploit the information in his or her social network might be a strong factor behind innovative work behavior. Following Burt's theory of social capital, we have explored how a structural network position may enable or constrain a middle manager's innovative work behavior.

Next to an external social network, individual characteristics are also known to affect behavior in general. In particular some personality traits (e.g., conscientiousness) positively influence innovative behavior. In this thesis, the individual personality perspective is not considered contrary but rather supplementary to the network approach. The network

position of a middle manager may provide certain information or other advantages, it still depends on personal traits if a middle manager is able to capitalize on those advantages.

Thirdly, from an organizational perspective, one must consider that nowadays middle managers are often found in complex organizations. Middle managers often operate in multi-site organizations at a certain spatial distance from head office and peers. Middle managers also face complex cooperative structures like franchising, joint ventures, and other organizational structures. As a result, a middle manager is faced with multiple stakeholders, potentially with different interests. Taken together this implies that modern organizational structures potentially influence the discretionary space and autonomy of middle managers, and so affect innovative work behavior.

To investigate these questions, three empirical studies have been conducted, each focusing on one or more of those questions. These empirical studies are set in three different contexts, students at a business school who will likely become middle managers in the near future, an international multi-site company with a complex organizational structure that operates over a hundred leisure parks, and the administration of a municipality in Mexico City.

These research questions have led to the use of stochastic actor oriented modelling to model the longitudinal co-evolution of behavior and social network position, implemented in the SIENA software. This is a rather new method in management research and collecting the necessary complete longitudinal data sets proved to be a major challenge. To address this missing data challenge, an additional simulation study, using four real-life data sets, was conducted to establish an optimal strategy to deal with missing attribute data in longitudinal network studies.

The research resulted in the following outcomes. First, the results showed no relation between network constraint and innovative behavior. We ascribe this to contextual factors such as a collaborative organizational culture and a cohesive network. Additional interviews also indicate that potential network influences might be obfuscated by other factors. The findings also suggest that personal characteristics play a role in understanding innovative work behavior. In particular personality (conscientiousness) and goal orientation (career focus) positively influence the level of innovative work behavior. In addition, we found no evidence that autonomy due complex organizational structures or multi-site operations affects innovative work behavior of middle managers.

Concerning strategies to deal with missing attribute data in longitudinal network studies, we found that the default SIENA method performs satisfactorily as a strategy to properly address this missingness. This suggests that the lack of significant results is unlikely to be due to missingness in the data.

To conclude, middle managers' innovative work behavior is likely to be influenced by individual differences in personality and goal orientation, finding influences of network position is difficult also due to some empirical challenges, and influences of organizational factors related to autonomy could not be identified.

中文摘要

本论文重点研究为什么一些中层管理者比其他中层管理者在工作中更具创新性。 为了研究这个中心问题，本文作者探索了一系列创新行为理论。 本论文特别关注创新行为的以下三个驱动要素：中层管理者社交网络地位的实现或约束影响，中层管理者的个人特征，以及中层管理者自主创新的自由空间或自主权。

人们越来越认识到中层管理人员在组织工作创新中所起的至关重要的作用。中层管理人员不仅负责支持高层管理人员制定和执行公司战略，他们还负责为新战略提供意见。中层管理人员熟悉市场发展，并通过率先提出新的举措和应对组织环境的变化来为组织的成功做出贡献。同时，中层管理者的角色变得越发复杂：组织层面数量的减少，再加上高层管理人员可用信息的增加，导致高层管理人员对中层管理人员的控制增强，这意为着中层管理人员做决策的范围减小，也降低了他们实现创新的能力。组织结构变得越发复杂，为中层管理人员创造了一个不透明的环境，并使中层管理人员的运营变得更加具有挑战性。在这个复杂而极具挑战性的环境中，中层管理人员却担着实现创新的责任。也是在这个环境中，本论文研究了可驱动中层管理人员创新工作行为的三个因素。

这三个因素源自三种不同的观点：社会学观点，个人或人格观点，和组织观点。 第一个（社会学）观点与中层管理者的核心角色息息相关：处理和传达信息。 由于中层管理人员在组织中居于中心地位，他们对运营和发展都拥有深刻的见解。 此外，他们与众多同行和外部合作伙伴保持着密切的联系。 这表明，中层经理和中层管理者利用其社交网络中信息的能力可能是创新工作行为的重要因素。 遵循伯特（Burt）的社会资本理论，我们探索了结构化网络职位如何拓展或束缚中层经理的创新工作行为。

第二，个人特征通常也会影响行为，特别是某些人格特质（例如，尽责性）会积极影响创新行为。 在本论文中，人格被视为对网络观点的补充，而并非与其相对立。 中层管理人员的社交网络位置可能会提供给他们特殊的信息或其他的优势，但是中层管理人员是否能够利用这些优势仍然取决于他们的个人特质。

第三，从组织的角度来看，必须考虑到当今中层管理人员经常工作在复杂的组织中。中层管理人员通常在多站点组织中运作，与总部和同事之间都有一定的距离。 中层管理人员还面临着复杂的合作结构，例如特许经营机制，合资企业和其他组织结构。所以中层经理面临着多种利益相关者，而这些利益相关者可能有着不同的利益目标。 综

上所述，这意味着现代组织结构可以影响中层管理人员的自由裁量空间和自主权，从而影响他们的创新工作行为。

为了调查这些问题，本论文作者进行了三项实证研究，每项研究都集中于这些问题中的一个或多个层面。 这些实证研究是在三种不同的背景下进行的：可能会在不久的将来成为中层管理人员商学院的学生，一家国际性的多站点公司（其组织结构复杂，拥有超过100个休闲公园），和墨西哥城的市政府。

这些研究数据的分析使用了SIENA软件，面向随机行为者的建模来对行为和社交网络位置的纵向协同建模。 这是管理研究中的一种相当新型的研究和数据分析方法，而收集必要的完整纵向数据成为了一个重大挑战。 为了解决这一缺失数据的挑战，我们首先进行了一项额外的模拟研究，该研究使用了四个真实数据集，以建立一种在纵向网络研究中处理缺失属性数据的最佳策略。

本论文研究得出以下结果：首先，网络约束与创新行为之间并无关联性。 我们将此发现归因于环境因素，例如协作组织文化和凝聚力网络。 额外的采访还表明，其他因素可能会掩盖潜在的网络影响。研究结果表明，个人特征在理解创新工作行为中起着作用。 特别是个性（责任心）和目标取向（事业重点）对创新工作行为的水平产生积极影响。 此外，我们没有发现证据表明由于复杂的组织结构或多站点运营而产生的自主权会影响中层管理人员的创新工作行为。

关于在纵向网络研究中处理缺失属性数据的策略，我们发现SIENA软件中的默认方法可以令人满意地正确解决此数据缺失问题。 这表明缺少显著结果的原因不大可能是由于数据缺失所导致的。

本论文的结论如下：中层管理人员的创新工作行为很可能受到个性和目标取向的个体差异的影响。由于实践研究方法挑战，很难找到网络位置对于创新行为的影响，与自主性相关的组织因素对于创新行为的影响也不能被确认。

Samenvatting

Centraal in dit proefschrift staat de vraag waarom sommige middenmanagers meer innovatief zijn dan anderen. Het onderzoek naar deze vraag heeft verschillende theoretische gezichtspunten gehanteerd. Meer specifiek richt deze thesis zich op drie verklaringen van innovatief gedrag: De mogelijkheden en beperkingen die het sociale netwerk van een middenmanager biedt, de persoonlijke kenmerken van een middenmanager, en de autonomie die een middenmanager heeft om te innoveren.

De cruciale rol van middenmanagers in innovatie wordt steeds meer herkend. Zij zijn niet alleen verantwoordelijk voor ondersteuning van topmanagement bij het opstellen en uitvoeren van strategieën, maar leveren ook input voor nieuwe strategieën. Middenmanagers zijn bekend met ontwikkelingen in de markt. Zij dragen bij aan het succes van een organisatie door nieuwe initiatieven te nemen en te reageren op veranderingen in de externe omgeving. Tegelijkertijd is de rol van middenmanagers complexer geworden. Het verminderen van managementlagen, gecombineerd met een betere beschikbaarheid van informatie voor topmanagers, heeft ertoe geleid dat topmanagers meer controle hebben over middenmanagers. De autonomie van middenmanagers om beslissingen te nemen en innovaties te realiseren is daardoor genomen. Organisatorische structuren zijn steeds complexer geworden en maken het voor middenmanagers soms moeilijk opereren. In dit proefschrift is onderzoek gedaan hoe de drie eerdergenoemde factoren het innovatief gedrag van middenmanagers bepalen.

Deze factoren zijn op drie verschillende perspectieven gebaseerd, een sociologisch perspectief, een individueel of persoonlijkheidsperspectief, en een organisatorisch perspectief. De eerste (sociologische) factor houdt verband met de belangrijke taak van middenmanagers: het verwerken en doorgeven van informatie. Door hun centrale positie in organisatie hebben middenmanagers een scherp inzicht in zowel operationele als strategische ontwikkelingen. Bovendien onderhouden ze intensieve contacten met andere middenmanagers en externe partners. Dit suggereert dat de structuur van een sociaal netwerk mogelijk invloed heeft op innovatief gedrag. In navolging van Burt zijn theorie over sociaal kapitaal is onderzocht hoe een structurele netwerkpositie innovatief gedrag mogelijk maakt of juist beperkt.

Behalve door een extern sociaal netwerk wordt in het algemeen gedrag ook bepaald door individuele kenmerken. Meer specifiek hebben persoonlijkheidskenmerken zoals consciëntieusheid een positieve invloed op innovatief gedrag. In dit proefschrift wordt het persoonlijkheidsperspectief niet als tegengesteld maar juist als aanvullend gezien met betrekking tot de netwerkbenadering. Want ook al bevat de netwerkpositie van een

middenmanager een potentieel voordeel, het zijn de individuele eigenschappen die bepalen of hij/zij hier gebruik van weet te maken.

Als derde factor richt het organisatieperspectief zich op de complexiteit van moderne organisaties. Middenmanagers opereren vaak in organisaties met meerdere locaties die zich op zekere afstand van het hoofdkantoor bevinden en in complexe samenwerkingsverbanden zoals franchising of joint ventures. Als gevolg hiervan worden middenmanagers vaak geconfronteerd met verschillende belangen van meerdere stakeholders. Dergelijke complexe structuren beïnvloeden de autonomie en daarmee het innovatief gedrag van middenmanagers.

Om deze vragen te onderzoeken zijn er drie empirische studies uitgevoerd die zich elk op één of meer van deze vragen richten. Elke empirische studie is in een andere context uitgevoerd: Studenten van een managementopleiding die zeer waarschijnlijk een positie als middenmanager zullen vervullen in de nabije toekomst, een internationaal bedrijf met een complexe organisatorische structuur en meerdere locaties dat meer dan honderd vakantieparken exploiteert, en het bestuur van een gemeente in Mexico City.

Om de onderzoeksvragen te beantwoorden is er gebruik gemaakt van Stochastic Actor-Oriented Models waarmee de longitudinale co-evolutie van gedrag en sociale netwerkpositie gemodelleerd kan worden. Deze voor de bedrijfskunde betrekkelijk nieuwe methode is geïmplementeerd in de SIENA-software. Het verzamelen van de benodigde complete longitudinale data is in de praktijk vaak lastig te realiseren. Om dit probleem op te lossen is er, gebaseerd op vier bestaande datasets, een additionele simulatiestudie uitgevoerd. Het doel van deze simulatiestudie was het bepalen van een optimale strategie voor het omgaan met ontbrekende attribuut data in longitudinale netwerkstudies.

De onderzoeken hebben de volgende resultaten opgeleverd. Ten eerste is er geen relatie gevonden tussen netwerkpositie en innovatief gedrag. Mogelijke verklaringen liggen in de context, zoals een organisatiecultuur waarin samenwerken belangrijk is of een sterk geïntegreerd en samenhangend netwerk. Aanvullende interviews geven ook aan dat een potentieel effect van netwerkpositie mogelijk ondersneeuwt door andere factoren. De uitkomsten suggereren dat persoonlijke kenmerken een rol spelen bij het verklaren van innovatief gedrag. In het bijzonder persoonlijkheid (consciëntieusheid) en doeloriëntatie (carrièrefocus) hebben een positief effect op innovatief gedrag. Er is geen bewijs gevonden voor de hypothese dat complexe organisatorische structuren of meerdere locaties innovatief gedrag beïnvloeden.

Voor wat betreft de vraag naar een strategie voor ontbrekende attribuut data in longitudinale netwerkstudies vonden we dat de default SIENA-methode voldoende presteert. Dit betekent dat het ontbreken van significante uitkomsten in de studie waarschijnlijk niet het gevolg is van ontbrekende data.

Samenvattend: De resultaten suggereren dat innovatief gedrag van middenmanagers waarschijnlijk wordt beïnvloed door individuele verschillen in persoonlijkheid en doel-oriëntatie. Potentiële invloeden van netwerkpositie zijn niet gevonden. Invloed van organisatorische factoren die aan autonomie zijn gelieerd kon niet worden vastgesteld.

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Acknowledgements

One of the final parts of a thesis is looking back at the process, implicitly asking the question if it was worth the effort. Many people claim that pursuing a PhD, and in particular a part-time PhD, is a lonely affair. That may be true at some occasions. But the moments where I could share ideas and questions with others are much stronger on my mind. Thanks to all those people, it was a deeply rewarding experience.

First of all, I must thank Rafael Wittek. Our cooperation started with two conversations, which convinced you to ad my project to your extremely busy workload. I am still grateful for that first moment of trust. Since that moment I was certain that I would finish this project. Those two conversations were followed by an intense series of discussions that led to a strong foundation for the research. This combination of trust and support, provided me the opportunity to follow my own path, to learn what I needed to learn, and to finish this project. Thanks for being such a great role model.

Similarly, I must thank Mark Huisman. We have cooperated intensely and I've learned a lot from you. We easily understood each other. Our meetings taught me there must be something like an econometrician's DNA. We hardly ever discussed formula's, but focused on the ideas behind them. That's how you explained stochastic actor oriented modelling to me. It was a huge pleasure to work with you. Thanks for your cooperation and your support.

Gabriël Anthonio played an important role in the background. I remember you saying a long time ago how you enjoyed facilitating researchers. At some moments your interventions were crucial. Besides that, we had many interesting conversations about science, philosophy, life, and whatever occupied our minds. Those conversations helped me strongly to rethink and define the boundaries of my research.

During a certain period, I had the privilege to cooperate closely with Fernando Nieto Morales. Apart from being a very pleasant and amiable person, this was also a great lesson. We started with a number of open conversations, that soon developed into focused meetings. I've seldom witnessed such a strong combination of open thinking, to be followed by focused action.

I also want to thank the members of the assessment committee, Tom Elfring, Andreas Flache and Gerben van der Vegt for taking the time to read and review my dissertation.

Besides those people who contributed more directly to my PhD, there are many people who at certain moments played important roles. Michel Altan who strongly motivated me to start this PhD-project. Frans Swint and Elena Cavagnaro who gave feedback on some chapters.

Ran Zhang, a friend with whom I shared many intense conversations about our research and almost anything else. You were always willing to help out, for example with editing or with translating a summary into Mandarin.

NHL Stenden University of Applied Sciences played a major role by facilitating me in this PhD-process.

And most of all, Zwanet, for giving me both the freedom and support necessary. Let’s gear up, and move on to a new future.