THE SOCIAL CAPITAL OF POWER-DEPENDENCE RELATIONS

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

Yunsub Lee

August 2022

THE SOCIAL CAPITAL OF POWER-DEPENDENCE RELATIONS

Yunsub Lee, Ph. D.

Cornell University 2022

This dissertation aims to explore what structural features can generate power-dependence relations in social networks (i.e., A's bargaining power over B is equal to B's dependence on A in the dyadic relation) and how those relations shape individuals' access to social capital. The first study identifies power-dependence relations in structural holes and network closure. Existing network theories and graph-theoretic measures explain how ego within structural holes and network closure becomes a recipient of valuable resources from donor-alters. Yet, their potential bargaining situations are often overlooked. I suggest new propositions and measures of *Total Power* (i.e., mutual dependence) and *Relative Power* (i.e., unequal dependence) in bargaining between ego and alters and apply them to examine the relationship between the social capital of actors and directors and their career-survival in the U.S. film industry, 1929-2019. Event history analysis results reveal very different survival mechanisms of actors and directors that previous theories and measures do not capture. The second study identifies power-dependence relations in centrality within context-specific network flows. Centrality measures identify influential nodes that are more involved in certain network flows. Yet, those network flows are purely defined in graph-theoretic terms (e.g.,

shortest-paths) and do not account for many context-specific patterns potentially embedded in social networks (e.g., paths through racially homogenous nodes). Applying the respondent-driven sampling (RDS) method, I propose a Monte Carlo approach to measuring centrality and power-dependence relations within complex and flexible network flows. I use this approach to explore the well-known networks of Florentine families, 1394-1434, and find interesting snapshots of their power game. The third study identifies power-dependence relations in chain of remittance flows. Remittances are often considered to yield a unidirectional flow of capital—the money from migrant workers' residential country to their home country. However, as social exchanges, remittances could provide certain rewards to migrant workers (e.g., social status in their family; emotional satisfaction), which may lead them to be more committed to their jobs. This hypothesis of the bi-directional flow of capital is tested using the Mexican Migration Project (MMP) datasets and formalized as a new model of power-dependence relations potentially embedded in social networks.

BIOGRAPHICAL SKETCH

Yunsub Lee was born in Seoul, South Korea. Before coming to Cornell, he received a Bachelor of Arts in Sociology and a Bachelor of Science in Mathematics from Hanyang University, South Korea in 2011 and a Master of Arts in Sociology from the University of North Carolina at Charlotte in 2015. His research interests are centered on developing new network theories of social capital, mainly based on the micro-level processes of social exchange, bargaining, and emotion. His current works are selected as the winners of the Best Graduate Student Paper Award from the Section on Rationality and Society of the American Sociological Association and the Rober W.McGinnis Award from the Department of Sociology at Cornell University.

부모님과 동생에게

그리고 열정적이었던 과거의 나에게

ACKNOWLEDGMENTS

The hardest part of writing this dissertation was finding the right words to express how thankful and grateful I am for all the help of my advisor, Filiz Garip. Without her endless comments and tireless efforts in mentoring, this dissertation would have never been possible. I am honored to say my academic journey started with meeting a great mentor.

I also feel enormously thankful to my committee members, Michael W. Macy and Douglas Heckathorn. Whenever Michael gave me comments on my work, they were always insightful and touched on fundamental issues, leading me to develop theoretically meaningful contributions in the works, which I never knew before his comments. Doug was the one who influenced my methodological approaches. Taking his respondent-driven sampling class was a turning point for me, and he motivated me to develop a new theory-based social network analysis method. Many parts of this dissertation are the results of those procedures.

My gratitude goes as well to Anna Haskins and Benjamin Cornwell. I have worked as Anna's teaching assistant for five academic semesters, which is unusual in graduate school life. Although we have very different academic interests, her enthusiastic teaching has largely influenced me, and the way that she thoughtfully took care of the TAs—who often struggle with balancing research and teaching—truly helped me to finish this dissertation. Ben was not my committee member, but he was always willing to provide helpful comments on my work. Many parts of this dissertation are influenced by his careful comments.

Lastly, I would like to thank my department colleagues, SangKyung Lee, Abdullah Shahid, Jaeun Lim, Xinwei Xu, Lisha Liu, and Nicole Dreier. During my years of Ph.D. life, I have been influenced and learned a lot from their academic talent and passion. Many parts of this dissertation originated from very random conversations with them, and their names also deserve to be in the opening credits of this dissertation.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

This dissertation aims to explore what structural features can generate power-dependence relations in social networks (i.e., A's bargaining power over B is equal to B's dependence on A in the dyadic relation) and how those relations shape individuals' access to social capital (e.g., information; controlling others' behaviors; wealth). Using various methodological approaches—including formal analysis and simulation modeling—I identify power-dependence relations embedded in three different structural features of social networks (e.g., structural holes and network closure; centrality within context-specific network flows; chain of remittance flows) and test certain hypotheses about power and social capital with diverse empirical cases (e.g., movie actors/directors in Hollywood; Florentine families in the early 15th century; Mexican migrant workers in the United States).

Classic works in anthropology, economics, and sociology highlight that individuals in pre-modern societies (e.g., tribal society) helped each other, exchanging necessary resources, and their interdependent relationships eventually led to the emergence of social order as well as the flow of resources without markets (Malinowski 2002 [1922]; Mauss 2002 [1929]; Lévi-Strauss 1971 [1949]; Polanyi 2013 [1944]; Weber 1978 [1921]). Influenced by the classic works, different traditions present different theories on what structural features of social networks shape those relational-based exchanges even in modern society. Economic sociologists argue that one's network position differentiates their access to valuable resources from others (also known as 'social capital') (Granovetter 1985; 1992; Lin 1999; 2002; Portes 1998; Portes and Landort 2000; Adler and Kwon 2002; Burt 1992; Coleman 1988; Borgatti, Jones, and Everett 1998; Borgatti and Halgin 2011). Social exchange theorists emphasize that equal or unequal dependencies between exchange partners shape their power and bargaining processes (i.e., A's bargaining power over B is equal to B's dependence on A), laying the ground for certain psychological elements for social order, such as trust, emotion, and cohesion in their partnerships or group membership (Homans 1958; Blau 1964; Emerson 1962; Cook and Emerson 1978; Cook et al. 1983; Markovsky, Willer, and Patton 1988; Willer 1999; Lawler and Bacharach 1987; Lawler, Thye, and Yoon 2009; Molm 1990; 1997; Molm, Takahashi, and Peterson 2000).

The two theoretical approaches are, however, rarely combined. Economic sociologists are mainly interested in demonstrating who earns more benefits through the relational-based transaction—but not in its consequences for social order. Exchange theorists test their theories about power-dependence relations and social order with rigorous laboratory experiments (i.e., group processes)—but rarely in real social networks. My dissertation fills this theoretical and empirical gap by suggesting novel computational and network approaches to identifying power-dependence relations in social networks.

Chapter Outline

This dissertation consists of 6 chapters that include 3 empirical studies. In the Chapter 2, I review the two current theoretical approaches and justifies why they need to be combined based on relational sociological perspectives (Emirbayer and Goodwin 1994; Emirbayer 1997; Emirbayer and Mische 1998; Dépelteau 2008; Mische 2011; Burkitt 2016).

The Chapter 3 *"Power-Dependence Relations in Structural Holes and Network Closure: Evidence from Different Career Survival Mechanisms of Actors and Directors in the U.S. Film Industry"* focus on the power-dependence relations embedded in structural holes and network closure (Burt 1992; Coleman 1988). I develop new propositions and measures of how ego can access resources from alters through bargaining, using their *Total Power* (i.e., mutual dependence) and *Relative Power* (i.e., unequal dependence) embedded in structural holes and network closure. The measures are constructed with the weighted shortest-paths and network size difference between ego- and alter-networks. I apply them to examine the relationship between the social capital of actors and directors and their career-survival in the U.S. film industry. The networks are estimated by the potential connections between 64324 actors and 17540 directors who participated in 89060 projects of the U.S. film industry during 1929-2019, based on the data archived in the Internet Movie Database (IMDB). Event history analysis results reveal very different survival mechanisms of actors and directors that previous theories and measures do not capture.

In the Chapter 4 *"Power-Dependence Relations in Centrality within Context-Specific Network Flows: A Markov Chain Monte Carlo Approach to Identifying Power Dynamics between 15th Century Florentine Families,"* I focus on the power-dependence relations under context-specific flows of resources. This chapter consists of two parts. First, I suggest *actor-based centrality* by applying the simulation model of respondent-driven sampling (RDS)—a chain-referral sampling method (Heckathorn 1997; 2002; Heckathorn and Cameron 2017; Salganik and Heckathorn 2004). This allows incorporating complex and flexible network flows through manipulating the Markov Chain Monte Carlo (MCMC) algorithm within an RDS simulation framework. With this approach, researchers can effectively construct multiple actor-based centrality measures customized for different 'relational' contexts. Second, I use this approach to estimate *total power* and *relative power* in the well-known networks of Florentine families during 1394-1434, studied by Padgett and Ansell (1993). I argue that by adding one more assumption to actor-based centrality, the two bargaining powers within certain relational contexts can be captured and provide interesting snapshots of their power game.

The Chapter 5 *"Power-Dependence Relations in Chain of Remittance Flows: How Can Mexican Local Communities Contribute to the Social Capital of the U.S firms?"* focuses on the interdependence between migrants' work choices in the U.S. and their remittance exchanges back home. Remittance exchanges are often considered a unidirectional flow of capital—the money from migrant workers' residential country to their home country. However, as social exchanges, remittances could provide certain rewards to migrant workers, such as social status in their family or emotional satisfaction. When those rewards are clearly expected, migrant workers who send remittances could make choices (such as taking high-risk and low-premium jobs) that are not 'rational' from an individual perspective. In turn, the flow of capital becomes bidirectional—in order to reap the social and emotional rewards of remittances, migrants would be motivated to accept worse jobs, which could be a 'capital' for the firms in the United States. This hypothesis, which is backed up by social exchange theories and Zelizer's idea about the social meaning of money (1989; 1997), is tested by using the Mexican Migration Project (MMP) datasets.

In the final chapter—Chapter 6—I summarize the potential implications and future studies of this dissertation, mainly focusing on the emergence of social order in social networks.

REFERENCES

Adler, Paul S and Seok-Woo Kwon. 2002. "Social Capital: Prospects for a New Concept." *Academy of management review* 27(1):17-40.

Blau, Peter Michael. 1964. *Exchange and Power in Social Life*: Transaction Publishers.

Borgatti, Stephen P, Candace Jones and Martin G Everett. 1998. "Network Measures of Social Capital." *Connections* 21(2):27-36.

Borgatti, Stephen P and Daniel S Halgin. 2011. "On Network Theory." *Organization science* 22(5):1168-81.

Burkitt, Ian. 2016. "Relational Agency: Relational Sociology, Agency and Interaction." *European Journal of Social Theory* 19(3):322-39.

Burt, Ronald S. 1992. *Structural Holes*: Harvard university press.

Coleman, James S. 1988. "Social Capital in the Creation of Human Capital." *American journal of sociology* 94:S95-S120.

Cook, Karen S and Richard M Emerson. 1978. "Power, Equity and Commitment in Exchange Networks." *American Sociological Review*:721-39.

Cook, Karen S, Richard M Emerson, Mary R Gillmore and Toshio Yamagishi. 1983. "The Distribution of Power in Exchange Networks: Theory and Experimental Results." *American journal of sociology* 89(2):275-305.

Dépelteau, François. 2008. "Relational Thinking: A Critique of Co-Deterministic Theories of Structure and Agency." *Sociological Theory* 26(1):51-73.

Emerson, Richard M. 1962. "Power-Dependence Relations." *American Sociological Review*:31-41.

Emirbayer, Mustafa and Jeff Goodwin. 1994. "Network Analysis, Culture, and the Problem of Agency." *American journal of sociology* 99(6):1411-54.

Emirbayer, Mustafa. 1997. "Manifesto for a Relational Sociology." *American journal of sociology* 103(2):281-317.

Emirbayer, Mustafa and Ann Mische. 1998. "What Is Agency?". *American journal of sociology* 103(4):962-1023.

Granovetter, Mark. 1985. "Economic Action and Social Structure: The Problem of Embeddedness." *American journal of sociology* 91(3):481-510.

Granovetter, Mark. 1992. "Problems of Explanation in Economic Sociology." *Networks and organizations: Structure, form, and action*:25-56.

Heckathorn, Douglas D. 1997. "Respondent-Driven Sampling: A New Approach to the Study of Hidden Populations." *Social problems* 44(2):174-99.

Heckathorn, Douglas D. 2002. "Respondent-Driven Sampling Ii: Deriving Valid Population Estimates from Chain-Referral Samples of Hidden Populations." *Social problems* 49(1):11-34.

Heckathorn, Douglas D and Christopher J Cameron. 2017. "Network Sampling: From Snowball and Multiplicity to Respondent-Driven Sampling." *Annual review of sociology* 43:101-19.

Homans, George C. 1958. "Social Behavior as Exchange." *American journal of sociology* 63(6):597-606.

Lawler, Edward J and Samuel B Bacharach. 1987. "Comparison of Dependence and Punitive Forms of Power." *Social forces* 66(2):446-62.

Lawler, Edward J, Shane R Thye and Jeongkoo Yoon. 2009. *Social Commitments in a Depersonalized World*: Russell Sage Foundation.

Lévi-Strauss, Claude. 1971. *The Elementary Structures of Kinship*: Beacon Press.

Lin, Nan. 1999. "Building a Network Theory of Social Capital." *Connections* 22(1):28-51.

Lin, Nan. 2002. *Social Capital: A Theory of Social Structure and Action*, Vol. 19: Cambridge university press.

Malinowski, Bronislaw. 2002. *Argonauts of the Western Pacific: An Account of Native Enterprise and Adventure in the Archipelagoes of Melanesian New Guinea*: Routledge.

Markovsky, Barry, David Willer and Travis Patton. 1988. "Power Relations in Exchange Networks." *American Sociological Review*:220-36.

Mauss, Marcel. 2002. *The Gift: The Form and Reason for Exchange in Archaic Societies*: Routledge.

Mische, Ann. 2011. "Relational Sociology, Culture, and Agency." *The SAGE handbook of social network analysis*:80-97.

Molm, Linda D. 1990. "Structure, Action, and Outcomes: The Dynamics of Power in Social Exchange." *American Sociological Review*:427-47.

Molm, Linda D. 1997. *Coercive Power in Social Exchange*: Cambridge University Press.

Molm, Linda D, Nobuyuki Takahashi and Gretchen Peterson. 2000. "Risk and Trust in Social Exchange: An Experimental Test of a Classical Proposition." *American journal of sociology* 105(5):1396-427.

Padgett, John F and Christopher K Ansell. 1993. "Robust Action and the Rise of the Medici, 1400-1434." *American journal of sociology* 98(6):1259-319.

Polanyi, Karl. 1944. "The Great Transformation."

Portes, Alejandro. 1998. "Social Capital: Its Origins and Applications in Modern Sociology." *Annual review of sociology* 24(1):1-24.

Portes, Alejandro and Patricia Landolt. 2000. "Social Capital: Promise and Pitfalls of Its Role in Development." *Journal of Latin American Studies* 32(2):529-47.

Salganik, Matthew J and Douglas D Heckathorn. 2004. "Sampling and Estimation in Hidden Populations Using Respondent-Driven Sampling." *Sociological methodology* 34(1):193-240.

Weber, Max. 1978. *Economy and Society: An Outline of Interpretive Sociology*, Vol. 1: Univ of California Press.

Willer, David. 1999. *Network Exchange Theory*: Greenwood Publishing Group.

Zelizer, Viviana A. 1989. "The Social Meaning of Money:" Special Monies"." *American journal of sociology* 95(2):342-77.

Zelizer, Viviana A Rotman. 1997. *The Social Meaning of Money*: Princeton University Press.

CHAPTER 2

THEORETICAL BACKGROUND

Classic Works on Social Networks and Economic Actions

Many classic works of anthropology, economics, and sociology point out that pre-modern societies were able to maintain their economic system and social order even without markets and relevant institutions (e.g., transaction laws; currency system) because necessary resources for the members could successfully flow through social relationships.

Anthropologists found that goods and services in tribal society were often exchanged as gifts for friends or family members (Malinowski 2013 [1922]; Mauss 2002 [1929]; Lévi-Strauss 1971 [1949]). Within this gift exchange system, the norm of reciprocity was strongly forced on the members, and thereby resources could be distributed with less conflict of negotiation. Their findings also reveal that the gift exchange system even contributed to social order. For example, people of 18 island communities in the Massim archipelago gifted an accessory to each other, called the Kula ring, as a sign of mutual trust and friendship (Malinowski 2013 [1922]). Although the Kula ring itself had no tradable value, the receivers of Kula rings could become influential among the communities. Moreover, the receivers could not possess Kula rings for a long time and thereby had to pass them to others. Thus, Kula rings could flow more widely and quickly, and most people behaved well and cared about their reputation to receive more Kula Rings. Within this chained exchange system, the tribals of 18 islands whose networks were very sparsely connected could successfully maintain their social cohesion.

Polanyi (1957) also argues that pre-modern Western societies—before transforming into the capitalist society where individuals could earn goods and services with government currency—had maintained their economic systems with relational-based exchanges. Before the 19th century, peasants were still the primary mean of production of the local economy in many Western societies. Their moving to another village was thus strongly prohibited, and producers in a local community, such as crafters, fishers, and blacksmiths, only needed to sell their goods and services to peasants who already had social relationships with the producers. Thus, although the modern market system already existed in Western societies even before the 19th-century (e.g., bank, government currency, transaction laws), many economic transactions still relied on trust-based exchanges and social norms. However, after the rise of liberalism and colonization, individuals' moving began to be more allowed, and many producers had to face more transactions with consumers who had no previous relationships with them. This change made people rely more on modern market systems, and economic systems in Western societies became disembedded from social systems. In turn, this "great transformation" is not simply because of the development of modern market systems but because of the rise of transactions in arm's length ties (i.e., no relational-based exchanges).

Weber's (1978 [1921]) argument about social actions and institutions also supports that relational-based exchanges contributed to the maintenance of pre-modern society. According to his notions, "*Action is "social" [only] insofar as its subjective meaning takes account of the behavior of others and is thereby oriented in its course,*" and economic action has "*no need to be social action.*" Weber points out that social action is close to economic action only if certain rationality for materialistic utility (or goal) is guided by institutions (Swedberg 2000). In other words, when there is no institutional guidance of how actors can maximize materialistic utility (e.g., more income), it is rational for social actors to follow what other actors have done habitually (i.e., traditional actions). This means that many individual exchanges in pre-modern society are oriented not by their lack of rationality but by their lack of institutions that allow certain utility-based (or economic) actions.

Current Approaches to Social Networks and Economic Actions (1): Social Capital Studies

The classic works support that a social network could be a field of economic transactions, and those relational-based exchanges may contribute to the flow of resources without markets as well as the emergence of social order. Influenced by the classic works, two very different theoretical approaches to social networks and economic actions have developed in sociology: social capital studies and social exchange theories. While the classic works mainly focus on how macro-level social entities (e.g., historical change; culture; norms; institutions) matter for one's relational-based transactions, the current two theoretical approaches focus on how structural features embedded in social networks (i.e., how actors are connected) matter to shape those actions.

Social capital—from a more individualistic perspective—is defined as the resources embedded in social relations that one can access from others (e.g., information; wealth and power; social control) (Lin 1999; 2002). Various theories and studies of social capital offer different statements about how one (or ego) can access valuable resources from others (or alters) in their network. The point is that those accessible resources are not available to every ego. There are certain situations where ego and alters have motivations to be a recipient and donor of the resources, respectively—not to be a buyer and seller who struggle with rewards and costs of transactions (Portes 1998; Portes and Landort 2000; Adler and Kwon 2002). In such situations, ego can access resources from alters with surplus values compared to what they invest in the relations with alters (Lin 1999; 2002), and using the resources, ego can earn benefits, such as job offers, career success, or innovation (Portes 1998; Portes and Landort 2000; Adler and Kwon 2002).

Many follow-up studies of social capital mainly focus on clarifying the "situations" where ego and alters become a recipient and donors, respectively. In general, from Granovetter's embeddedness framework (1985; 1992), those studies tend to presume that the situations are shaped by "structural" features of social networks. Granovetter argues that various economic actions are embedded in social relations, and the embeddedness of the actions can be "relational" or "structural." Within this framework, studies on relational embeddedness focus on the actions rooted in deep relational characteristics within a dyadic relation, such as mutual trust or strength of ties. On the contrary, studies of structural embeddedness focus on how one's network position, which is differentiated by one's connections with others, generates certain economic actions.

From Granovetter's point of view, many theories and studies of social capital follow the structural embeddedness framework; they are primarily based on formal network measures that identify network positions where ego is expected to access valuable resources from alters. For instance, Burt (1992) argues that an individual network is rich in structural holes (i.e., empty spaces between alters) when ego has relationships with alters who do not know each other. He points out that the sparsely connected alters likely belong to different social groups (or clusters) and thereby have resources, which are heterogeneous and valuable to each other but not exchangeable without ego's brokerage (e.g., job information about diverse firms). Thus, by suggesting brokerage between those alters, ego who is positioned in structural holes can efficiently access their heterogeneous resources. On the contrary, Coleman (1988) argues that ego earns benefits from network closure (i.e., ties between alters). When ego and alters make transactions with each other, they are forced to follow certain norms, such as no malfeasance in transactions. If alters know each other, the enforcement becomes strong because one who violates the norms will be collectively sanctioned by ego and other alters. Thus, in a dense network, ego can access resources, the values of which are guaranteed by alters who are aware of the negative consequences of their norm violation (e.g., trustworthy information).

Some empirical studies of social capital utilize network centrality measures that identify influential nodes in a network (Borgatti, Jones, and Everett 1998). From a graph-theoretic perspective, all centrality measures define a walk structure between nodes (e.g., shortest-paths; random walks) and evaluate each node's involvement in that structure. Nodes (or egos) more involved in particular walks (e.g., shortest-paths between other nodes; shorter walks) in a particular way (e.g., passed or terminated by; originated from) are identified as central (Borgatti and Everett 2006). Those central nodes are influential because certain transferrable resources (e.g., information, opinions, gossip, reputations) are expected to flow through a defined walk structure, and thereby more opportunities to utilize the resources are given to the central nodes (e.g., brokering information between others; spreading opinions quickly) (Borgatti 2005; Borgatti and Halgin 2011; Friedkin 1991). In this sense, centrality measures can explain who can access more social capital utilizing their network position. For example, Alderson and Beckfield (2004) use betweenness centrality as an indicator of a city's brokerage power in the world-city system, explaining *"... city A in the star network [where all other nodes have only a tie with A] is advantaged because it stands between all the other pairs of actors. It thus has greater power in the sense that it brokers all exchanges"*. This hypothesis is available because centrality measures have theoretical explanations about how ego can earn benefits by their influence when certain products flow through social networks (Friedkin 1991).

Although many studies of social capital are based on the structural embeddedness framework, some studies also show how non-structural contexts of relations, such as a cultural meaning of providing resources in certain relations, matter to one's economic actions (i.e., relational embeddedness). For example, several empirical studies support that Burt's structural hole theory may not have a strong explanatory power because, in some cultures, members of the same social group tend to not share important information with someone who has fewer connections with the group members (Xiao and Tsui 2007; Chai and Rhee 2010). In turn, one's brokerage actions could not be allowed under certain cultural contexts—even if one is positioned within structural holes. Zelizer (1989; 1997) also argues that money has various meanings when it is used for social interactions, and thus its currency can be differentiated. For example, the meaning of $10 for tipping a waiter (i.e., gratitude with social distinction) is not the same as $10 tipping a lawyer (i.e., disrespecting one's profession). This implies that one's access to social capital in a network may be not only shaped by its structural features, but also by the cultural meaning of providing resources shared by actors in a network.

Current Approaches to Social Networks and Economic Actions (2): Social Exchange Theories

Social exchange theories—in line with social capital studies—also focus on how one can earn benefits from exchanges with others, utilizing their network position. One distinction between social exchange theories and social capital studies is that the theories focus on power-dependence relations between individuals and test certain hypotheses about bargaining and its consequences.

The power-dependence framework is influenced by the pioneer studies of Homans (1958) and Blau (1964). The two theorists assumed that any type of exchange in social relations also has logic, which is similar to the logic of economic transactions between buyer and seller. In turn, there are issues of costs and rewards in social exchanges, and even some propositions like bargaining rules can explain its various patterns (e.g., exchanges are repeated when it guarantees fair rewards and costs for all participants; one's power comes from the monopoly of exchangeable resources). Influenced by the pioneer studies, Emerson (1962; 1964; 1976) suggests a theoretical framework of power and dependence embedded in social relations. Suppose, in a dyadic relation, actors A and B exchange valued outcomes to achieve their desired goals. Then, B's dependence on A (= D_{BA}) is defined as equal to A's power over B (= P_{AB})—and vice versa.

Based on the power-dependence framework, many social exchange theories have been suggested and tested with laboratory experiments. Although each theory has its unique characteristics, most of them are distinct by their explanations of (1) what structural features of a network shape one's power over another, (2) what types of power-dependence relations and bargaining actions can be generated in each dyad (e.g., A and B are on equal power), and (3) what consequences emerge under those power-dependence relations.

One's power over another—thereby another's dependence on one—is basically differentiated by an exchange network structure (e.g., line; branch; kite; stem) that determines one's number of alternative exchange partners. For example, in an exchange network B1-A-B2, while B1 and B2 have no alternative (i.e., only exchange with A is available), A has potential exchange relationships with either or both of B1 and B2. Suppose each actor may choose only one exchange partner (i.e., exclusive connection). Then, B1 and B2's dependence on A increases ($D_{BiA} > D_{ABi}$) because A could exclude one of them from the exchange relationships, but they have no alternative relation. Thus, A's power over B1 and B2 ($P_{ABi} = D_{BiA}$) becomes stronger than B1 and B2's power over A ($P_{BiA} = D_{ABi}$) due to their unequal dependence (i.e., $P_{ABi} > P_{BiA}$ because $D_{BiA} > D_{ABi}$). However, when B1 and B2 are connected with another actor C1 and C2, respectively, the network C1-B1-A-B2-C2 could produce equal power ($P_{ABi} = P_{BiA}$) because B1 and B2 now have alternatives, which decrease their dependence on A.

Moreover, if C1 and C2 offer better rewards to B1 and B2 to avoid the exclusion, B1 and B2 no longer need to maintain the exchange relationship with A—repeating exchanges with C1 and C2 provide better rewards. Thus, D_{BiA} significantly decreases, and B1 and B2 have stronger power than A ($P_{ABi} < P_{BiA}$) although A looks most central in the network (Cook and Emerson 1978; Cook et al. 1983; Cook and Yamagishi 1992).

Certain exchange conditions in a network can also determine one's power over another (e.g., one's exchange with another is exclusive or inclusive; positive/negative rewards) (Willer 1992; 1999; Skvoretz and Willer 1993; Walker et al. 2000). For example, in the B1-A-B2 network, the actors could have equal power ($P_{ABi} = P_{BiA}$) if each actor may choose a maximum of two exchange partners (i.e., inclusive connection). This is because A can earn more benefits when maintaining exchange relationships with both B1 and B2, rather than only one of them, which increases D_{ABi} (Markovsky, Willer, and Patton 1988; Markovsky et al. 1993). Even $P_{ABi} < P_{BiA}$ can be produced if A's failure of exchange with B1 or B2 yields negative rewards. In other words, when B1 and B2 are allowed to induce sanctions or negative consequences to A (i.e., coercion), the network B1-A-B2 can significantly increase A's dependence on B1 and B2 (Molm 1997a; 1997b). In another case, if A cannot earn rewards unless successfully making exchanges with both B1 and B2 (i.e., brokerage; ordered exchanges), the B1-A-B2 network may also produce $P_{ABi} < P_{BiA}$. This is because the possibility of no rewards increases A's dependence on both B1 and B2 (Corra and Willer 2002).

When one's power over another in a network is determined by its structure as well as exchange conditions, actors in each dyad may have certain power-dependence relations (e.g., A and B are on equal power) that lead them to choose specific bargaining strategies. Two types of power-dependence relations and bargaining strategies have been mainly discussed. Suppose actor B is more dependent on actor A in a dyadic exchange relation. Then, their unequal dependence (i.e., $D_{BA} - D_{AB}$) makes A have stronger ***relative power*** over B. Many laboratory experiments support that in such a situation, A is likely to use the power in bargaining with B to earn more rewards (i.e., hostile strategy). On the contrary, some experiments support that A may not use his/her power even within an unequal dependence situation. When their mutual dependence (i.e., $D_{BA} + D_{AB}$)—***total power***—is strong enough, the power-use (or hostile strategy) implies that A risks losing a valuable exchange relationship with B. This means that when A's dependence on B is as strong as B's dependence on A, A has no reason to take the risk to earn only slightly better rewards—even if B is more dependent on A. Thus, in such a situation, A and B are more likely to cooperate and less likely to use their power in bargaining (i.e., conciliatory strategy) (Lawler and Bacharach 1987; Lawler 1992; Molm 1990). Formally, let D_{BA} be actor B's dependence on A and P_{AB} be actor A's power over B in their exchange relation. Then, the two concepts of power can be formalized simply below.

$$Relative\ Power\ of\ A\ over\ B\colon\ D_{BA} - D_{AB} = P_{AB} - P_{BA}$$

$$Total\ Power\ between\ A\ and\ B\colon\ D_{BA} + D_{AB} = P_{AB} + P_{BA}$$

Under the suggested power-dependence relations and bargaining strategies, the consequences happen to the exchange actors related to their exchange rewards and psychological elements for social order. Needless to say, one who has a strong relative or total power over another can earn more exchange rewards through bargaining. But at the same time, the actors may have positive or negative psychological elements for social order. Lawler and his colleagues argue that when exchange actors have strong total power and equal relative power (or mutual and equal dependence), their successful bargaining promotes them to have psychological elements for social order, such as trust, positive emotion, and cohesion in their exchange relationships (person-to-person) or asocial group (person-to-unit). Thus, with the generated psychological elements, exchange actors are likely to maintain their exchange relationships even if they have better alternative partners (i.e., committed behaviors) (Lawler and Yoon 1996; Lawler, Thye, and Yoon 2000; 2008; 2009; Lawler 2001; Kuwabara 2011). Molm and her colleagues also argue that unequal relative power in bargaining is harmful to developing the psychological elements for committed behaviors, but its negative effect significantly decreases in non-bargaining situations, including reciprocal and generalized exchanges (Molm, Takahashi, and Peterson 2000; Molm, Collett, and Schaefer 2007; Molm, Whitham, and Melamed 2012).

Similar to social capital studies, social exchange theories focus mainly on structural features of a network that determine certain power-dependence relations, actions, and consequences. One distinct part is that the theories also focus on how psychological consequences of exchanges under certain power-dependence relations can change or affect their bargaining actions (e.g., positive emotion from repeated exchanges leads to committed behaviors). In turn, affective actions that potentially emerge in exchange relations are also considered in the theories. Yet, unlike social capital studies on relational embeddedness, exchange theories focus less on the relation between culture and bargaining actions, although there are non-experimental empirical studies that support the potential existence of the relation—especially in work settings (Shore et al. 2007; Zhang and Zia 2010).

Critiques on the Two Approaches: From Relational Sociological Perspectives

Compared to the classic works, the current two theoretical approaches focus mainly on specifying the situations that shape certain economic actions between connected actors. Social networks and exchange networks are assumed as social structures. One's access to valuable resources from others (e.g., brokerage; trust-based transactions) and power-use in bargaining (e.g., hostile or conciliatory strategy) are considered actions. Individuals' network positions, which are differentiated by a network structure (e.g., within structural holes or network closure; network centrality; strong relative or total power), generate particular situations that make actors in the positions choose those actions (i.e., structure ⇒ situation ⇒ action) (Cook and Whitmeyer 1992; Cook 2005)

Despite many successful studies under the two theoretical approaches, their way of explanation—clarifying the relationship between network positions and actions—could face some criticism from relational sociologists, who propose theory-driven perspectives on network studies (Emirbayer and Goodwin 1994; Emirbayer 1997; Emirbayer and Mische 1998; Dépelteau 2008; Mische 2011; Burkitt 2016; Erikson 2013). Relational sociologists argue that network studies need to satisfy several conditions, which are distinct from the conditions of general "variable-centered" sociological studies. Those conditions can be summarized as follows.

First, one's actions in social networks must be viewed as *trans-actions* with others (i.e., action $\Leftrightarrow$ action), not *inter-actions* (i.e., structure $\Longrightarrow$ action). Many empirical studies in sociology tend to explain individuals' actions by their social characteristics (e.g., gender, class, income). This is based on the presumption that social structure (e.g., class system; gender inequality) has static and substantial effects on one's actions, independently from others' actions (i.e., structure $\Longrightarrow$ action). Similarly, network studies are also based on the assumption that positions (or structures) can shape one's roles (or actions) in a network (Borgatti and Everett 1992; Faust and Wasserman 1994). Yet, from a relational sociological perspective, the roles can be shaped by positions only if others choose certain actions (i.e., action $\Leftrightarrow$ action). For instance, central nodes can be influential because they are more involved in specific network flows that can only be available by others' actions. In other words, the influence by central nodes (e.g., brokerage) and the flow patterns between other nodes cannot be separated—they must be equally considered as social actions, which are interdependent. This implies that network positions cannot yield static and substance-based (or deterministic) results: rather, the outcomes are dynamic and process-based, depending on how others to act.

Second, it is necessary to assume that trans-actions are dynamically unfolded in each relationship with the actors' agency, and their agency is shaped by multiple structural, cultural, and social-psychological contexts embedded in their relations (Emirbayer and Mische 1998; Mische 2011; Burkitt 2016). Agency is defined as one's internal process of engaging in some actions to respond to a given situation. This is mainly guided by past iterations (i.e., habitual/routinized activities), but it also could be oriented to future projection (i.e., creative ways to overcome the limitations of habitual/routinized activities) or present practical evaluation (i.e., judgments on alternative ways when habitual/routinized activities become a dilemma). All agentic orientations are largely embedded in social relations, where structural (or network positional), cultural, and social-psychological contexts of transactions are constituted. In turn, through the common experiences within social relations, actors figure out what habitual/routinized activities are culturally accepted by others, emotionally acceptable to themselves, and beneficial within their own network position, as well as what limitations or dilemmas the activities have under the multiple contexts.

Third, network analysis can be theoretical only if a network measure (e.g., centrality) is based on "formalized" terms of a network that reflect its "relational" characteristics (Emirbayer and Goodwin 1994). In turn, two theoretical frameworks in social network analysis—formalism and relationalism—must be unified, which are widely considered mutually exclusive or often mixed with logical inconsistences (Erikson 2013). A network of actors and relations is often formalized as a graph of nodes and ties expressed homogeneously by binary elements 1 or 0 (i.e., existing or not). When every network is expressed as a graph with the same formalization, a network measure based on this formal expression can be applied to every network. However, when the graph-theoretic expression cannot capture the heterogeneous contents (or characteristics) of ties and nodes, the measure may fail to explain the relationship between positions and roles by the trans-actions within multiple relational contexts. On the contrary, when the characteristics of nodes and ties are expressed without formalization, the expression cannot be applied to many networks, and thereby a network measure with the relational expression may not have a general explanation as a theory.

Based on the relational sociological perspectives, I argue that the current two theoretical approaches may have limitations in capturing various snapshots of economic actions potentially embedded in social networks.

In social capital studies, although the studies successfully suggest or utilize many well-formalized network measures, their assumptions about actions between recipient-ego and donor-alters are relatively simple and overlook the existence of the complex trams-actions between ego and alters. Usually, ego—as a recipient—utilizes their network position to earn more benefits by accessing valuable resources from donor-alters. Ego uses enforced norms (Coleman 1988), chances of brokerage (Burt 1992), and social influence given to their position (Everett and Borgatti 2005). However, alters—as donors—are assumed to provide resources to ego, simply following enforced norms, expecting (but uncertain) brokerage returns, or even without a particular rationale (e.g., resources flow through shortest-paths between nodes). Moreover, those donor-alters' actions that can be oriented by multiple cultural and social-psychological contexts are not considered in the formal measures of social capital studies (i.e., studies on structural embeddedness and relational embeddedness tend to be separated). In turn, cultural and social-psychological contexts are not fully considered, and the suggested ego-centric structural contexts (e.g., densely connected alters) overlook the existence of alters' complex actions with their agency.

Unlike social capital studies, social exchange theories assume that the actions of ego and alters are oriented by the same motivation and rationality. Both ego and alters—

as exchange actors—are assumed to have the same motivational investment in their desired goals, which can be reached through exchange outcomes. Thus, it is assumed that every actor equally wants to earn more rewards and spend fewer costs of exchanges to reach their desired goals (Cook, Cheshire, and Gerbasi 2006; Molm 1997a). Bargaining is thus necessary between actors, and many exchange theoretical statements try to explain the complex trans-actions between actors in their power-dependence relations. Nevertheless, their statements are only applied and tested with laboratory experiments because of the lack of formal power-dependence measures applicable to general social networks. Moreover, the suggested bargaining situations are assumed to be primarily shaped by structural contexts (i.e., power-dependence relations) and psychological contexts (i.e., psychological consequences after bargaining), ignoring potential cultural contexts embedded in social networks.

In sum, from relational sociological perspectives, studies under the two current theoretical approaches may fail to satisfy the three important conditions. Social capital studies tend to overlook complex and diverse trans-actions between ego and alters (*unsatisfactory first condition*), although their theoretical statements are based on well-formalized terms of network positions (*satisfactory third condition*). On the contrary, while social exchange theories reveal complex bargaining processes between exchange actors (*satisfactory first condition*), many of their theoretical statements cannot be tested in large social networks due to the lack of formal network measures to identify power-dependence relations in social networks (*unsatisfactory third condition*). In addition, both approaches are not entirely successful in considering the potential economic actions within multiple relational contexts (*partially satisfactory second condition*).

Social capital studies consider structural, cultural, and social-psychological contexts of accessing resources in social networks, but the studies of structural contexts (i.e., structural embeddedness) and cultural/social-psychological contexts (i.e., relational embeddedness) are clearly separated. Exchange theories consider both structural and social-psychological contexts of bargaining actions, but cultural contexts are lacking.

Discussion: Combining the Two Approaches

This dissertation is thus motivated to overcome the limitations of the two theoretical approaches and thereby contribute to the understanding of social networks and economic actions. Here, I argue that those suggested limitations could be overcome by combining the two approaches.

In social capital studies, an overlooked point is that the different motivations of recipient-ego and donor-alters could also be rooted in the same fundamental motivation: to reach desired goals (or benefits) with social capital. Ego is motivated to be a recipient because the accessible resources from alters will help ego reach his/her desired goals, such as innovation or success in the market. Likewise, alters are motivated to be donors because the future returns from ego will help alters reach their desired goals. The point is that if ego and alters are not strongly motivated in their goals, they will not be willing to be a recipient and donor even within certain ego-centric situations suggested in social capital studies. In other words, their different motivations in such situations are instrumental (or goal-directed) (Portes 1998) and can be maintained only if ego's returns satisfy what alters want as recipients after being donors. Thus, ego and alters can also be considered the same recipient-donor or donor-recipient actors who equally and eventually want to achieve their desired goals—as assumed in social exchange theories. This implies that the trans-actional point of view (*first condition*) can be extended in social capital studies by applying the assumptions of bargaining processes in social exchange theories.

In social exchange theories, although laboratory experiments strongly support their statements, it is unclear under what circumstances the specified power-dependence situations emerge in social networks. This is mainly because existing measures of power-dependence relations are not applicable to social networks. Most power measures are proposed to estimate the power distribution in an experimental network—not in social networks—since the scope of those measures is to test certain exchange theories under rigorous concepts of power-dependence relations—not to reflect general situations in social networks (Markovsky, Willer, and Patton 1988; Cook and Yamagishi 1992; Yamaguchi 1996). This implies that if the well-formalized measures of social capital studies (e.g., structural holes; centrality) can consider power-dependence relations between ego and alters in social networks, those theoretical statements of exchange theories can be tested not only in laboratory experiments but also in real social networks. In this sense, the lack of "formalism" in social exchange theories (i.e., the theories are hardly testable in general social networks) can be improved by this integration (*third condition*).

Moreover, the combining approach helps to reflect cultural and social-psychological contexts of relational actions in formal network measures (*second condition*). Social exchange theories clarify that power-dependence relations could contribute to one's generation of psychological elements for social order, such as trust, positive emotion, and cohesion in exchange partnerships, and thereby lead them to choose certain affective actions (e.g., commitment behavior). In this sense, if power-dependence relations in social networks are identifiable under the combining approach, the relationship between structural features of social networks and those social-psychological contextual actions can become testable. In line with this, social capital studies on relational embeddedness help to consider how culture matters to one's economic actions within power-dependence relations. Although the findings and statements of relational embeddedness studies are not fully considered in the existing network measures of structural embeddedness studies, they can be newly analyzed within the power-dependence framework. For instance, the social meanings of money and providing resources could be related to the issue of bargaining and inter-dependence between ego and alters.

In sum, by combining the two theoretical approaches, my dissertation aims to suggest new propositions and measures that explain one's bargaining process of accessing social capital within power-dependence relations. Social capital studies will help to figure out what structural features of social networks could generate power-dependence relations (*satisfactory second condition*). Social exchange theories will help to clarify complex bargaining between ego and alters within those structural features (*satisfactory first condition*). Multiple relational contexts of actions—structural, cultural, and social-psychological—are considered in the measures and propositions within social capital and power-dependence frameworks (*satisfactory third condition*). Utilizing those propositions and measures, empirical studies of this dissertation contribute to the understanding of social networks and economic actions, which are not clarified by existing network theoretical propositions and measures.

Table 1 summarizes the quality of the three theoretical conditions in the existing two theoretical approaches—social capital studies and social exchange theories—and the combining approach from relational sociological perspectives.

	Social Capital Studies	**Social Exchange Theories**	**Combining Approach**
Condition 1: *Trans-actional* view (action ⟺ action), not *Inter-actional* view (structure ⟹ action)	Unsatisfactory (X): Simpler receiving-donating processes between ego and alters who have different motivations and rationalities in social networks	Satisfactory (O): Complex bargaining processes between actors who have the same motivation and rationality in exchange networks	Satisfactory (O): Complex bargaining processes between ego and alters in social networks
Condition 2: Consideration of agency within multiple relational contexts	Partially Satisfactory (△): Studies of structural contexts and cultural/psychological contexts are separated	Partially Satisfactory (△): Both structural and social-psychological contexts of relations and actions are considered—but culture is overlooked	Satisfactory (O): Multiple relational contexts of bargaining in social networks can be considered
Condition 3: Balance of formalism and relationalism	Satisfactory (O): Many formal measures of social capital are applicable to social networks, reflecting various situations of one's access to resources	Unsatisfactory (X): Lack of measures of power and dependence applicable to social networks.	Satisfactory (O): Power-dependence relations shaped by various structural features of social networks are identifiable.

Table 2.1 The quality of the three theoretical conditions in social capital studies, social exchange theories, and combining approach

REFERENCES

Adler, Paul S and Seok-Woo Kwon. 2002. "Social Capital: Prospects for a New Concept." *Academy of management review* 27(1):17-40.

Alderson, Arthur S and Jason Beckfield. 2004. "Power and Position in the World City System." *American journal of sociology* 109(4):811-51.

Blau, Peter Michael. 1964. *Exchange and Power in Social Life*: Transaction Publishers.

Borgatti, Stephen P and Martin G Everett. 1992. "Notions of Position in Social Network Analysis." *Sociological methodology*:1-35.

Borgatti, Stephen P, Candace Jones and Martin G Everett. 1998. "Network Measures of Social Capital." *Connections* 21(2):27-36.

Borgatti, Stephen P. 2005. "Centrality and Network Flow." *Social networks* 27(1):55-71.

Borgatti, Stephen P and Martin G Everett. 2006. "A Graph-Theoretic Perspective on Centrality." *Social networks* 28(4):466-84.

Borgatti, Stephen P and Daniel S Halgin. 2011. "On Network Theory." *Organization science* 22(5):1168-81.

Burkitt, Ian. 2016. "Relational Agency: Relational Sociology, Agency and Interaction." *European Journal of Social Theory* 19(3):322-39.

Burt, Ronald S. 1992. *Structural Holes*: Harvard university press.

Chai, Sun-Ki and Mooweon Rhee. 2010. "Confucian Capitalism and the Paradox of Closure and Structural Holes in East Asian Firms." *Management and Organization Review* 6(1):5-29.

Coleman, James S. 1988. "Social Capital in the Creation of Human Capital." *American journal of sociology* 94:S95-S120.

Cook, Karen S and Richard M Emerson. 1978. "Power, Equity and Commitment in Exchange Networks." *American Sociological Review*:721-39.

Cook, Karen S, Richard M Emerson, Mary R Gillmore and Toshio Yamagishi. 1983. "The Distribution of Power in Exchange Networks: Theory and Experimental Results." *American journal of sociology* 89(2):275-305.

Cook, Karen S and Joseph M Whitmeyer. 1992. "Two Approaches to Social Structure: Exchange Theory and Network Analysis." *Annual review of sociology* 18(1):109-27.

Cook, Karen S and Toshio Yamagishi. 1992. "Power in Exchange Networks: A Power-Dependence Formulation." *Social networks* 14(3-4):245-65.

Cook, Karen Schweers. 2005. "Networks, Norms, and Trust: The Social Psychology of Social Capital 2004 Cooley Mead Award Address." *Social Psychology Quarterly*:4-14.

Cook, Karen S, Coye Cheshire and Alexandra Gerbasi. 2006. "Power, Dependence, and Social Exchange." *Contemporary social psychological theories* 73(2):194-216.

Corra, Mamadi and David Willer. 2002. "The Gatekeeper." *Sociological Theory* 20(2):180-207.

Dépelteau, François. 2008. "Relational Thinking: A Critique of Co-Deterministic Theories of Structure and Agency." *Sociological Theory* 26(1):51-73.

Emerson, Richard M. 1962. "Power-Dependence Relations." *American Sociological Review*:31-41.

Emerson, Richard M. 1972. "Exchange Theory, Part Ii: Exchange Relations and Networks." *Sociological theories in progress* 2:58-87.

Emerson, Richard M. 1976. "Social Exchange Theory." *Annual review of sociology* 2(1):335-62.

Emirbayer, Mustafa and Jeff Goodwin. 1994. "Network Analysis, Culture, and the Problem of Agency." *American journal of sociology* 99(6):1411-54.

Emirbayer, Mustafa. 1997. "Manifesto for a Relational Sociology." *American journal of sociology* 103(2):281-317.

Emirbayer, Mustafa and Ann Mische. 1998. "What Is Agency?". *American journal of sociology* 103(4):962-1023.

Erikson, Emily. 2013. "Formalist and Relationalist Theory in Social Network Analysis." *Sociological Theory* 31(3):219-42.

Everett, Martin G and Stephen P Borgatti. 2005. "Extending Centrality." *Models and methods in social network analysis* 35(1):57-76.

Friedkin, Noah E. 1991. "Theoretical Foundations for Centrality Measures." *American journal of sociology* 96(6):1478-504.

Granovetter, Mark. 1985. "Economic Action and Social Structure: The Problem of Embeddedness." *American journal of sociology* 91(3):481-510.

Granovetter, Mark. 1992. "Problems of Explanation in Economic Sociology." *Networks and organizations: Structure, form, and action*:25-56.

Homans, George C. 1958. "Social Behavior as Exchange." *American journal of sociology* 63(6):597-606.

Kuwabara, Ko. 2011. "Cohesion, Cooperation, and the Value of Doing Things Together: How Economic Exchange Creates Relational Bonds." *American Sociological Review* 76(4):560-80.

Lawler, Edward J and Samuel B Bacharach. 1987. "Comparison of Dependence and Punitive Forms of Power." *Social forces* 66(2):446-62.

Lawler, Edward J. 1992. "Power Processes in Bargaining." *Sociological Quarterly* 33(1):17-34.

Lawler, Edward J and Jeongkoo Yoon. 1996. "Commitment in Exchange Relations: Test of a Theory of Relational Cohesion." *American Sociological Review*:89-108.

Lawler, Edward J, Shane R Thye and Jeongkoo Yoon. 2000. "Emotion and Group Cohesion in Productive Exchange." *American journal of sociology* 106(3):616-57.

Lawler, Edward J, Shane R Thye and Jeongkoo Yoon. 2008. "Social Exchange and Micro Social Order." *American Sociological Review* 73(4):519-42.

Lawler, Edward J, Shane R Thye and Jeongkoo Yoon. 2009. *Social Commitments in a Depersonalized World*: Russell Sage Foundation.

Lévi-Strauss, Claude. 1971. *The Elementary Structures of Kinship*: Beacon Press.

Lin, Nan. 1999. "Building a Network Theory of Social Capital." *Connections* 22(1):28-51.

Lin, Nan. 2002. *Social Capital: A Theory of Social Structure and Action*, Vol. 19: Cambridge university press.

Malinowski, Bronislaw. 2002. *Argonauts of the Western Pacific: An Account of Native Enterprise and Adventure in the Archipelagoes of Melanesian New Guinea*: Routledge.

Markovsky, Barry, David Willer and Travis Patton. 1988. "Power Relations in Exchange Networks." *American Sociological Review*:220-36.

Markovsky, Barry, John Skvoretz, David Willer, Michael J Lovaglia and Jeffrey Erger. 1993. "The Seeds of Weak Power: An Extension of Network Exchange Theory." *American Sociological Review*:197-209.

Mauss, Marcel. 2002. *The Gift: The Form and Reason for Exchange in Archaic Societies*: Routledge.

Mische, Ann. 2011. "Relational Sociology, Culture, and Agency." *The SAGE handbook of social network analysis*:80-97.

Molm, Linda D. 1990. "Structure, Action, and Outcomes: The Dynamics of Power in Social Exchange." *American Sociological Review*:427-47.

Molm, Linda D. 1997. "Risk and Power Use: Constraints on the Use of Coercion in Exchange." *American Sociological Review*:113-33.

Molm, Linda D. 1997. *Coercive Power in Social Exchange*: Cambridge University Press.

Molm, Linda D, Nobuyuki Takahashi and Gretchen Peterson. 2000. "Risk and Trust in Social Exchange: An Experimental Test of a Classical Proposition." *American journal of sociology* 105(5):1396-427.

Molm, Linda D, Jessica L Collett and David R Schaefer. 2007. "Building Solidarity through Generalized Exchange: A Theory of Reciprocity." *American journal of sociology* 113(1):205-42.

Molm, Linda D, Monica M Whitham and David Melamed. 2012. "Forms of Exchange and Integrative Bonds: Effects of History and Embeddedness." *American Sociological Review* 77(1):141-65.

Polanyi, Karl. 1944. "The Great Transformation."

Portes, Alejandro. 1998. "Social Capital: Its Origins and Applications in Modern Sociology." *Annual review of sociology* 24(1):1-24.

Portes, Alejandro and Patricia Landolt. 2000. "Social Capital: Promise and Pitfalls of Its Role in Development." *Journal of Latin American Studies* 32(2):529-47.

Salganik, Matthew J and Douglas D Heckathorn. 2004. "Sampling and Estimation in Hidden Populations Using Respondent-Driven Sampling." *Sociological methodology* 34(1):193-240.

Shore, Lynn M, Jacqueline AM Coyle-Shapiro, Xiao-Ping Chen and Lois E Tetrick. 2009. "Social Exchange in Work Settings: Content, Process, and Mixed Models." *Management and Organization Review* 5(3):289-302.

Skvoretz, John and David Willer. 1993. "Exclusion and Power: A Test of Four Theories of Power in Exchange Networks." *American Sociological Review*:801-18.

Walker, Henry A, Shane R Thye, Brent Simpson, Michael J Lovaglia, David Willer and Barry Markovsky. 2000. "Network Exchange Theory: Recent Developments and New Directions." *Social Psychology Quarterly*:324-37.

Wasserman, Stanley and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications*, Vol. 8: Cambridge university press.

Weber, Max. 1978. *Economy and Society: An Outline of Interpretive Sociology*, Vol. 1: Univ of California Press.

Willer, David. 1992. "Predicting Power in Exchange Networks: A Brief History and Introduction to the Issues." *Social networks* 14(3-4):187-211.

Willer, David. 1999. *Network Exchange Theory*: Greenwood Publishing Group.

Xiao, Zhixing and Anne S Tsui. 2007. "When Brokers May Not Work: The Cultural Contingency of Social Capital in Chinese High-Tech Firms." *Administrative Science Quarterly* 52(1):1-31.

Yamaguchi, Kazuo. 1996. "Power in Networks of Substitutable and Complementary Exchange Relations: A Rational-Choice Model and an Analysis of Power Centralization." *American Sociological Review*:308-32.

Zelizer, Viviana A. 1989. "The Social Meaning of Money:" Special Monies"." *American journal of sociology* 95(2):342-77.

Zelizer, Viviana A Rotman. 1997. *The Social Meaning of Money*: Princeton University Press.

Zhang, Zhe and Ming Jia. 2010. "Using Social Exchange Theory to Predict the Effects of High-Performance Human Resource Practices on Corporate Entrepreneurship: Evidence from China." *Human Resource Management* 49(4):743-65.

CHAPTER 3

POWER-DEPENDENCE RELATIONS IN STRUCTURAL HOLES AND NETWORK CLOSURE: EVIDENCE FROM DIFFERENT SURVIVAL MECHANISMS OF ACTORS AND DIRECTORS IN THE U.S FILM INDUSTRY

Introduction

In this chapter, I develop new propositions and measures of structural holes (SH) and network closure (NC) (Burt 1992; 2000; 2004; 2009; Coleman 1988; 1990), considering the potential bargaining situations between ego and alters within the power-dependence framework in social exchange theories—i.e., ego's power over alters is equal to alters' dependence on ego. As with the theories and existing measures of SH and NC, the power propositions and measures also explain how ego can access heterogeneous or trustworthy resources from alters of SH or NC, respectively. Yet, in the previous theories, ego is assumed to be a recipient of resources from alters who are willing to be donors by potential collective sanctioning or brokerage rewards "from ego to alters." In contrast, the power propositions assume that ego and alters are in bargaining, based on their interdependence by potential collective sanctioning or brokerage rewards "between each other." More specifically, when ego is rich in SH or NC (i.e., alter-networks are *separated* by holes or *overlapping* by ties), ego can access resources from alters utilizing one of the bargaining powers structurally determined—***Total Power*** (i.e., mutual dependence) and ***Relative Power*** (i.e., unequal dependence). These propositions are reflected in graph-theoretic measures, based on weighted shortest-paths and network size difference between ego- and alter-networks.

This new concept of bargaining power in social networks is tested by examining the relationship between the social capital of film actors and directors in project-based networks and their career-survival. Although both directors and actors are artists collaborating for their film projects, they have very career interests—and thereby, they need very different types of social capital. To maintain their careers, artistst must choose between a single focused identity and multivalent identities. For actors, multivalent identities are beneficial. They have to be cast in heterogeneous movies to avoid being considered "typecast" actors, which would shorten their careers (Zuckerman et al., 2003). Thus, structural holes will provide more benefits because actors can access valuable information about casting calls from heterogeneous movies. But unlike actors, directors need a focused identity. Many empirical studies support that for a longer career, directors must prove their works' distinctiveness in various terms, such as genre, style, and storytelling, to appeal to critics and consumers (Svejenova 2005; Alvarez et al. 2005; Hsu 2006). In this sense, it is predictable that directors will earn more benefits from network closure. To justify their unique identities, directors need some "muses" who will be committed to their film characters with reliable performances and reflect directors' artistic intentions well (e.g., Robert De Niro in Martin Scorsese's movies). Using structural sanctioning within NC, directors can force their actors—who are aware of no future acting jobs due to collective sanctions—to perform like their muses even without mutual trust and deep interactions.

These predictions based on the theories of structural holes and network closure are supported by the results of event history analysis (Allison 1984; Yamaguchi 1991; Broström 2018)—only if the power measures are applied. The existing measures (i.e., ego-centric) and power measures (i.e., alter-centric) of SH and NC are applied in project-based networks of 64324 actors and 17540 directors who participated in 89060 projects of the U.S. film industry during 1929-2019. The models of event history analysis with previous ego-centric measures fail to support the predictions. The results show that structural holes have an equally positive effect on both actors' and directors' career-survival. In contrast, the models with the power measures support that the hypotheses are correct. As predicted, structural holes matter for actors’ longer careers; both total and relative power within SH enhance actors' career-survival. Likewise, network closure matters for directors’ longer careers. But one unexpected finding is that only relative power within NC is essential for directors’ career-survival, whereas total power within NC hurts it. In other words, when a director is connected with actors whose networks are overlapping, the director can earn benefits from the network closure only if the structure generates strong relative power (i.e., director can induce more severe sanctions to actors)—not total power (i.e., both director and actors can induce severe sanctions to each other).

In the discussion part, based on the power propositions, I explain how different bargaining strategies for using total power and relative power may differentiate an ego-director’s access to social capital from alter-actors—especially in the context of their different career interests.

Theories of Structural Holes and Network Closure

The theories of structural holes (SH) and network closure (NC) are differentiated by the suggested mechanisms of how ego earns benefits from their network position (Burt 2000). Burt (1992; 2000; 2004; 2009) argues that ego earns benefits from the network position where no ties (or empty spaces) between alters exist (i.e., structural holes). In the left-hand side graph of Figure 3.1, alters (B1, C1, D1, and E1) have no direct connections. They are likely to belong to different social groups because if they are involved in the same social group (or cluster), each triad (e.g., B1-A-C1) is highly likely to have closure (e.g., a tie between B1 and C1). The point is that since their social groups (B, C, D, and E) are heterogeneous, their resources are likely to be heterogeneous as well and thereby valuable to each other. However, even if the alters in different clusters want to exchange their resources, this is only available through A's brokerage. Moreover, the alters would have no other choice without ego; ties across different social groups (or clusters) rarely exist as ties within each social group are very likely to be clustered. In turn, for ego A, the alters' demands (e.g., rewards after providing resources) "*...would be the most negotiable*" (Burt 1992) because of their needs of ego A. Thus, when ego A is motivated to use the opportunities, alters—as donors—provide their resources to A, looking for brokerage returns, and ego A—as a recipient—can easily access their heterogeneous resources.

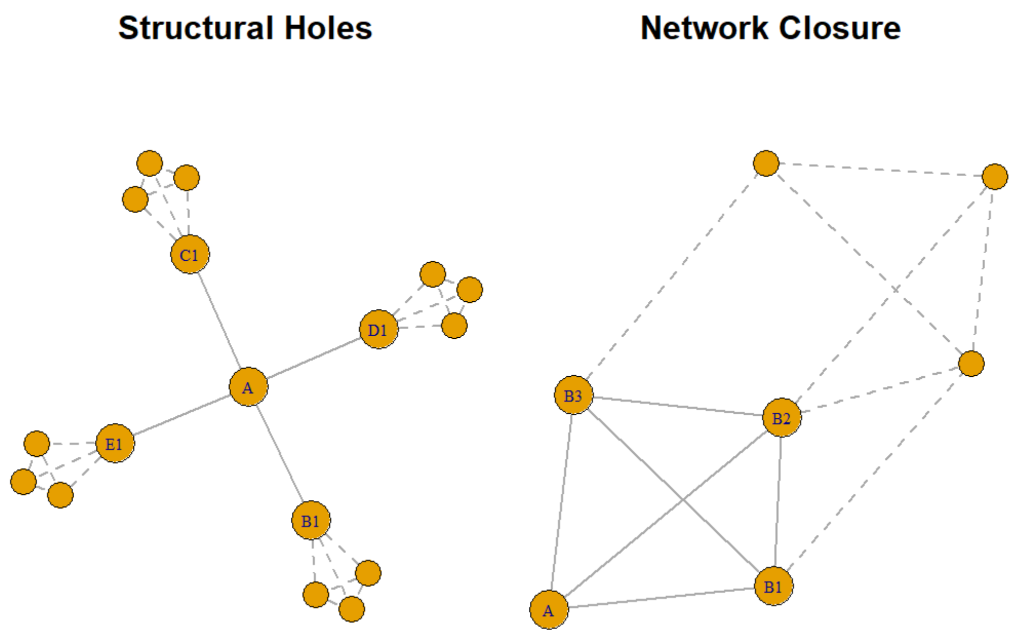


Figure 3.1 Ego-centric networks within structural holes (i.e., empty spaces between alters; sparse network) and network closure (i.e., ties between alters; dense network). Dash-lines represent the expected structures of ties near structural holes and network closure.

On the contrary, according to Coleman (1988; 1990), ego's position where many ties between alters exist (i.e., network closure) provides benefits. Suppose ego A in the right-hand side graph of Figure 3.1 has strong bonds and mutual trust with B1 and B2. It is expected that A can access trustworthy resources only from the two, but the resources are also accessible from B3. Within the dense network, when trustworthiness is enforced as the norm, the enforcement will be strong because all ego and alters know each other. For example, B3's violation of the norm (e.g., malfeasance in a transaction with A) will be rapidly informed to B1 and B2, and due to their strong bonds with A, they will collectively sanction B3. In the worst-case scenario, B3 may lose the transaction relationships not only with A but also with B1 and B2. Thus, B3—

as a donor—will provide trustworthy resources to ego, and A—as a recipient—can access the resources from every alter, saving the cost of building mutual trust with all of them. From Coleman's (1988) expression, the effective sanctioning by ego *"...can monitor and guide behavior..."* of alters.

The theories of SH and NC become testable by graph-theoretic measures that quantify how much alters in an ego-centric network are sparsely or densely connected (Lin and Erickson 2008; Borgatti and Halgin 2011). SH is usually measured by the effective network size of ego (Burt 1992; Borgatti 1997; Walker, Bruce, and Shan 1997; Zaheer and Bell 2005). It is calculated by the number of groups of alters who are distinct in terms of whether they share connections (i.e., redundant ties) or not. Ego is expected to brokerage between multiple heterogeneous groups when alters are more sparsely connected. On the contrary, NC is usually measured by ego-centric density. It is formalized as the sum of ties between alters in an ego-centric network divided by the maximum possible number of ties between alters (Rowley, Behrens, and Krackhardt 2000; Bae and Gargiulo 2004; Rost 2011; Moran 2005). It represents how strong the norms in an ego-network will be, enforced by potential collective sanctions.

Let n be the number of alters in an ego-centric network—excluding ego—and t be the number of ties between alters. The effective network size for SH and ego-centric density for NC are formalized below, respectively.

$$Effective\ network\ size\ (for\ SH):\ n - \frac{2t}{n}$$

$$Egocentric\ Density\ (for\ NC):\ \frac{t}{n(n-1)/2} = \frac{2t}{n(n-1)}$$

Scope Conditions of Power-Dependence Relations in Structural Holes and Network Closure

I develop new propositions and measures of structural holes and network closure, considering the power-dependence relations and bargaining between ego and alters. The new propositions and measures explain how ego can access heterogeneous or trustworthy resources from alters, using one of two bargaining powers—***relative power (i.e., unequal dependence; difference of power)*** or ***total power (i.e., mutual dependence; sum of power)*** embedded in structural holes and network closure. In turn, it is presumed that social capital is available to ego, only if alters are more dependent on ego (= strong relative power) or if ego and alters are mutually dependent on each other (= strong total power). Since their interdependence can be largely shaped by whether they have alternative partners in their own networks, I apply an alter-centric approach that focuses on both ego- and alter-networks and their connections.

It is noteworthy that although the previous two theories also briefly discuss how alter-network structure matters to ego's access to social capital, these ideas are largely based on the assumption about recipient-ego and donor-alters. Burt (1992) points out that ego's access to social capital becomes more successful when there is no tie between alter-networks (i.e., secondary holes) because it increases alters' dependence on ego's brokerage, and thereby ego has a strong power over alters. Yet, from an exchange theory perspective, his statement did not clarify the power of alters over ego (i.e., ego's dependence on alters), and thereby bargaining situations from unequal or mutual dependence between them are overlooked. Likewise, Coleman

(1988) argues that dense alter-networks can also be the source of ego's social capital. For example, students' education performance can also be improved when they have parents who know each other (i.e., dense alter-networks). However, in Coleman's example, the alters are parents of ego who are willing to be givers for their children's educational success. It is also overlooked that ego and alters may be in bargaining, coercing each other with collective sanctions.

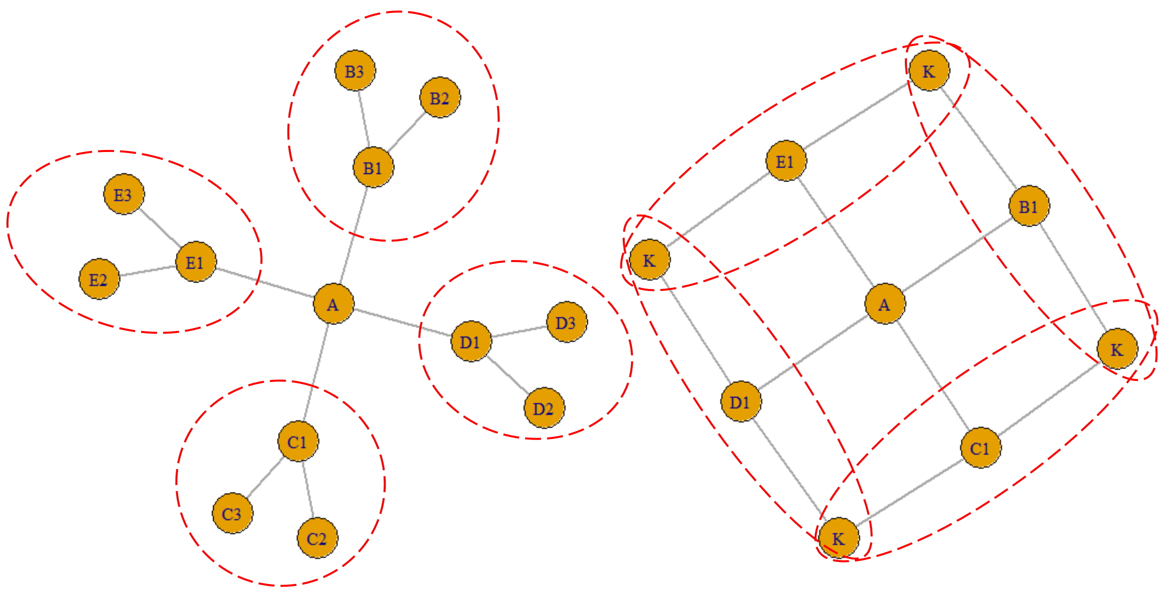
Several scope conditions are considered to justify the new propositions and measures. First, ego and alters have the same motivation, desire, and rationality for their transactions to reach their desired goals. In other words, the basic assumption of actors of structural holes and network closure are in line with the assumptions of social exchange actors (Cook, Cheshire, and Gerbasi 2006; Molm 1997a).

Second, the value and amount of exchangeable resources ego and alters have are differentiated by their network positions. For example, ego within network closure can offer more sanctioning (i.e., negative rewards) on alters. Likewise, ego within structural holes can offer more brokerage returns to alters. Note that This assumption is different from many exchange theories of power in which all actors tend to have the same amount of exchangeable resources (Willer 1999; Skvoretz and Willer 1993; Walker et al. 2000).

Third, exchange connections are inclusive—not exclusive. Thus, inter-dependence between ego and alters is only determined by how many alternatives they have in their networks, not by the dependencies and actions of second/third-order alters (i.e., alters of alters; alters of alters of alters). This means that the alter-centric approach (i.e., only ego- and alter-networks are considered) is enough to capture the bargaining situations between ego and alters. For example, in the C-B-A-B-C network, A and B equally have two available partners. Under the inclusive connection, $D_{BA} = D_{AB}$ is expected. However, under the exclusive connection, as noted, the possibility of exclusion makes C more dependent on B (i.e., $D_{CB} < D_{BC}$), and it may generate $D_{BA} < D_{AB}$. But the dependence situation will also change when C has alternatives that reduce D_{CB}. In turn, under the exclusive connection, ego's power over alters (i.e., alters' dependence on ego) is affected not only by alters' networks, but also by nth-order alters' networks (i.e., chain of exclusions from alters of alters of alters…) (Markovsky, Willer, and Patton 1988; Bonacich 1987).

Propositions of Power-Dependence Relations in Structural Holes and Network Closure

Figures 3.2 and 3.3 show the different alter-centric networks of ego A who retains the same ego-centric network in each case. In Figure 3.2, A's ego-centric network is identical to the graph of Figure 3.1—an example of structural holes. But alters' ego-centric networks (where ties to ego A are not included) are differently positioned in the two alter-centric networks: alter-networks in the left-hand side graph are more "separated" by holes (or empty spaces) than they are in the right-hand side graph. In turn, alter-networks are connected by "longer" shortest-paths that tend to pass through ego. Likewise, in Figure 3.3, A's ego-centric network is identical with the graph of Figure 3.2—an example of network closure. But alter-networks in the left-hand side graph are more "overlapping" by ties than they are in the right-hand side graph. In turn, alter-networks are connected by "shorter" shortest-paths.



More separated alter-networks

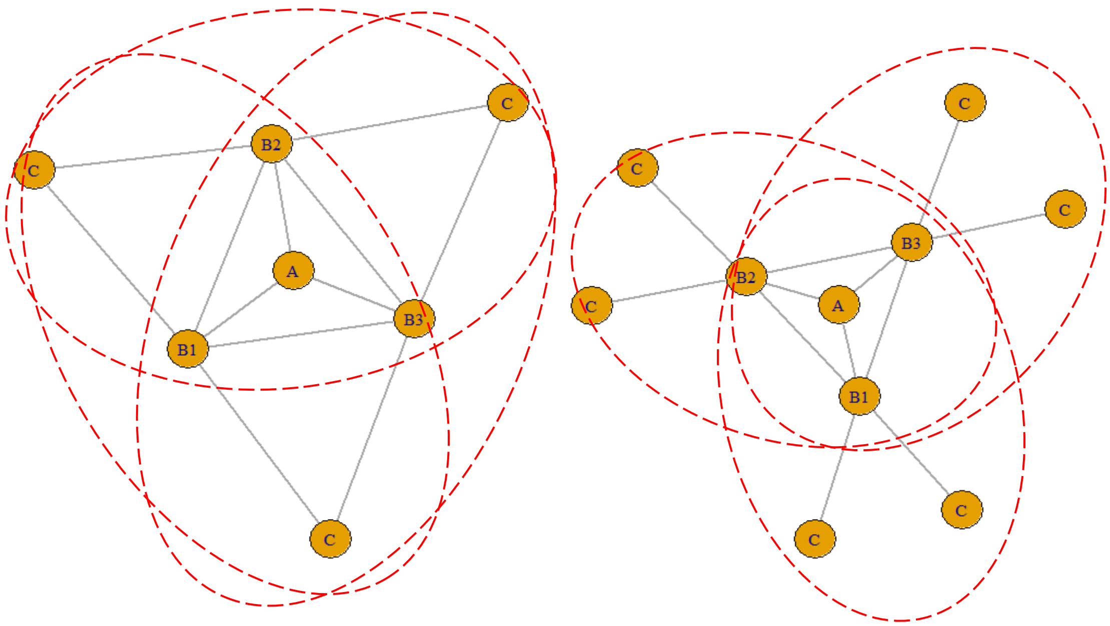
Less separated alter-networks

Figure 3.2 Two alter-centric networks of ego A, who retains the same ego-centric network but is rich in different structural holes (i.e., alter-networks are separated by holes)

Ego is rich in ***structural holes*** (SH) when alter-networks are *separated* by holes (or empty spaces). In such a situation, ego and alters will share strong ***Total power*** (i.e., mutual dependence; the sum of power). But when the holes only exist between alters—not alter-networks—their total power may become weak because both ego and alters can find alternative partners for brokerage transactions.

In the left-hand side graph of Figure 3.2, each alter's dependence on ego A, which is equal to A's power over each alter, is expected to be strong because each alter has no alternative broker without A due to the holes between alter-networks. Ego A will also be strongly dependent on each alter (i.e., alter's power over ego will be strong) because each alter is the only option to access each different cluster's resources within the holes, which are necessary for A to maintain the brokerage role. For example, without B1, ego cannot access the resources embedded in B1's network (or cluster B) and will fail to provide it to C1 and D1 as a broker. On the contrary, in the right-hand side graph of Figure 3.2, the mutual dependence between ego and alters is expected to be weak. Even without A's brokerage, each alter can access other alters' resources through the alternative partner K, even though they have no direct ties between each other. Ego A also will be less dependent on each alter because they are not the exclusive options for A to access resources of different clusters. For example, through C1, A can access the resources embedded in B1's network and provide it to D1 as a broker[1].

[1] Their weak mutual dependence due to the existence of alternative broker K is in line with Burt's term (1992) "secondary holes". Burt points out that ties between alter-networks may constrain ego's brokerage opportunities because these alternative routes will decrease alters' dependence on ego. However, unlike Burt's point, the power propositions assume that the change of interdependence is because of alternative broker K's actions who is equally motivated to use the brokerage opportunities like ego A. Additionally, while Burt only focuses on alters' dependence on ego (= ego's power over alters), the propositions consider interdependence between ego and alters.



More overlapping alter-networks

Less overlapping alter-networks

Figure 3.3 Two alter-centric networks of ego A who retains the same ego-centric network but is rich in different network closure (i.e., alter-networks are overlapping by ties)

Ego is rich in ***network closure*** (NC) when alter-networks are *overlapping* by ties. In such a situation, ego and alters will share strong ***Total power*** (i.e., mutual dependence; the sum of power). But when the ties only exist between alters—not alter-networks—their total power may become weak because, for both ego and alters, their alternative choices (i.e., rejecting trust-based transactions and focusing on other exchange relationships) may not generate the huge negative consequences (i.e., loss of many relationships by collective sanctions)[2].

[2] From Molm's point of view (1997a; 1997b), one's dependencies on another from no alternative to maximize positive rewards (e.g., brokerage benefits) and from no alternative to minimize negative rewards (e.g., collective sanction) are equal. In turn, the suggested power-dependence concepts of SH and NC are equally based on the concept of alternatives in exchange theories

In the left-hand side graph of Figure 3.3, each alter is strongly dependent on ego A because their failure of exchange with A may yield collective sanctions by A, which could severely damage their networks (i.e., negative rewards) due to the close connections between alter-networks. For example, suppose A asks B2 and B3 for sanctions on B1. Then, B1 may lose the transaction relationships not only with B2 and B3 but also with C because of B2 and B3's direct influence on C. Similarly, ego A is also strongly dependent on alters because each alter can induce strong collective sanctions on A, not only directly asking other alters, but also indirectly through their friends (= C). In other words, they have no alternative to minimize the potential negative rewards. On the contrary, in the right-hand side graph of Figure 3.4, the mutual dependence between ego and alters is expected to be weaker. Ego A cannot severely damage each alter's network because their friends (=C) are less likely to be influenced by A or other alters. Likewise, each alter cannot use their relationships (= C) to sanction A.

Within SH or NC, ego's ***relative power*** over alters (i.e., unequal dependence; the difference of power) in bargaining increases when ego has a larger network than alters. When ego is rich in SH or NC, the network-size difference between ego and alters will correlate with their unequal amounts of mobilizable resources for brokerage transactions or collective sanctioning. This generates their unequal dependence. For example, in the left-hand side graph of Figure 3.2, A has a larger network (=4) than B1 (=3) within SH. Then, B1 will be more dependent on A. This is because when A and B1 exchange their resources, mobilizing them from their own networks (i.e., from C1/D1/E1 and B2/B3), the amount of brokerage returns A can provide to B1 will be larger than the brokerage resources B1 can provide to A[3]. Unlike this situation, in the right-hand side graph of Figure 3.3, A's network (=3) is smaller than B1's network (=5) within NC. In such situations, the collective sanctions induced by B1 will be more severe on A than sanctions by A on B1, and to minimize its negative consequences, A will be more dependent on transactions with B1.

In sum, strong ***total power (i.e., mutual dependence)*** between ego and alters will reduce one's power-use in bargaining, making them more cooperative and more likely to use ***conciliatory*** strategy. Thus, when ego is greatly rich in ***structural holes (i.e., alter-networks are separated by holes)*** or ***network closure (i.e., alter-networks are overlapping by ties)***, ego can access heterogeneous or trustworthy resources from alters with less conflict. In other words, the rationale or norms of cooperation will be shared by ego and alters within alter-level SH or NC due to their mutual dependence situations, leading them to bargain smoothly. But if ego within SH or NC has strong ***relative power (i.e., unequal dependence)*** over alters, ego may use the power in bargaining (i.e., ***hostile*** strategy), yielding conflicts. Ego's use of power would be the exclusion (Skvoretz and Willer 1993) of an alter from brokerage relationships. Coercion (Molm 1997a; 1997b) can be another way of using power when ego can generate collective sanctions on an alter.

[3] Note that one's dependencies on another to access brokerage returns (for alters) and brokerage resources (for ego) are assumed to be equal. Burt (1992) expects that alters will be more dependent on ego within SH because alters have difficulty finding alternative brokers without ego. However, ego will also be strongly dependent on alters because ego cannot perform brokerage roles without alters' resources. In turn, to access heterogeneous resources, ego must succeed in the multiple exchanges with alters, whereas alters can only focus on the single exchange with ego. This situation (i.e., ordered exchange) can increase ego's dependence on alters, even making broker-ego have weaker power (Corra and Willer 2002).

Measures of Power-Dependence Relations in Structural holes and Network Closure

The power propositions are testable by graph-theoretic measures that quantify those power-dependence relations between ego and alters. Based on the weighted shortest-paths and network-size difference between ego- and alter-networks, I suggest the following measures of total power and relative power that reflect the interdependence between ego and alters.

Let L be the MxN matrix of unweighted/weighted shortest-path lengths between nodes of ego i's and alter j's networks—except the partner node in each network (i.e., alter j in ego-network and ego i in alter-network)—and ℓ_{mn} (unweighted), $\ell_{mn,SH}$ and $\ell_{mn,NC}$ (weighted) be the possible matrix elements. Then, examples of L for the graphs of Figures 3.2 and 3.3 are expressed below.

ℓ_{mn} / $\ell_{mn,SH}$	B1 (Alter)	B2	B3	Row mean of ℓ_{mn} / $\ell_{mn,SH}$	
A (Ego)	1 / .2	2 / .5	2 / .5	**1.67 / .4**	
C1	2 / .5	3 / 1	3 / 1	**2.67 / .83**	
D1	2 / .5	3 / 1	3 / 1	**2.67 / .83**	
E1	2 / .5	3 / 1	3 / 1	**2.67 / .83**	
Column mean of ℓ_{mn} / $\ell_{mn,SH}$	**1.75 / .43**	**2.75 / .88**	**2.75 / .88**	ℓ_{AB1} : ℓ_{B1A} **7.25 : 9.68**	$\ell_{AB1,SH}$: $\ell_{B1A,SH}$ **2.19 : 2.89**

Table 3.1 Unweighted (=ℓ_{mn}) and weighted (=$\ell_{mn,SH}$) shortest-path lengths between nodes of A and B1's networks in the left-hand side graph of Figure 3.2

ℓ_{mn} / $\ell_{mn,SH}$	B1	K	K	Row mean of ℓ_{mn} / $\ell_{mn,SH}$	
A (Ego)	1 / .2	2 / .5	2 / .5	**1.67 / .4**	
C1	2 / .5	1 / .2	3 / 1	**2 / .57**	
D1	2 / .5	3 / 1	3 / .2	**2.67 / .83**	
E1	2 / .5	3 / 1	1 / .2	**2 / .57**	
Column mean of ℓ_{mn} / $\ell_{mn,SH}$	**1.67 / .4**	**2 / .57**	**2 / .57**	ℓ_{AB1} : ℓ_{B1A} **5.67 : 8.34**	$\ell_{AB1,SH}$: $\ell_{B1A,SH}$ **1.54 : 2.37**

Table 3.2 Unweighted (=ℓ_{mn}) and weighted (= $\ell_{mn,SH}$) shortest-path lengths between nodes of A and B1's networks in the right-hand side graph of Figure 3.2

ℓ_{mn} / $\ell_{mn,NC}$	B1 (Alter)	B2	B3	C	C	Row mean of ℓ_{mn} / $\ell_{mn,NC}$
A (Ego)	1 / .5	1 / .5	1 / .5	2 / .2	2 / .2	**1.4 / .38**
B2	1 / .5	0 / 1	1 / .5	1 / .5	2 / .2	**1 / .54**
B3	1 / .5	1 / .5	0 / 1	2 / .2	1 / .5	**1 / .54**
Column mean of ℓ_{mn} / $\ell_{mn,NC}$	**1 / .5**	**.67 / .67**	**.67 / .67**	**1.67 / .3**	**1.67 / .3**	ℓ_{AB1} : ℓ_{B1A} **5.67 : 3.4**; $\ell_{AB1,NC}$: $\ell_{B1A,NC}$ **2.43 : 1.46**

Table 3.3 Unweighted (=ℓ_{mn}) and weighted (=$\ell_{mn,NC}$) shortest-path lengths between nodes of A and B1's networks in the left-hand side graph of Figure 3.3

ℓ_{mn} / $\ell_{mn,NC}$	B1 (Alter)	B2	B3	C	C	Row mean of ℓ_{mn} / $\ell_{mn,NC}$
A (Ego)	1 / .5	1 / .5	1 / .5	2 / .2	2 / .2	**1.4 / .38**
B2	1 / .5	0 / 1	1 / .5	2 / .2	2 / .2	**1.2 / .48**
B3	1 / .5	1 / .5	0 / 1	2 / .2	2 / .2	**1.2 / .48**
Column mean of ℓ_{mn} / $\ell_{mn,NC}$	**1 / .5**	**.67 / .67**	**.67 / .67**	**2 / .2**	**2 / .2**	ℓ_{AB1} : ℓ_{B1A} **6.33 : 3.8**; $\ell_{AB1,NC}$: $\ell_{B1A,NC}$ **2.23 : 1.34**

Table 3.4. Unweighted (=ℓ_{mn}) and weighted (=$\ell_{mn,NC}$) shortest-path lengths between nodes of A and B1's networks in the right-hand side graph of Figure 3.3

Each *row mean* of unweighted shortest-path lengths (=ℓ_{mn}) can represent how much a node in ego i's network is closely (~0) or apartly (~3) connected to alter j's network due to the network closure or structural holes (i.e., alter-networks are overlapping or seperated). Each *column mean* of unweighted shortest-path lengths represents how much a node in alter j's network is closely (~0) or apartly (~3) connected to ego i's network due to the network closure or structural holes. Note that the longest shortest-path length between any two nodes of ego- and an alter-network is 3. The two nodes must be connected by the path that passes through ego and alter (e.g., B and C in the path B-Ego-Alter-C), in which the length between them cannot exceed 3. In turn, due to the existence of the path, the longest shortest-path length between the two nodes also cannot exceed 3.

Thus, *the sum of row means* represents the size of ego i's network connected to alter j's network within the network closure (~0) or structural holes (~3), and the *sum of column means* represents the size of alter j's network connected to ego i's network within the network closure (~0) or structural holes (~3). As noted, the size of ego-network within SH or NC is expected to correlate with an alter's dependence on ego within SH or NC—and vice versa. From this point of view, the sum of row means and the sum of column means in L can represent alter j's dependence on ego i (= ego i's power over alter j) and ego i's dependence on alter j (= alter j's power over ego i), respectively. In Tables, each sum of row means and each sum of column means increases (= longer shortest-paths between ego- and alter-networks) when alter-networks are more separated, whereas it decreases (= shorter shortest-paths between ego- and alter-networks) when alter-networks are more overlapping.

However, the unweighted shortest-path length cannot fully capture the power-dependence between ego and alters because its increment is linear—not exponential. For example, suppose ego- and an alter-network tend to have 3 shortest-path lengths (i.e., no connections between ego's and alter's friends, except the tie between ego and alter). They will then be strongly dependent on each other. Alters have no alternative broker without ego. Ego has no alternative without each alter who can provide brokerage resources embedded in each different cluster. But when they are connected with 2 shortest-path lengths (i.e., there is someone who knows both ego's and alter's friends), their dependence will rapidly decrease by the alternative path that passes through the someone. Likewise, suppose ego- and an alter-network are is connected with 0-length (i.e., ego and alter share the same friends). They will then be strongly dependent on each other because one may immediately lose multiple exchange relationships by the other's sanctions. But if their networks are connected with 1-length (i.e., ego's and alter's friends know each other), their inter-dependence will become much weaker because one's collective sanctions on another are only available through indirect influence—ego must ask their friends to influence alter's friends.

To consider the exponential increment of inter-dependence within SH or NC, I use the weighted shortest-path lengths, the formulas of which are $\ell_{mn,SH} = \frac{\ell_{mn}^2 + 1}{10}$ and $\ell_{mn,NC} = \frac{1}{\ell_{mn}^2 + 1}$. Based on the formulas, alter j's dependence on ego i and ego i's dependence on alter j are expressed as the sum of row means (= $D_{a_{ij}e_i}$) and the sum of column means (=$D_{e_i a_{ij}}$) in L, respectively, where each element ℓ_{mn} is weighted as $\ell_{mn,SH}$ or $\ell_{mn,NC}$. Thus, ego i's power over alter j (= $P_{e_i a_{ij}}$) and alter j's power over ego i (= $P_{a_{ij}e_i}$) within SH and NC are formally expressed below. Note again that N and M represent the number of rows and columns of matrix L, respectively.

$$P_{e_i a_{ij}}(SH) = D_{a_{ij}e_i}(SH)$$

$$D_{a_{ij}e_i}(SH) = \sum_{m=1}^{M} \frac{1}{N} \sum_{n=1}^{N} \frac{\ell_{mn}^2 + 1}{10}$$

$$\therefore P_{e_i a_{ij}}(SH) = \frac{1}{N} \sum_{m=1}^{M} \sum_{n=1}^{N} \ell_{mn,SH}$$

$$P_{a_{ij}e_i}(SH) = D_{e_i a_{ij}}(SH)$$

$$D_{e_i a_{ij}}(SH) = \sum_{n=1}^{N} \frac{1}{M} \sum_{m=1}^{M} \frac{\ell_{mn}^2 + 1}{10}$$

$$\therefore P_{a_{ij}e_i}(SH) = \frac{1}{M} \sum_{n=1}^{N} \sum_{m=1}^{M} \ell_{mn,SH}$$

$$P_{e_i a_{ij}}(NC) = D_{a_{ij}e_i}(NC)$$

$$D_{a_{ij}e_i}(NC) = \sum_{m=1}^{M} \frac{1}{N} \sum_{n=1}^{N} \frac{1}{\ell_{mn}^2 + 1}$$

$$\therefore P_{e_i a_{ij}}(NC) = \frac{1}{N} \sum_{m=1}^{M} \sum_{n=1}^{N} \ell_{mn,NC}$$

$$P_{a_{ij}e_i}(NC) = D_{e_i a_{ij}}(NC)$$

$$D_{e_i a_{ij}}(NC) = \sum_{n=1}^{N} \frac{1}{M} \sum_{m=1}^{M} \frac{1}{\ell_{mn}^2 + 1}$$

$$\therefore P_{a_{ij}e_i}(NC) = \frac{1}{M} \sum_{n=1}^{N} \sum_{m=1}^{M} \ell_{mn,NC}$$

The sum and difference of $P_{e_i a_{ij}}$ and $P_{a_{ij} e_i}$ will represent ego's *total power* with and *relative power* over an alter in bargaining for heterogeneous or trustworthy resources, respectively. As shown in the matrix tables for L, the sum of $P_{AB1}(SH)$ and $P_{B1A}(SH)$ (=$\ell_{B1A,SH}$ and $\ell_{AB1,SH}$) within more separated alter-networks is higher than that within less separated alter-networks (2.89 + 2.19 > 2.37 + 1.54). The sum of $P_{AB1}(NC)$ and $P_{B1A}(NC)$ (= $\ell_{B1A,NC}$ and $\ell_{AB1,NC}$) within more overlapping alter-networks is also higher than that within less overlapping alter-networks (1.46 + 2.43 > 1.34 + 2.23). The difference of $P_{AB1}(SH)$ and $P_{B1A}(SH)$ where A has a larger network than B1 shows positive indices (2.89 – 2.19 > 0; 2.37 – 1.54 > 0; stronger relative power), whereas the difference of $P_{AB1}(NC)$ and $P_{B1A}(NC)$ where A has a smaller network than B1 shows negative indices (1.46 – 2.43 < 0; 1.34 - 2.23 < 0; weaker relative power).

This approach, however, may overestimate the effect of network size on relative and total power. As noted, one's dependence on another within SH or NC is expected to increase by the other's network size and vice versa. But this does not mean that their mutual or unequal dependence simply increases by their sum or difference of network size. For instance, if two actors in a dyadic relation are positioned within perfectly SH or NC, their mutual dependence will be strong enough—no matter what each actor's network size is. Thus, ego i's total power (= $P_{e_i a_{ij}}(T)$) with and relative power (= $P_{e_i a_{ij}}(R)$) over alter j within SH and NC are measured by the below formulas that control the network size effect. Under the formulas, $P_{e_i a_{ij}}(T)$ increases by how much ego is rich in structural holes or network closure (i.e., alter-networks are separated by holes or overlapping by ties)—regardless of ego i's and alter j's network size. In contrast, $P_{e_i a_{ij}}(R)$ increases by how much ego i's network is relatively larger than alter j's network within SH or NC.

$$P_{e_i a_{ij}}(SH,T) = \frac{P_{e_i a_{ij}}(SH) + P_{a_{ij} e_i}(SH)}{N + M}$$

$$P_{e_i a_{ij}}(SH,R) = \frac{P_{e_i a_{ij}}(SH) - P_{a_{ij} e_i}(SH)}{N + M}$$

$$P_{e_i a_{ij}}(NC,T) = \frac{P_{e_i a_{ij}}(NC) + P_{a_{ij} e_i}(NC)}{N + M}$$

$$P_{e_i a_{ij}}(NC,R) = \frac{P_{e_i a_{ij}}(NC) - P_{a_{ij} e_i}(NC)}{N + M}$$

Finally, ego i's ***total power (i.e., mutual dependence)*** with and ***relative power (i.e., unequal dependence)*** over alters within SH and NC are measured by the mean of $P_{e_i a_{ij}}(T)$ and mean of $P_{e_i a_{ij}}(R)$ for SH and NC, respectively. Note that n_{e_i} represents the number of alters in ego i's ego-centric network. When n_{e_i}= 0 (i.e., ego i has no alters), ego i is assumed to have 0 relative power (= no unequal dependence) and 0 total power (= no mutual dependence). When n_{e_i}> 0, the power measures quantify how much ego i's network position tends to provide advantages in bargaining with alters to access heterogeneous or trustworthy resources.

$$P_{e_i}(SH,T) = \frac{1}{n_{e_i}} \sum_{j=1}^{n_{e_i}} P_{e_i a_{ij}}(SH,T)$$

$$P_{e_i}(SH,R) = \frac{1}{n_{e_i}} \sum_{j=1}^{n_{e_i}} P_{e_i a_{ij}}(SH,R)$$

$$P_{e_i}(NC,T) = \frac{1}{n_{e_i}} \sum_{j=1}^{n_{e_i}} P_{e_i a_{ij}}(NC,T)$$

$$P_{e_i}(NC,R) = \frac{1}{n_{e_i}} \sum_{j=1}^{n_{e_i}} P_{e_i a_{ij}}(NC,R)$$

Based on the formulas, each measure of total power and relative power has the range [0, 1] and [-1, 1], respectively, and represents how much ego and alters are mutually dependent (when it is closer to 1) and how much alters are more dependent on ego (when it has a positive index) within each structure—SH or NC. Table 3.5 summarizes ego A's bargaining powers in the graphs of Figures 3.2 and 3.3. Note that the measures can be applied to any undirected graph, and the relevant R codes for application are publicly accessible.

	Ego A within *More Separation*	Ego A within *Less Separation*	Ego A within *More Overlap*	Ego A within *Less Overlap*
Total Power within SH	**.725**	**.592**	.267	.307
Relative Power within SH	**.103**	**.085**	-.067	-.077
Total Power within NC	.175	.242	**.487**	**.447**
Relative Power within NC	.025	.034	**-.121**	**-.112**

Table 3.5 Ego A's bargaining powers in the graphs of Figures 3.2 and 3.3.

The results support that the power measures reflect well the concept of power-dependence relations in SH and NC suggested in the propositions. In Figure 3.2, ego A's total power within structural holes is stronger when A has more separated alter-networks (.725 > .592). Similarly, in Figure 3.3, ego A's total power within network closure is stronger when A has more overlapping alter-networks (.487 > .447). The measured relative powers also follow the propositions. In both graphs of Figure 3.1, ego A's network size is larger than each alter's network size, and therefore ego A is expected to have stronger relative power over alters within SH. This is described as the positive indices of relative power (.103 and .085). Unlike Figure 3.1, ego A in both graphs of Figure 3.2 has a smaller network than alters. Thus, ego A was expected to have weaker relative power over alters (or alters have stronger relative power over ego) within NC, and the negative indices of relative power (-.121 and -.112) represent this.

One interesting point is that, although ego A and alters in both graphs of Figure 3.2 have the same network-size difference, the strength of ego A's relative power decreases when alter-networks are less separated (.103 → .085). Similarly, the weakness of ego A's relative power in Figure 3.3 decreases when alter-networks are less overlapping (-.121 → -.112). Those results are consistent with the power propositions. If ego is not greatly rich in structural holes or network closure, the network-size difference between ego and alters will be less correlated with their unequal amounts of mobilizable resources for brokerage transactions or collective sanctioning. Thus, their unequal dependence will decrease, and one's relative power over another (i.e., ego's relative power over alters; alters' relative power over ego) will become weak as well.

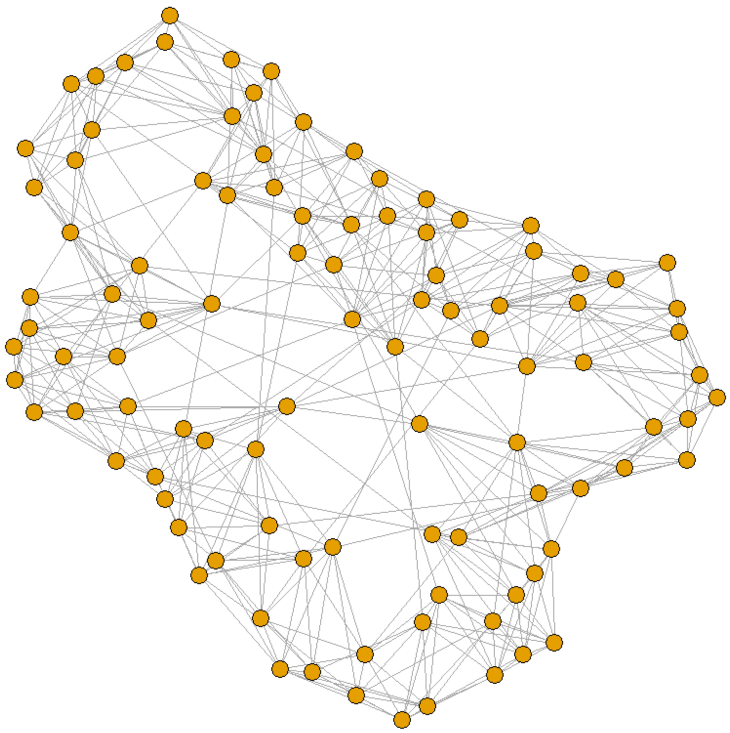


Figure 3.4 A randomly generated small-world graph with the conditions of 100-nodes, 20-neighborhoods (or clusters), and .05 rewiring probability between all pairs of nodes.

	(1)	(2)	(3)	(4)	(5)
(1) Structural Holes					
(2) Network Closure	-.937				
(3) Total Power SH	**.918**	-.964			
(4) Total Power NC	-.919	**.981**	-.989		
(5) Relative Power SH	.691	-.434	**.393**	-.428	
(6) Relative Power NC	.703	-.504	.438	**-.378**	**.939**

Table 3.6 Correlation Matrix of network measures from Figure 3.4

I apply the power (or alter-centirc) measures of SH and NC as well as existing ego-centric measures of SH and NC to a randomly generated small-world graph (Watts and Strogatz 1998) (see Figure 3.4), which can represent a typical social network. The correlations of the measures implies three points (see Table 3.6). First, the strong correlations between total power measures and previous measures of SH and NC support that the new definitions of SH and NC (i.e., alter-networks are separated by holes or overlapping by ties) are still in line with the previous definitions (i.e., alters are sparsely or densely connected). In turn, at least in small-world networks, ego who is rich in ego-level SH/NC is also likely to be rich in alter-level SH/NC. Second, the weak correlations between relative and total power in each structure (SH or NC) support that at least, they are not mutually exclusive. This implies that both relative and total power measures can be simultaneously considered for empirical tests. Third, the two relative powers are strongly correlated but not identical. In turn, even if multiple egos have the same network-size difference with their alters, their relative powers for a particular transaction—brokerage or trust-based—may be diverse depending on how much their alter-networks are separated or overlapping.

Hypotheses for Empirical Test

I apply the power propositions and measures to examine the relationship between the social capital of film actors and directors in project-based networks and their career-survival. Many empirical studies have explored how networks matter to careers in cultural industries, such as film, music, performing arts, and TV production industry, where most products are based on collaboration. Existing empirical studies often take project-based networks (e.g., ties among members of the same film project) as a measure of social capital and study how one's position in these networks shape one's career or the project's success (e.g., a longer-acting career; financial performances of movies/musicals; award-winning). The findings tend to support that structural holes are beneficial for these outcomes (Uzzi and Spiro 2005; Zaheer and Soda 2009), whereas network closure is harmful (Lutter 2015), but under certain circumstances, both could be beneficial (Soda, Usai, and Zaheer 2004). Some studies also support the importance of network positions, but the explanations are not based on the access (or flow) of resources (Rossman, Esparza, and Bonacich 2010; Cattani and Ferriani 2008; Cattani, Ferriani, and Allison 2014).

Those empirical studies reveal that one's career in cultural industries is largely affected by network features, including network closure and structural holes. Nevertheless, the role of alter-network structure is less focused, although bargaining situations between ego and alters are very likely to be embedded in project-based networks. The nature of cultural industries is basically competitive because most of the collaborative projects are based on short-term contracts. For example, in the film industry, the members of a film project, including directors and actors, are temporarily organized and disbanded—and the process repeats itself. Thus, the careers of actors and directors are not merely based on external market success (i.e., on consumer choices) but also on internal market success (i.e., on casting calls from productions) (Faulkner and Anderson 1987). However, the process of being cast is very competitive and uncertain. Even past success of films, confirmed by the external market, cannot guarantee the next casting calls—and many actors and directors fail to continue their careers beyond their first film (Jones 1996; Menger 1999). Under this circumstance, actors and directors cannot simply be friends among each other—or willing recipient-donor pairs. They need to cooperate on the same project, but they also have to compete for the limited number of castings after that project.

In this sense, when the network theories of social capital are applied to explain the career success in cultural industries, the alter-centric (or power) propositions and measures may provide very different "snapshots" compared to the previous ego-centric approaches—and even support the theories more strongly. To clarify this potential, I suggest two different hypotheses about the careers of actors and directors in the film industry. Usually, a film project consists of multiple actors and a single director. As artists, they must deeply interact with each other, compared to any other project members (e.g., writers or cinematographers), and there are tons of popular stories about their complex relationships—from love to enmity. But at the same time, they have very different career interests, taking different roles in a film project (Baker and Faulkner 1991). Thus, they also need very different types of social capital to achieve their career success.

Both actors and directors—as artists—must choose between a single focused identity and multivalent identities. For a longer career, actors must be considered artists with multivalent rather than focused identities (Zuckerman et al. 2003). Those who are "typecast" actors (e.g., taking only mother roles in every movie) are less likely to maintain their careers. To avoid this position, an actor needs to take acting roles in heterogeneous movies differentiated by genres, directors, or storytelling. Thus, from Burt's point, if actors are rich in structural holes, they can survive longer accessing valuable information about casting calls from heterogeneous movies. Similarly, from the point of power propositions, an actor with strong bargaining powers in structural holes can easily access those resources from their colleagues—actors and directors—who have collaborated with the focal actor.

Hypothesis 1: Actors whose network positions are advantageous for brokering between their colleagues have higher chances for a longer career.

On the contrary, directors need a single focused identity. In general, a film is responsible by a single director. Thus, directors have to prove how much their movies are distinctive in terms of genre, style, or storytelling (Svejenova 2005; Alvarez et al. 2005; John, Ravid, and Sunder 2017), and this is essential to appeal to critics and consumers (Hsu 2006). To enact this position, a director needs the actors—often called a director's "muses" (e.g., Robert De Niro in Martin Scorsese's movies)—who will be committed to the film characters, reflecting a director's artistic intentions perfectly well. Although one might think that it would be difficult for a director to have a "muse" (given that actors need to diversify per the above discussion), their availability of collective sanctioning within network closure could make it possible. From Coleman's point—and power propositions as well—even without mutual trust and deep interactions, a director with these structural features could make their actors show more reliable and committed performances. This is because actors are likely to be aware of the negative consequences of collective sanctions by the director (i.e., no future casting calls from the director; no more help from other actors who mainly work with the director) and thereby perform like the director's genuine muses. Their performances—as trustworthy resources—will then help the director prove the distinctiveness of his/her works, which makes him/her have a longer career.

Hypothesis 2: Directors whose network positions are advantageous for enforcing certain norms to their colleagues have higher chances for a longer career.

Data, analysis, and variables

To test these hypotheses, I use the data archived in the Internet Movie Database (IMDB)[4], focusing on actors and directors who participated in the film projects released in the U.S. from 1929 to 2019[5]. IMDB datasets are open-source and widely used in many sociological and organizational studies on what makes a project—or its members—succeed in the film industry (Rossman, Esparza, and Bonacich 2010;

[4] Data updated on March 23, 2020 is used.

[5] Adult films are excluded from the analysis. Note that 1929 is generally considered the year when film-making began to be industrialized and faced a "new era" with the development of the sounding

Cattani, Ferriani, and Allison 2014; Lutter 2015). Note that statistical modeling techniques used in this study (e.g., selection of a statistical model; variable creation) are largely influenced by those previous studies—especially Lutter (2015), who studied gender inequality in film actors' social capital for their career-survival.

I estimate project-based networks based on the assumption that all film actors and directors in the same project have social ties with each other, which are maintained for 5-years after their generation. Thus, a particular year's project-based network in the U.S. film industry is captured by the ties among actors and directors who participated in the same projects during the last 5-years. Under this approach, the generated project-based networks are assumed to reflect the possible social relationships among 64324 actors and 17540 directors who have taken 244878 acting roles and 60863 directing roles of 89060 films released in the U.S. during 1929-2019[6]. The characteristics of the actors, directors, and their films constitute the data.

---

system (Cook 2016), and many empirical studies consider this point to limit their analytic scope (Lutter 2015; Mezias and Mezias 2000).

[6] Second-unit and assistant directing roles are not considered. Data of some actors and directors whose age information seems incorrect (e.g., missing; 0-year-old; extremely old (> 200); negative values) are excluded.

	Mean	SD	Min	Max
Career-duration as actor (years)	8.008	9.957	0	79
Career-end as actor	.217	.412	0	1
Career-duration as director (years)	7.636	9.034	0	61
Career-end as director	.228	.42	0	1
Age	39.83	13.289	1	109
Gender (1 = Female; actor only)	.358	.479	0	1
Cumulative mean of billing position (actor)	2.719	1.336	1	10
Cumulative mean of billing position (director)	4.901	.79	1	10
Cumulative N of past acting roles	9.519	13.325	1	182
Cumulative N of past directing roles	9.709	16.611	1	205
Globality (= N of released countries)	11.88	11.064	1	90
Popularity (= user votes / mean user votes)	1.724	8.691	0	394.876
Genre: Thriller/Horror/Mystery/Sci	.226	.418	0	1
Genre: Family/Ani/fantasy	.083	.276	0	1
Genre: Action/Adventure	.221	.415	0	1
Genre: History/Documentary/Bio	.077	.266	0	1
Genre: Comedy, western	.34	.474	0	1
Genre: Drama	.489	.5	0	1
Genre: Romance	.151	.358	0	1
Genre: Crime	.137	.344	0	1
Mean user votes for a film per year	5957.3	4342.758	183.8	16416.4
Available acting roles per year	6468	5539.909	1851	19005
Available directing roles per year	2024	1930.223	495	6304
Degree	15.63	19.669	0	231
Structural Holes	12.54	.372	0	217.12
Network Closure	.437	1.198	0	1
Total Power SH	.456	.191	0	.797
Total Power NC	.303	.145	0	.625
Relative Power SH	-.003	.151	-.6	.606
Relative Power NC	-.001	.079	-.295	.207

Table 3.7 Descriptive statistics of dependent variables and covariates.

This study uses the Cox proportional-hazards regression model (Allison 1984; Yamaguchi 1991; Broström 2018) to analyze the covariates of career-survival of actors and directors. The dependent variable is the ratio of the career-ending event occurrence to actors/directors in each discrete career-duration (i.e., hazard ratio). This consists of two elements. (1) *Career-end*: a binary status that represents whether an actor/director's film at a particular career year is the last career (=1; career-end occurs) or not (=0)[7]. (2) *Career-duration*: the interval between the release years of an actor/director's first and last films during 1929-2019. For example, if a director takes the first and last directing roles in 1998 and 2008, the director's career-duration is counted as 10-years, and the career-end is assumed to occur (=1) in 10th career year. Note that the careers as actors and directors are considered separately. Thus, two main Cox regression models are built and analyzed. If one has taken both acting and directing roles (e.g., Clint Eastwood), the careers are considered separately as well—the person is assumed to have two different careers.

The explanatory covariates of the models are the alter-centric measures of structural holes (SH) and network closure (NC)—*relative power* and *total power*—that actors/directors differently have in each year's network. Thus, the Cox-regression models evaluate the effect of actors/directors' social capital on career-survival. The previous ego-centric measures are also considered to compare the explanatory power of the models with existing measures and power measures. Additionally, network

[7] The data does not capture the career-ending event of some actors/directors whose films are very current (i.e., right-censored data). If career-end is simply considered as an actor/director's last film during 1929-2019, it may underestimate the careers of current "stars" in the field. To avoid this problem, I assume that the careers of some actors/directors whose last films are released between 2015-2019 (i.e., less than 5 years of inactivity) are still ongoing (=0).

degree is included in each model to clarify whether the effect of bargaining power is simply because of one's network size. The correlations among the network measures follow the result in the measurement section (See Appendix A for more details).

The control covariates are related to the characteristics of actors/directors, their films, and the market environment. The characteristics of actors/directors are considered in the models with their age at a particular year when their film was released, gender (only for actors), the cumulative number of past acting/directing roles, and the cumulative mean of billing position. Being old and female are known to jeopardize actors' casting opportunities (Lincoln and Patrick 2004). More experiences of acting/directing are expected to increase one's career-survival rate. A billing position (or film credits) can represent one's importance in a film project. If an actor/director has cumulatively taken the top billing position, it represents the actor/director has a higher status in the field, which decreases their risk of career-end. Note that in IMDB, each film has a maximum of 10-billing positions.

Genres, the number of countries where a film is released, and the ratio of IMDB user votes for a film can reflect a film's characteristics. Some actors/directors who participate in specific genre movies may have longer careers. Note that IMDB classifies films with numerous genres, and each film can have multiple genres. In this study, I categorize them as 8-features, using the varimax method of factor analysis (See Appendix B for more details). The number of released countries represents how much a film is globally known. The ratio of user votes is measured as the number of votes for a focal film divided by the average votes per film at the focal film's release year. It represents how much a film is relatively popular compared to other films released in the same year. If the index is more than or less than 1, it represents the more or less popular film than the average level. Both variables can reflect a film's status in the market, and it could extend the careers of the participating actors/directors.

The market environment for actors/directors is considered in the models with the number of acting/directing roles per year and the average IMDB user votes for a film per year[8]. When more acting/directing roles are available in a particular year, actors/directors are more likely to survive within the less competitive inter-market condition. When more IMDB users submit ratings for a film in a particular year, actors/directors are more likely to survive because more consumers in the cultural market are interested in films and participating actors and directors.

---

[8] For those covariates, data of some actors and directors whose age information seems incorrect are *not* excluded in order to measure the market environment, which is macro-level, more precisely.

Results

	Models (for Actors)					
	1	2-1	2-2	3-1	3-2	4
Individual Characteristics						
Age (ln)	-.610***	-.662***	-.676***	-.691***	-.686***	-.713***
	(.013)	(.012)	(.012)	(.012)	(.012)	(.012)
Gender	.010	.008	-.001	.024**	-.003	.015
	(.009)	(.009)	(.009)	(.009)	(.009)	(.009)
Cumulative mean of billing position	.089***	.089***	.085***	.082***	.083***	.079***
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Cumulative N of past acting roles	-.176***	-.128***	-.124***	-.106***	-.119***	-.100***
	(.001)	(.002)	(.002)	(.001)	(.001)	(.001)
Film Characteristics						
Globality (= N of released countries)	-.036***	-.033***	-.035***	-.023***	-.033***	-.023***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Popularity (= user votes / mean user votes)	.015	.015	.021	-.047**	.011	-.044**
	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
Genre: Thriller, Horror, Mystery, Sci	-.048***	-.048***	-.052***	-.003	-.045***	-.003
	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
Genre: Family, Ani, Fantasy	.046**	.030	.012	-.007	-.001	-.036*
	(.015)	(.015)	(.015)	(.015)	(.015)	(.016)
Genre: Action, Adventure	-.062***	-.044***	-.046***	-.022	-.039**	-.016
	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
Genre: History, Documentary, bio	.153***	.133***	.152***	.033	.159***	.063***
	(.017)	(.017)	(.017)	(.018)	(.017)	(.018)
Genre: Comedy, Western	-.092***	-.073***	-.083***	-.040***	-.079***	-.047***
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
Genre: Drama	-.125***	-.115***	-.130***	-.083***	-.130***	-.098***
	(.010)	(.010)	(.010)	(.010)	(.010)	(.010)
Genre: Romance	-.070***	-.032*	-.037**	-.030*	-.035*	-.031*
	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
Genre: Crime	-.085***	-.058***	-.063***	-.031*	-.054***	-.027
	(.015)	(.015)	(.015)	(.015)	(.015)	(.015)
Market Characteristics						
Mean user votes for a film per year (ln)	.103***	.017**	.021***	.027***	.015**	.020***
	(.005)	(.006)	(.006)	(.006)	(.006)	(.006)
Acting roles per year (ln)	-.469***	-.490***	-.463***	-.484***	-.453***	-.453***
	(.007)	(.007)	(.007)	(.007)	(.007)	(.007)
Network Characteristics						
Degree		-.028***	-.036***	.003***	-.028***	.007***
		(.004)	(.001)	(.001)	(.001)	(.001)
Structural Holes (ego-centric)		-.017***				
		(.004)				
Network Closure (ego-centric)			.323***			
			(.013)			
Total Power SH (alter-centric)				-3.016***		**-3.044*****
				(.037)		**(.042)**
Total Power NC (alter-centric)					1.249***	.755***
					(.034)	(.030)
Relative Power SH (alter-centric)				-1.371***		**-1.841*****
				(.049)		**(.113)**
Relative Power NC (alter-centric)					-1.076***	.460**
					(.066)	(.153)
Log Likelihood	-594,277.700	-593,021.600	-592,713.000	-589,922.600	-592,249.300	-589,574.800
Wald Test	34,190.570	36,377.700	37,933.180	45,797.570	39,846.500	45,832.880
Likelihood Ratio Test	67,436.340	69,948.660	70,565.760	76,146.530	71,493.100	76,842.090

Notes: N (acting roles) = 244878; number of actors = 64324; events (career-end) = 53210. Breslow method is used for tied events. All goodness-of-fit tests are significant at the .001 level.
$^{*}P < .05$; $^{**}P < .01$; $^{***}P < .001$ (two-tailed tests).

Table 3.8 Cox proportional-hazards regression models of actors' career-end in the U.S. film industry, 1929-2019.

	Models (for Directors)					
	1	2-2	2-2	3-1	3-2	4
Individual Characteristics						
Age (ln)	-.885***	-.937***	-.981***	-.895***	-.973***	-.949***
	(.038)	(.038)	(.038)	(.037)	(.038)	(.038)
Cumulative mean of billing position	.079***	.078***	.062***	.122***	.063***	.089***
	(.010)	(.011)	(.011)	(.010)	(.011)	(.011)
Cumulative N of past directing roles	-.134***	-.113***	-.109***	-.106***	-.109***	-.101***
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)
Film Characteristics						
Globality (= N of released countries)	-.038***	-.038***	-.038***	-.032***	-.038***	-.032***
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Popularity (= user votes / mean user votes)	-.217***	-.209***	-.203***	-.242***	-.212***	-.225***
	(.031)	(.031)	(.031)	(.031)	(.031)	(.031)
Genre: Thriller, Horror, Mystery, Sci	-.102***	-.099***	-.105***	-.068**	-.107***	-.072**
	(.025)	(.025)	(.025)	(.025)	(.025)	(.025)
Genre: Family, Ani, Fantasy	.124***	.112***	.105***	.120***	.123***	.094**
	(.030)	(.030)	(.030)	(.031)	(.031)	(.031)
Genre: Action, Adventure	.031	.045	.046	.059*	.041	.065**
	(.025)	(.025)	(.025)	(.025)	(.025)	(.025)
Genre: History, Documentary, bio	-.087**	-.096***	-.057*	-.193***	-.058*	-.124***
	(.027)	(.028)	(.028)	(.028)	(.028)	(.028)
Genre: Comedy, Western	.033	.040	.032	.064**	.033	.053*
	(.022)	(.022)	(.022)	(.022)	(.022)	(.022)
Genre: Drama	-.043*	-.043*	-.060**	-.015	-.057**	-.038
	(.020)	(.020)	(.020)	(.020)	(.020)	(.020)
Genre: Romance	-.007	.014	.009	.008	.005	.006
	(.029)	(.029)	(.029)	(.029)	(.029)	(.029)
Genre: Crime	-.054	-.039	-.041	-.044	-.051	-.034
	(.031)	(.031)	(.031)	(.031)	(.031)	(.031)
Market Characteristics						
Mean user votes for a film per year (ln)	.225***	.170***	.163***	.189***	.176***	.171***
	(.011)	(.012)	(.012)	(.013)	(.012)	(.013)
Directing roles per year (ln)	-.218***	-.218***	-.212***	-.253***	-.224***	-.233***
	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
Network Characteristics						
Degree		.025***	-.019***	.004*	-.014***	.003
		(.008)	(.002)	(.002)	(.002)	(.002)
Structural Holes (ego-centric)		-.055***				
		(.009)				
Network Closure (ego-centric)			.316***			
			(.023)			
Total Power SH (alter-centric)				-1.528***		-1.407***
				(.072)		(.086)
Total Power NC (alter-centric)					.463***	**.552*****
					(.052)	**(.053)**
Relative Power SH (alter-centric)				-1.412***		.064
				(.097)		(.243)
Relative Power NC (alter-centric)					-1.642***	**-2.411*****
					(.124)	**(.323)**
Log Likelihood	-136,356.200	-136,240.000	-136,167.600	-136,028.000	-136,128.300	-135,908.200
Wald Test	7,582.970	7,556.410	7,867.640	8,626.090	8,069.250	8,879.930
Likelihood Ratio Test	14,013.920	14,246.350	14,391.040	14,670.290	14,469.600	14,909.910

Note: N (directing roles) = 60863; number of directors = 17540; events (career-end) = 13894. Breslow method is used to control tied events. All goodness-of-fit tests are significant at the .001 level.
$^{*}P < .05$; $^{**}P < .01$; $^{***}P < .001$ (two-tailed tests)

Table 3.9 Cox proportional-hazards regression models of directors' career-end in the U.S. film industry, 1929-2019

Tables 3.8 and 3.9 summarize the results of Cox regression models for actors' and directors' career-survival, respectively. Note that some of the control covariates are logged to reduce skewness. The results on total power support hypothesis 1 on the actors—but not hypothesis 2 on the directors. As hypothesized, total power within SH decreases the likelihood of actors' career-end (i.e., actors are likely to have a longer career). This is predicted in Model 3-1 and 3-2, where bargaining powers within SH and NC are distinctively considered, and Model 4, where all power measures are included. However, against hypothesis 2, every model predicts that total power within NC increases the likelihood of directors' career-end. As with actors, directors need strong total power within SH for a longer career.

These results are still in line with the results of Model 2-1 and 2-2 tested with ego-centric measures of SH and NC. The results show that both actors and directors have higher chances of a longer career within structural holes, whereas they are less likely to survive within network closure. One interesting finding is that while Model 2-1 predicts that SH is more effective on the career-survival of directors than actors (-0.17 vs. -0.55), Model 4 predicts the opposite—total power within SH is more effective on actors than directors (-3.044 vs. -1.407)[9]. These contradictory results clarify that the benefits of social capital for actors and directors can be differentiated not only by

[9] Each Model 4 (for actors and directors) includes the same covariates, except gender. When gender is excluded in the actor-model, the coefficient of total power SH becomes -3.041, which is almost identical to -3.044. To test the coefficient difference of total power SH for actors and directors, the formula $Z = \frac{b_1+b_2}{\sqrt{SEb_1^2+SEb_2^2}}$ is used where b_1 and b_2 are the coefficients of the focal variable for the first and second groups, and SEb_1 and SEb_2 are the standard errors of the coefficients (Clogg, Petkova, and Haritou 1995; Paternoster et al. 1998). From the formula, the z-scores for Model 4 with and without gender are -17.10 and -16.60, respectively. Both scores are significant at the .001 level of the two-tailed test. The z-scores for Model 2-1 with and without gender are the same 3.85, which is significant at the .001 level of the two-tailed test.

“holes” (or empty spaces) between alters, but also by holes between alter-networks.

The results on relative power support both hypotheses 1 and 2. In Model 3-1 and 3-2, both types of relative power enhance actors' and directors' career-survival. However, when all power measures are included, Model 4 predicts that while actors survive longer with strong relative power within SH, directors survive longer with strong relative power within NC. As noted, the two measures of relative power are strongly correlated because they are equally affected by the network-size difference between ego and alters. Thus, when the effect of network-size difference is controlled in Model 4 by including both relative power measures, the result clarifies that actors and directors need different types of relative power. It is noteworthy that these results are not captured by Model 2-1 and 2-2 where only ego-centric measures of SH and NC are used.

Given the strong correlation between the two relative power measures, multicollinearity among the measures may occur in Model 4. The variance inflation factors (VIF) of relative power measures are 6.64 (NC) and 8.34 (SH) in the actor-model and 7.56 (NC) and 9.7 (SH) in the director-model, respectively, whereas other covariates tend to have less than 3 VIF. While the VIF indices remain below 10, the generally accepted threshold of detecting multicollinearity, their high values are likely the reason for the large standard errors of the relative power coefficients. This may reduce the robustness of the predictions about the relative power effect on career-survival.

	Models	
	5 (for Actors)	5 (for Directors)
Individual Characteristics		
Age (ln)	-.712***	-.950***
	(.012)	(.038)
Gender	.015	
	(.009)	
Cumulative mean of billing position	.079***	.089***
	(.003)	(.011)
Cumulative N of past acting/directing roles	-.100***	-.100***
	(.001)	(.003)
Film Characteristics		
Globality (= N of released countries)	-.023***	-.032***
	(.001)	(.002)
Popularity (= user votes / mean user votes)	-.044**	-.224***
	(.015)	(.031)
Genre: Thriller, Horror, Mystery, Sci	-.003	-.072**
	(.012)	(.025)
Genre: Family, Ani, Fantasy	-.036*	.094**
	(.016)	(.031)
Genre: Action, Adventure	-.016	.065**
	(.012)	(.025)
Genre: History, Documentary, bio	.063***	-.124***
	(.018)	(.028)
Genre: Comedy, Western	-.047***	.053*
	(.011)	(.022)
Genre: Drama	-.098***	-.038
	(.010)	(.020)
Genre: Romance	-.031*	.007
	(.014)	(.029)
Genre: Crime	-.027	-.034
	(.015)	(.031)
Market Characteristics		
Mean user votes for a film per year (ln)	.020***	.171***
	(.006)	(.013)
Acting/directing roles per year (ln)	-.453***	-.233***
	(.007)	(.012)
Network Characteristics		
Degree	.006***	.003
	(.001)	(.002)
Total Power SH	-3.037***	-1.394***
	(.042)	(.085)
Total Power NC	.756***	.550***
	(.030)	(.053)
Network-Size Difference	**-.489*****	**-.832*****
	(.025)	**(.049)**
Relative Power Difference (SH<0<NC)	**1.256*****	**-1.076*****
	(.126)	**(.271)**
N (acting/directing roles)	244878	60863
N of actors/directors	64324	17540
N of events (career-end)	53210	13894
Log Likelihood	-589,570.000	-135,903.900
Wald Test	45,872.910	8,882.670
Likelihood Ratio Test	76,851.720	14,918.360

Note: Breslow method is used to control tied. All goodness-of-fit tests are significant at the .001 level.
$^{*}P < .05$; $^{**}P < .01$; $^{***}P < .001$ (two-tailed tests).

Table 3.10 Cox regression models for robustness testing with alternative measures of relative power

To test the robustness of the analysis, I apply alternative measures of relative power in Model 4. It consists of two measures: one is the network-size difference, and the other is the power-difference. Network-size difference is measured by the mean of ratio-difference between ego- and each alter-network size. For example, suppose ego-network size is 5, and every alter-network size is 3. Then, the network-difference is (5-3)/(4+2) = 0.33. This is the same with each relative power measure when the weighted values for the alter-network separation and overlap are not considered. Power-difference is calculated by the difference between ego's relative power within NC and SH (= relative power NC – relative power SH). Since the two measures are equally correlated with the network-size difference, power-difference is determined only by the weighted values for the alter-network overlap and separation. Thus, its positive indices represent that ego has more advantages for using relative power within NC than SH due to the overlapping alter-networks. Its negative indices thereby represent that ego has more advantages for using relative power within SH than NC due to the separated alter-networks.

Table 3.10 summarizes the results of cox regression models with the two alternative measures. The results of Model 5 show that network-size difference enhances the career-survival of both actors and directors. Power-difference has an opposite effect on actors' and directors' career-survival. When the network-size difference is controlled, directors who have more advantages for using relative power within NC are likely to survive longer. In contrast, actors who have more advantages for using relative power within SH are likely to survive longer.

It is noteworthy that in every Model 5, all VIF indices are less than 3.05. Therefore, with fewer concerns about the multicollinearity problem, Model 5 clarifies that—as predicted by Model 4—strong relative power within SH (≈ more network-size difference between ego and alters and more separation of alter-networks) increases the likelihood of actors' career-survival and strong relative power within NC (≈ more network-size difference between ego and alters and more separation of alter-networks) increases the likelihood of directors' career-survival. This additional test result improves the robustness of the predictions of Model 4.

Discussion

The overall results of the Cox regression models fully support hypothesis 1 and partially support hypothesis 2. As predicted, actors rich in structural holes—with strong *relative power* and *total power*—have higher chances of a longer career. Also predicted, network closure provides directors with benefits; directors with strong *relative power* embedded in network closure are more likely to have a longer career. However, if directors are simply rich in network closure (i.e., strong total power), it even decreases the chances of directors' career-survival. As with actors, directors need strong total power within structural holes. Nevertheless, its effect on directors is significantly less than actors. This may be because what directors can earn from the separation of alter-networks are some "good ideas" (Burt 2004), which could be beneficial for directing good movies but not directly affect their career duration.

Why does total power within NC hurt directors' career-survival, even though relative power within NC helps it? In other words, why are the benefits from the network closure available to directors only if their networks are larger than their actors' networks? The different career interests of actors and directors could be the reason. Suppose a director—Alex—and some actors—including Blake—have been working with only each other. Embedded in the perfect network closure (i.e., alter-networks are perfectly overlapping) with the same network size, Alex and Blake will have mutual and equal dependence (i.e., strong total power and equal relative power). If Alex induces collective sanctioning, Blake may lose all exchange relationships with other actors as well as the only straight route for future casting calls (= Alex). At the same time, if Blake induces collective sanctioning, Alex may lose all potential "muses" who understand him/her well. This means that the negative consequences of sanctioning will be quite similar for both parties, whether it’s by Alex on Blake, and vice versa, because they share the same level of coercion within the network overlap. In this sense, when taking a new movie with Blake, Alex will use the *conciliatory* strategy in bargaining to make him/her fully committed to a film character.

However, the *conciliatory* strategy may not be easy for Alex to use. As aforementioned, actors need multivalent identities for a longer career, whereas directors need a single focused identity. If Blake works with Alex repeatedly, Blake may fail to create multivalent identities because Alex's movies are likely to be homogeneous in terms of genres, style, storytelling, or main characters. In other words, the exchange rewards from the cooperation will be unfair between Alex and Blake; while Alex could successfully prove the distinctiveness of his/her movies, Blake may be considered a "typecast" actor. Thus, if Alex uses the *conciliatory* bargaining strategy, Blake may not cooperate with Alex.

This situation can change when Alex has strong relative power (i.e., Alex has a larger network than his/her actors—including Blake—within the network closure). Due to the unequal dependence from the unequal level of sanctioning, Alex can now use the *hostile* strategy in bargaining. His/her strategy may yield some conflicts with Blake—especially when Blake thinks his/her film character negatively impacts having multivalent identities. Alex may no longer work with some actors due to the influence from Blake within the overlapping networks. However, if Alex can still work with a few important muses who understand him/her well, losing relationships with some actors may not be a serious problem. On the contrary, for Blake, the negative consequences of refusing Alex's request could be enormous. Blake may lose every helpful relationship in the industry due to Alex's large influence, based on the largely overlapping networks of Blake and Alex's other colleagues. Thus, Alex's *hostile* strategy will make Blake more dedicated to his/her film character—even if it is not beneficial for Blake's career. With the great performances of the "structural muse," Alex is likely to have a longer career, successfully showing how much his/her works are distinctive and unique.

It is important to note that the previous theories and ego-centric measures of SH and NC do not provide the above explanations and findings. The analysis results with the previous ego-centric measures fail to support the hypotheses predicted from the SH and NC theories. They show that structural holes are beneficial for both actors and directors, whereas network closure is harmful. The previous theoretical statements also cannot explain the opposite benefits of network closure for directors. In contrast, the power (or alter-centric) measures support the hypotheses, and the propositions can explain the unexpected finding about the opposite benefits of network closure. In turn, this empirical test not only contributes to our understanding of the different career-survival mechanisms of actors and directors in the U.S. film industry, but also support the values of power propositions and measures that capture the important role of alter-network structure in ego's access to social capital.

REFERENCES

Allison, Paul D. 1984. *Event History Analysis: Regression for Longitudinal Event Data*: Sage.

Alvarez, José Luis, Carmelo Mazza, Jesper Strandgaard Pedersen and Silviya Svejenova. 2005. "Shielding Idiosyncrasy from Isomorphic Pressures: Towards Optimal Distinctiveness in European Filmmaking." *Organization* 12(6):863-88.

Bae, Jonghoon and Martin Gargiulo. 2004. "Partner Substitutability, Alliance Network Structure, and Firm Profitability in the Telecommunications Industry." *Academy of Management journal* 47(6):843-59.

Baker, Wayne E and Robert R Faulkner. 1991. "Role as Resource in the Hollywood Film Industry." *American journal of sociology* 97(2):279-309.

Bonacich, Phillip. 1987. "Power and Centrality: A Family of Measures." *American journal of sociology* 92(5):1170-82.

Borgatti, Stephen P. 1997. "Structural Holes: Unpacking Burt's Redundancy Measures." *Connections* 20(1):35-38.

Borgatti, Stephen P and Daniel S Halgin. 2011. "On Network Theory." *Organization science* 22(5):1168-81.

Broström, Göran. 2018. *Event History Analysis with R*: CRC Press.

Burt, Ronald S. 1992. *Structural Holes*: Harvard university press.

Burt, Ronald S. 2000. "The Network Structure of Social Capital." *Research in organizational behavior* 22:345-423.

Burt, Ronald S. 2004. "Structural Holes and Good Ideas." *American journal of sociology* 110(2):349-99.

Burt, Ronald S. 2009. *Structural Holes: The Social Structure of Competition*: Harvard university press.

Cattani, Gino and Simone Ferriani. 2008. "A Core/Periphery Perspective on Individual Creative Performance: Social Networks and Cinematic Achievements in the Hollywood Film Industry." *Organization science* 19(6):824-44.

Cattani, Gino, Simone Ferriani and Paul D Allison. 2014. "Insiders, Outsiders, and the Struggle for Consecration in Cultural Fields: A Core-Periphery Perspective." *American Sociological Review* 79(2):258-81.

Clogg, Clifford C, Eva Petkova and Adamantios Haritou. 1995. "Statistical Methods for Comparing Regression Coefficients between Models." *American journal of sociology* 100(5):1261-93.

Coleman, James S. 1988. "Social Capital in the Creation of Human Capital." *American journal of sociology* 94:S95-S120.

Coleman, James S. 1990. "Foundations of Social Theory." *Cambridge, MA: Belknap*.

Cook, Karen S, Coye Cheshire and Alexandra Gerbasi. 2006. "Power, Dependence, and Social Exchange." *Contemporary social psychological theories* 73(2):194-216.

Cook, David A. 2016. *A History of Narrative Film*: WW Norton & Company.

Corra, Mamadi and David Willer. 2002. "The Gatekeeper." *Sociological Theory* 20(2):180-207.

Faulkner, Robert R and Andy B Anderson. 1987. "Short-Term Projects and Emergent Careers: Evidence from Hollywood." *American journal of sociology* 92(4):879-909.

Hsu, Greta. 2006. "Jacks of All Trades and Masters of None: Audiences' Reactions to Spanning Genres in Feature Film Production." *Administrative Science Quarterly* 51(3):420-50.

John, Kose, S Abraham Ravid and Jayanthi Sunder. 2017. "Managerial Ability and Success: Evidence from the Career Paths of Film Directors." *Journal of Corporate Finance* 44:425-39.

Jones, Candace. 1996. "Careers in Project Networks: The Case of the Film Industry." *The boundaryless career: A new employment principle for a new organizational era* 58:75.

Lin, Nan and Bonnie H Erickson. 2008. "Theory, Measurement, and the Research Enterprise on Social Capital." *Social capital: An international research program*:1-24.

Lincoln, Anne E and Michael Patrick. 2004. "Double Jeopardy in Hollywood: Age and Gender in the Careers of Film Actors, 1926-1999." in *Sociological Forum*, Vol. 19: Citeseer.

Lutter, Mark. 2015. "Do Women Suffer from Network Closure? The Moderating Effect of Social Capital on Gender Inequality in a Project-Based Labor Market, 1929 to 2010." *American Sociological Review* 80(2):329-58.

Markovsky, Barry, David Willer and Travis Patton. 1988. "Power Relations in Exchange Networks." *American Sociological Review*:220-36.

Menger, Pierre-Michel. 1999. "Artistic Labor Markets and Careers." *Annual review of sociology* 25(1):541-74.

Mezias, John M and Stephen J Mezias. 2000. "Resource Partitioning, the Founding of Specialist Firms, and Innovation: The American Feature Film Industry, 1912–1929." *Organization science* 11(3):306-22.

Molm, Linda D. 1997. "Risk and Power Use: Constraints on the Use of Coercion in Exchange." *American Sociological Review*:113-33.

Molm, Linda D. 1997. *Coercive Power in Social Exchange*: Cambridge University Press.

Moran, Peter. 2005. "Structural Vs. Relational Embeddedness: Social Capital and Managerial Performance." *Strategic management journal* 26(12):1129-51.

Paternoster, Raymond, Robert Brame, Paul Mazerolle and Alex Piquero. 1998. "Using the Correct Statistical Test for the Equality of Regression Coefficients." *Criminology* 36(4):859-66.

Rossman, Gabriel, Nicole Esparza and Phillip Bonacich. 2010. "I'd Like to Thank the Academy, Team Spillovers, and Network Centrality." *American Sociological Review* 75(1):31-51.

Rost, Katja. 2011. "The Strength of Strong Ties in the Creation of Innovation." *Research policy* 40(4):588-604.

Rowley, Tim, Dean Behrens and David Krackhardt. 2000. "Redundant Governance Structures: An Analysis of Structural and Relational Embeddedness in the Steel and Semiconductor Industries." *Strategic management journal*:369-86.

Skvoretz, John and David Willer. 1993. "Exclusion and Power: A Test of Four Theories of Power in Exchange Networks." *American Sociological Review*:801-18.

Soda, Giuseppe, Alessandro Usai and Akbar Zaheer. 2004. "Network Memory: The Influence of Past and Current Networks on Performance." *Academy of Management journal* 47(6):893-906.

Svejenova, Silviya. 2005. "'The Path with the Heart': Creating the Authentic Career." *Journal of Management Studies* 42(5):947-74.

Uzzi, Brian and Jarrett Spiro. 2005. "Collaboration and Creativity: The Small World Problem." *American journal of sociology* 111(2):447-504.

Walker, Gordon, Bruce Kogut and Weijian Shan. 1997. "Social Capital, Structural Holes and the Formation of an Industry Network." *Organization science* 8(2):109-25.

Walker, Henry A, Shane R Thye, Brent Simpson, Michael J Lovaglia, David Willer and Barry Markovsky. 2000. "Network Exchange Theory: Recent Developments and New Directions." *Social Psychology Quarterly*:324-37.

Watts, Duncan J and Steven H Strogatz. 1998. "Collective Dynamics of 'Small-World'networks." *nature* 393(6684):440.

Willer, David. 1999. *Network Exchange Theory*: Greenwood Publishing Group.

Yamaguchi, Kazuo. 1991. *Event History Analysis*: Sage.

Zaheer, Akbar and Geoffrey G Bell. 2005. "Benefiting from Network Position: Firm Capabilities, Structural Holes, and Performance." *Strategic management journal* 26(9):809-25.

Zaheer, Akbar and Giuseppe Soda. 2009. "Network Evolution: The Origins of Structural Holes." *Administrative Science Quarterly* 54(1):1-31.

Zuckerman, Ezra W, Tai-Young Kim, Kalinda Ukanwa and James Von Rittmann. 2003. "Robust Identities or Nonentities? Typecasting in the Feature-Film Labor Market." *American journal of sociology* 108(5):1018-74.

CHAPTER 4

POWER-DEPENDENCE RELATIONS IN CENTRALITY WITHIN CONTEXT-SPECIFIC NETWORK FLOWS: A MONTE CARLO APPROACH TO IDENTIFYING POWER DYNAMICS BETWEEN 15TH CENTURY FLORENTINE FAMILIES

Introduction

Many centrality measures have been proposed to identify the most influential nodes in a network (Freeman 1978; Freeman, Borgatti, and White 1991; Bonacich 1972; 1987; 2007; Bonacich and Lloyd 2001; Everett and Borgatti 2014; Hubbell 1965; Katz 1953; Stephenson and Zelen 1989; Sade 1989; Page et al. 1999; Newman 2005; Opsahl, Agneessens, and Skvoretz 2010). Applying centrality measures, various studies of social capital show how network positions matter to one's access to social capital (Ibarra 1993; Yan and Ding 2009; Gulati 1999; Krackhardt 1990; Alderson and Beckfield 2004; Neal 2011). Yet, those measures identify very different nodes as influential, and thereby social capital studies applying the measuers support very different mechanisms of one's access to social capital. For example, in betweenness centrality (Freeman 1978), a node is influential when shortest-paths between other nodes are more likely to pass through that node. But in eigenvector centrality (Bonacichi 1972; 2007), a node is influential when the node itself has many ties and the node's neighbors—and even their neighbors—also have many ties. The former measure is typically used to capture one's brokerage potential to access heterogeneous resources (Krackhardt 1990; Alderson and Beckfield 2004), while the latter is applied to proxy for social status which is helpful to take roles for administrative and technical innovations (Ibarra 1993). Needless to say, the influential nodes under the two measures are rarely identical in the same network graph.

The different identification of influential nodes in centrality measures is rooted in their assumptions about how transferable products (e.g., information, opinions, gossip, reputations) flow through a network (Borgatti 2005; Borgatti and Everett 2006; Friedkin 1991; 2006). If information flows only through shortest-paths, nodes with higher betweenness centrality scores will have more opportunities to broker it between others. If one's reputation diffuses more efficiently through shorter walks (i.e., closer neighbors), nodes with higher eigenvector centrality scores will be widely accepted as high-status actors. In other words, centrality measures clarify the relationship between positions (i.e., central nodes) and roles (i.e., influences) under certain assumptions about network flow (Borgatti and Everett 1992; Borgatti 2005; Wasserman and Faust 1994).

The assumptions about network flow are thus essential to centrality measures. These assumptions are, however, often simply expressed in graph-theoretic terms (e.g., shortest-paths; random-walks) and lack customizability to accommodate the heterogeneity of nodes and ties in social networks. This means that existing centrality measures may identify nodes that are positioned in centers within graph-theoretic flows, but not influential within context-specific flows differently embedded in each network. For example, in some networks, important information may only be shared among racially homogeneous actors. Then, betweenness centrality will not capture actual brokerage power. Likewise, in other networks, one's reputation may be diffused only among actors who trust each other. Then, actors of higher eigenvector centrality scores will not always have the expected social status.

In this chapter, I suggest *actor-based centrality* based on the Markov Chain Monte Carlo (MCMC) estimation through respondent-driven sampling (RDS) method and explore the power-dependence relations between 15th-century Florentine families within context-specific network flows. RDS is a chain-referral sampling method similar to snowball sampling: one, as a seed, refers friends, who also refer their friends (Heckathorn 1997, 2002, 2007, 2011; Heckathorn and Cameron 2017; Salganik and Heckathorn 2004; Volz and Heckathorn 2008; Goel and Salganik 2009; Gile and Handcock 2010; Yamanis et al. 2013; Shi, Cameron, and Heckathorn 2019; Wejnert and Heckathorn 2008; Wejnert 2010).

Actor-based centrality is measured by a simulation model of RDS; nodes more sampled by referral chains, which are similar to random-walks, are identified as influential with more access to valuable resources that flow from other nodes. But unlike existing centrality measures that assume simple and fixed network flows, actor-based centrality allows incorporating complex and flexible network flows with the manipulation of the MCMC algorithm under an RDS simulation framework. By integrating this estimation approach with the resource dependence model (Casciaro and Piskorksi 2005), I construct multiple measures of ***total power (i.e., mutual dependence)*** and ***relative power (i.e., unequal dependence)*** within context-specific network flows. Then, applying the measures to marriage and business networks of 15th-century Florentine families, I find interesting snapshots of their power dynamics and bargaining, which are different from (but also in line with) the findings of Padgett and Ansell (1989) that use the same network datasets.

Reviews of Centrality Measures and Social Capital Studies

Tables 4.1 and 4.2 summarize the details of popular existing centrality measures, including their underlying assumptions about network flow, theoretical explanations of influential nodes, empirical usage for social capital studies, and formulas. The measures are categorized into three classes—degree-like, closeness-like, and betweenness-like measures—following Borgatti and Everett's (2006) suggestion. All distinct point centrality measures that have references and are registered in UCINET 6 (version 6.726. updated May 21, 2021; Borgatti, Everett, and Freeman 2002) are covered, which is widely used for social network analysis.

		Degree-like Measures	Closeness-like Measures	Betweenness-like Measures
Names		Degree (Freeman 1978); Eigenvector (Bonacichi 1972; 2007); Power (Bonachichi 1987); Influence (Hubbell 1965; Katz 1953); PN centrality (Everett and Borgatti 2014)	Closeness (Freeman 1978); Information (Stephenson and Zelen 1989)	Betweenness (Freeman 1978); Flow Betweenness (Freeman, Borgatti, and White 1991)
Assumptions about Network Flows	**Flow Process**	**Degree:** Things flow through every 1-step walk; **Eigenvector/Power/Influence/PN Centrality:** Things flow through every n-step walks, s.t $1 \leq n < \infty$	**Closeness /Information:** Things flow through shortest-paths/every paths between two nodes;	**Betweenness /Flow Betweenness:** Things flow through shortest-paths between any two nodes /every paths weighted by tie strength
	Evaluation of a node's involvement in flows	**Degree:** Lager volume of 1-step walks terminating to or originating from a focal node; **Eigenvector/Influence:** Larger volume of shorter n-step walks terminating to or originating from a focal node; **Power:** Larger volume of shorter (2n-1)-step walks and smaller volume of shorter 2n-step walks terminating to or originating from a focal node; **PN Centrality:** Larger volume of walks through positive ties and smaller volume of walks through negative ties terminating to or originating from a focal node	**Closeness :** Shorter length of shortest-paths terminating or originating at a focal node; **Information:** Shorter length of paths (or weighted length by tie strength) and smaller variation of paths for each pair of nodes.	**Betweenness /Flow Betweenness:** Larger volume of shortest-paths passing a focal node
Theoretical explanation of influential nodes		**Degree:** Direct access or influence; **Eigenvector/Influence:** More closure access toward nodes who are central; **Power:** More Power from the dependence of nodes who are not central (i.e., having fewer alternative exchange partners); **PN Centrality:** More chances of accessing resources that flow through positive ties	**Closeness:** Quick delivery/receipt of information; **Information:** Quick and stable delivery/receipt of information	**Betweenness /Flow Betweenness:** Controlling the flow of resources between two nodes who have no direct tie
Empirical Usage for Social Capital Studies		**Eigenvector/Influence:** One who knows more central persons in a firm is more likely to take roles for administrative and technical innovations (Ibarra 1993); **Power:** A city's Power increases when other cities are more dependent on the transactional relations with the city (Neal 2011)	**Closeness:** More central persons can have quick access to new information helpful for innovation (Gulati 1999)	**Betweenness:** Brokerage roles provide Power and status to actors in organizational network or cities in global network (Krackhardt 1990; Alderson and Beckfield 2004)
Other variations (by flow process)		N-path (Sade 1989); Eigenvector in directional network (Bonacich and Lloyd 2001); Eigenvector under Markov process (Page et al. 1999); Degree with tie-strength (Opsahl, Agneessens, and Skvoretz 2010)	Shortest-path with tie-strength (Opsahl, Agneessens, and Skvoretz 2010)	Random-walk (Newman 2005); Shortest-path with tie-strength (Opsahl, Agneessens, and Skvoretz 2010)

Table 4.1 Summaries of existing centrality measures

Types	Measure of Centrality	Equation	Notations for Variables
Degree-like measures	**Degree**	$x_i = \sum_{j=1}^{n} (\alpha + \beta x_j) a_{ij}$	**n**: number of nodes in a network $\boldsymbol{x_j}$: centrality score of node j $\boldsymbol{a_{ij}}$: element of adjacency matrix A_n representing whether a tie between node i and j exist (=1) or not (=0). $\boldsymbol{pn_{ij}}$: element of tie matrix (P-2N), such that the elements of matrix P and N represent whether a positive and negative tie between node i and j exist (=1) or not (=0), respectively. $\boldsymbol{\alpha}$: weight for a_{ij} (Degree = 1; Eigenvector = 0; Influence = 0 or 1; Power = a constant number; PN = 1) $\boldsymbol{\beta}$: weight for x_j (Degree = 0; Influence > 0; Power < 0; PN = 1/(2n-2); Eigenvector = 1/λ, such that λ is the eigenvalue of adjacency matrix A_n)
	Eigenvector		
	Influence		
	Power		
	PN	$x_i = \sum_{j=1}^{n} (\alpha + \beta x_j) pn_{ij}$	
Closeness-like measures	**Closeness**	$C_c(i) = \frac{1}{\sum_{j=1}^{n} d\,(i,j)}$	**n**: number of nodes in a network **d (i,j)** : shortest-path distance between node i and j
	Information	$I_i = \frac{1}{c_{ii} + (T - 2R)/n}$	**n:** number of nodes in a network $\boldsymbol{c_{ii}}$**:** element of inverse matrix of B_n, such that B_n's element b_{ii} represents 1 + node i's degree or node i's degree with tie-strength weights $\boldsymbol{c_{ij}}$**:** element of inverse matrix of B_n, such that B_n's element b_{ij} represents whether a tie between node i and j does not exist (=1), exist without tie-strength (=0), or exist with tie-strength (= 1 – tie-strength weight) **T:** sum of c_{jj} for node i (= $\sum_{j=1}^{n} c_{jj}$), such that $j \neq i$ **R:** sum of c_{ij} for node i (= $\sum_{j=1}^{n} c_{ij}$), such that $j \neq i$
Betweeness-like measures	**Betweenness**	$C_B(i) = \sum_{j=1,k=1}^{n} \frac{\delta_{jk}(i)}{\delta_{jk}}$	**n**: number of nodes in a network $\boldsymbol{\delta_{jk}}$: number of shortest-paths between node j and k, such that $k \neq i \neq j$ $\boldsymbol{\delta_{jk}}$ $(\boldsymbol{i})$: number of shortest-paths between node j and k that pass node i
	Flow Betweenness	$C_{BF}(i) = \sum_{j=1,k=1}^{n} \frac{F_{jk}(i)}{F_{jk}}$	**n:** number of nodes in a network $\boldsymbol{F_{jk}}$**:** number of possible paths between node j and k in a valued network matrix G_n, such that $k \neq i \neq j$, g_{lm} of G_n represents the strength (> 0) of a tie between any two nodes, and the number of possible paths between node j and k is equal to the sum of minimum g_{lm} in each distinct path. $\boldsymbol{F_{jk}}$ $(\boldsymbol{i})$: number of paths between j and k that pass node i

Table 4.2 Formulas of existing centrality measures

As shown in the tables, all centrality measures define a walk structure between nodes (e.g., shortest-paths; random walks), and nodes more involved in particular walks (e.g., shortest-paths between other nodes; shorter walks) in a particular way (e.g., passed or terminated by; originated from) are identified as central (Borgatti and Everett 2006). Those central nodes become influential because when certain transferable products (e.g., information, opinions, gossip, reputations) flow through a defined walk structure, the central nodes can have more opportunities (or situations) to utilize the products (e.g., brokering information between others; spreading opinions quickly) (Borgatti 2005; Friedkin 1991; 2006).

The use of centrality measures in a social capital study is thus justified by statements on how ego can utilize their influence to access valuable resources from alters (e.g., heterogeneous information; credentials) (Borgatti, Jones, and Everett 1998; Borgatti and Halgin 2011). For example, applying closeness centrality, Gulati (1999) states that *"Firms that have a high closeness centrality are likely to have access to more information about all the possible partners in the network than firms with low centrality."* He finds that those firms are more likely to enter into new beneficial alliances, using their influences.

Importance of Context-Specific Network Flows in Centrality Measures and Social Capital Studies

One feature shared by many existing centrality measures is that central nodes in graph-theoretic terms are presumed to have static and substantial influences in any network. In general, social network analysis methods help to clarify the relationship between positions and roles in a network; when some actors share the same network positions, they are assumed to have the same roles (Borgatti and Everett 1992; Faust and Wasserman 1994). Likewise, centrality measures expect that some actors who have positions well connected with others in certain graph-theoretic terms (i.e., through shorter walks; through shortest-paths) can possess distinct roles (or influences) in a network. In other words, when a network of actors and relations is formalized as a graph of nodes and ties expressed homogeneously by binary elements 1 or 0 (i.e., existing or not), some actors identified as having the same graph-theoretically central positions are assumed to have the same influences in any network. As Borgatti (2005) expresses, "*...centrality has been considered an abstract property of a node's position in a network, measurable without regard for what the nodes and links mean and what processes they might support.*"

This graph-theoretic perspective on network centrality, however, may have limitations when the flow of transferrable products is considered as the result of actions between nodes. In turn, the same network positions in certain graph-theoretic terms may not guarantee uniform involvement in actual network flows if some transferable products flow by context-specific patterns[10].

---

[10] This is in line with Borgatti's (2005) theoretical study of the relationship between central positions and network flows. Borgatti apply multiple commonly encountable flow processes (e.g., gossip spread through trails) into two well known existing centrality measures—closeness and betweenness centrality—and test them in the same network graph. He finds that when the original shortest-path assumption changes, nodes positioned with higher closeness or betweenness centrality easily lose the expected centrality. This study implies that the importance (or influence) of network positions cannot be independent from the type of flow process.

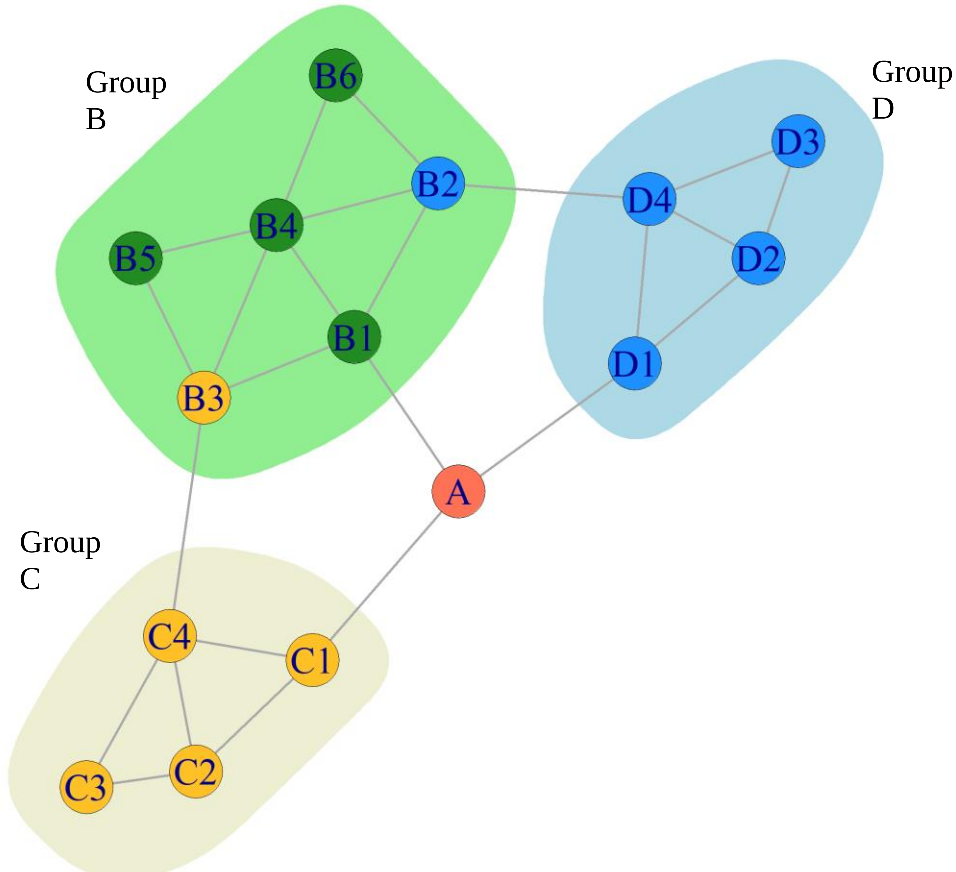


Figure 4.1 A network of "actors" who transact with each other and "relations" where multiple contexts of transactions are embedded (e.g., structural, cultural, and social psychological)

For example, in Figure 4.1, node A may be influential with brokerage power because of the highest betweenness centrality score (Freeman 1978). When valuable products, such as information, flow through shortest-paths, it is likely to pass node A, and thereby, A can have many opportunities to broker it between others in different social groups. But in some cultures, members of the same social group tend to not share important information with someone who has fewer connections with the group members (Xiao and Tsui 2007; Chai and Rhee 2010). If this culture is strongly embedded in the network, node A will lose brokerage power because the members of Groups C and D will not provide the resources that node A can broker to the members of Group B. Likewise, node B1, positioned with the highest closeness centrality score, is expected to be the opinion leader in the network because that node is well connected with other nodes through shorter shortest-paths, and thereby his/her opinions will quickly diffuse to them. However, recent studies show that people are more likely to adopt opinions from others similar in class, race, and gender (Aral, Muchnik, and Sundararajan 2009). If each node's color represents its social characteristic, node B1 may not become the opinion leader because node B1's opinions will only diffuse to the same green nodes—not to the yellow and blue nodes.

In this sense, one's influence becomes dynamic by the process of transactions between actors who have agency within their multiple relational contexts—structural, cultural, and social-psychological. There is no "central" position in itself that provides static and substance-based influences in a network because actors and relations (not only nodes and ties) in social networks are heterogeneous and do not generate universal network flows. In other words, from a graph-theoretic perspective, when multiple social networks (e.g., defined by different ethnic communities) share the same graph, a given centrality measure identifies the same nodes (or positions) as influential in each network. But if context-specific flows of resources are embedded in each social network (e.g., ethnic group) differently, influential nodes may be different in each network—even under the same centrality concept. This means that when a graph-theoretic measure of centrality is equally applied to any network, although the result will capture a single "snapshot" of positional influences, it may miss many other snapshots under complex and diverse transactions in social networks.

A new concept of centrality measure is thus necessary to overcome the potential limitations of existing graph-theoretic centrality measures and their use for social capital studies. Unlike existing centrality measures based on fixed and graph-theoretic network flows, this new measure is based on flexible and action-based network flows to identify influential "actors" within multiple "relational" contexts.

Introduction to the Concept of Actor-Based Centrality

I suggest *actor-based centrality*, which is a Markov Chain Monte Carlo (MCMC) approach to measuring centrality, and explain how this approach helps to measure ego's ***total power*** with and ***relative power*** over alters within context-specific network flows. Actor-based centrality is measured by the simulation model of respondent-driven sampling (RDS)—a chain-referral sampling method. Suppose a network with N nodes is expressed as an NxN Markov Chain matrix P under random walks. Then, multiple RDS simulations can generate multiple Monte Carlo estimates of the stationary distribution of P, which are differentiated by the assumptions about referral chains (i.e., flow processes), and those different estimates become different measures of centrality. Based on this approach, actor-based centrality has three unique characteristics.

First, researchers can construct multiple actor-based centrality measures, customizing the details of flow processes (e.g., unequal survival probabilities (or lengths) of flows; non-random walks; flows with multi-node selection). This is available by simply selecting a set of given assumptions about referral chains for an RDS simulation. Thus, researchers can consider complex and diverse network flows with the simulation approach—which guarantees more flexibility than previous formal approaches—without creating their own flow algorithms entirely based on heuristics (i.e., researchers must create their own flow algorithms without any guidance or example).

Second, in every actor-based centrality measure, central nodes are assumed to be influential because of more access to resources that flow from other nodes. In turn, all customized measures share the same theoretical explanation for influential nodes, and researchers only need to justify the theoretical/empirical rationale of their assumptions about context-specific flows.

Third, the explanation of network positions and influences under actor-based centrality is not based on the sole analysis with a single actor-based centrality measure, but on the comparison between results of the reference actor-based centrality measure (under random-walks) and customized actor-based centrality measures (under context-specific flows). Such a comparison will reveal how much actor-based centrality scores under non-context-specific flows (i.e., random-walks) can change by certain assumed patterns of actions within multiple relational contexts. For example, rumors flowing through strong ties may survive longer, whereas important information is more likely to flow through ties between homogeneous nodes regarding race, class, or gender.

Respondent-driven sampling (RDS) as Markov Chain Monte Carlo (MCMC)

RDS is a chain-referral sampling method invented to study hard-to-reach populations, such as drug users and sex workers (Heckathorn 1997; 2002; Salganik and Heckathorn 2004; Volz and Heckathorn 2008; Heckathorn and Cameron 2017).

The process is similar to "snowball" sampling: one, as a seed, refers friends, and they also refer their friends. Since members of a hard-to-reach population tend to know each other, researchers can easily reach out to them with only a few—or even a single—seeds of referrals. Figure 4.2 shows the process of RDS in the same network graph of Figure 4.1. Nodes A and B1 are assigned as seeds, and their referrals are chained with 2- or 3-length (e.g., B1-B2-B6; A-C1-C2-C3), sampling other nodes in three sampling waves.

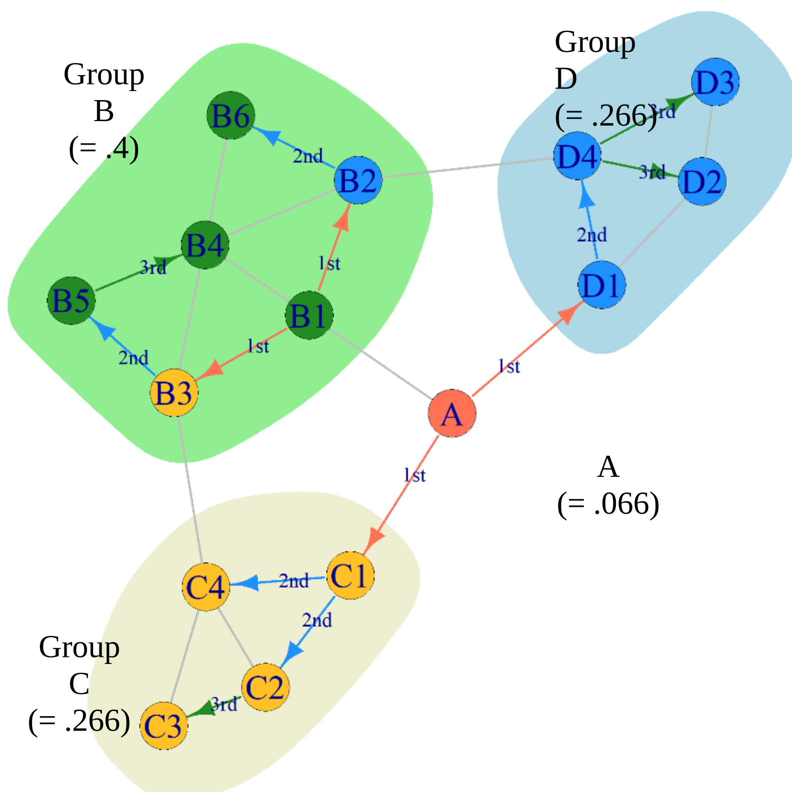


Figure 4.2 An example of respondent-driven sampling in three sampling waves

The main scope of RDS is to obtain an unbiased sample of a hard-to-reach population. In this sense, a successful RDS means the sample proportions of social groups (e.g., race, class, gender) are identical to the population proportions. For example, in Figure 4.2, there is node A and three social groups, and their population proportions are 0.066, 0.4, 0.266, and 0.266, respectively. If an RDS yields unbiased sampling, its sample proportions must be close to those proportions. However, it seems difficult to reach the goal because the referral chains may need to be very long, which is almost impossible unless every respondent is willing to refer their friends. In the case of Figure 4.2, those 3-length referral chains seem enough for unbiased sampling. But suppose 100 nodes are hidden in the network, only connected with Group C nodes. Then, the sample proportions from the 3-length referral chains become biased because it actually fails to capture Group C's large proportion.

$$P = \begin{array}{c|cccc} & \textbf{Node A} & \textbf{Group B} & \textbf{Group C} & \textbf{Group D} \\ \hline \textbf{Node A} & 0 & .333 & .333 & .333 \\ \textbf{Group B} & .083 & .75 & .083 & .083 \\ \textbf{Group C} & .143 & .143 & .714 & 0 \\ \textbf{Group D} & .143 & .143 & 0 & .75 \end{array}$$

$$P^6 = \begin{array}{c|cccc} & \textbf{Node A} & \textbf{Group B} & \textbf{Group C} & \textbf{Group D} \\ \hline \textbf{Node A} & .104 & .406 & .245 & .245 \\ \textbf{Group B} & .101 & .438 & .230 & .230 \\ \textbf{Group C} & .105 & .394 & .317 & .184 \\ \textbf{Group D} & .105 & .394 & .184 & .317 \end{array}$$

Table 4.3 A Markov Chain transition matrix P for the network of Figure 4.2 (by groups) and the result of P^6

Nevertheless, since RDS can be considered a *Markov Chain Monte Carlo* sampling (Goel and Salganik 2009; Volz and Heckathorn 2008), unbiased sampling is available in any network, even if referral chains are not long enough. Let P be an NxN transition matrix between N social groups in a network and e_{ij} be the matrix element representing the transition probability from group i to j through 1-step random-walk.

Then, e_{ij} will be equal to the proportion of ties that link group i and j among all ties of group i. For example, when the network of Figure 4.2 is expressed as a 4x4 transition matrix P as shown in Table 4.3, e_{CB} will be .143 (= 1/7) under random-walks because nodes of Group C have 7 ties, and only one of the ties link them to a node of Group B.

Within the defined P, since every e_{ij} is constant under any step of random-walks, P becomes an NxN Markov Chain transition matrix. Then, e_{ij} of P^k represents the transition probability from group i to j after k-step random-walk, and the calculation of P^k with a finite number k (≥ 6) can be enough to estimate the stationary distribution vector $X_n = (x_{1,n}, x_{2,n}, x_{3,n} \ldots\ldots, x_{j,n})$, such that $X_n = X_{n+1}$ and $x_{j,n} = \frac{1}{N}\sum_{i=1}^{N} e_{ij}$, which represents the transition probability from any group to group j after n-step random-walk. For example, with P^6 from Table 4.3, X_6 = ($x_{A,6}$, $x_{B,6}$, $x_{C,6}$, $x_{D,6}$) = (0.103, 0.408, 0.244, 0.244) can be obtained, and this is almost identical with X_n = (0.103, 0.414, 0.241, 0.241), such that $X_n = X_{n+1}$, which is calculated by the equation $X_n P = X_n$ for the stationary distribution of a discrete-time Markov Chain. In other words, any random-walk that proceeds with more than 6-steps will eventually reach each group with those probabilities regardless of where it starts.

This implies that when referral chains in RDS are close to random-walks, the sample proportions can be the Monte Carlo estimate of X_n of a Markov Chain transition matrix P. For example, suppose all six nodes (or actors) of Group B are asked to refer one of their neighbors (or friends), and node D4 of Group D is referred (or sampled) by node B2. Then, e_{BD} of P can be approximately estimated as 0.166 (= 1/6). Similarly, suppose the referrals are chained, and two nodes of Group D are referred in the second sampling wave. Then, e_{BD} of P^2 can be approximately estimated as 0.333 (= 2/6). With this approach, every e_{ij} of P^k can be estimated, and thereby X_k can also be estimated. These frequency-based (or Monte Carlo) estimates will be more accurate when the lengths of chains are longer, and many seeds are assigned for each group.

More formally, suppose each group has sufficiently many seeds of referral chains, and each chain has enough k-length (≥ 6) during k sampling waves. Each person refers only one other person, constantly following the probability e_{ij}. Then, the referral chains of RDS become the reproduction of all possible *k*-step random-walks in a network (= P^k), and the sample proportions of groups at kth-length referral chains (or kth sampling wave) (= X_k) will be the estimate of X_n with repeated random sampling, such that $X_n = X_{n+1}$. If $X_k \approx X_n$ is successful, since $X_n = X_{n+1}$ is expected, the sample proportions from the kth sampling wave will be similar to those from the (k+1)th sampling wave (i.e., $X_k = X_{k+1}$). Thus, if samples from later waves ($\geq$ k) take a large portion among all samples, the sample proportions from all sampling waves will also converge to X_n.

When the sample proportions are close to X_n of *P* under random-walks, they are expected to correlate with the population proportions because a group with more nodes will be more referred, and vice versa. However, there are two major problems. First, in reality, the referral chains are hard to be identical with random-walks. For example, if only one referral is allowed, most referral chains will be disconnected immediately because many hard-to-reach populations tend to refuse those surveys. Second, even if the sample proportions are close to X_n, they may not correlate with the population proportions due to unequal topological characteristics of social groups. For example, in Figure 4.2, X_n = (0.103, 0.414, 0.241, 0.241) is different from the population proportions (0.066, 0.4, 0.266, 0.266). This is mainly because node A has more ties (=3) than a general node in other groups (= 1.75~2), and thereby referrals will be more likely to reach A.

To solve those problems, many RDS studies aim to (1) clarify what assumptions about referral-chains are necessary to minimize sampling bias and (2) suggest several estimators that weight the sample proportions to control the bias from topological reasons.

(1) Assumptions about referral chains: Five main assumptions about referral chains for unbiased sampling are suggested by previous RDS studies. Formally, under the violation of one of those assumptions, the sample proportions of social groups become the biased estimate of the stationary distribution X_n of P, such that $X_n = X_{n+1}$. The first two assumptions are that the seed assignment for each group and the length of referral chains need to be uniform and long enough, respectively. But the sampling bias from the violation of the two assumptions is interdependent. In turn, even if one of the conditions is only satisfied, RDS can be unbiased. Basically, since RDS is a Markov Chain process, the samples from later waves become more independent from the seed assignment. It means that when referral chains have enough length (> 6), even if seed assignment is nonuniform, sample proportions estimated by later waves are still expected to reach to X_n of P. Conversely, when seed assignment is uniform enough, the sample proportions reach to X_n of P, even if referral chains have shorter lengths. However, due to network homophily (i.e., nodes are clustered by similar race/class/gender), even if the chains are long enough, nonuniform seed assignment could yield serious bias when the network homophily is extreme or unequal by social groups (Heckathorn 1997; 2002). For reliable unbiased estimation, referral chains need to be longer than the theoretical requirement (Gile and Handcock 2010).

The remaining three assumptions about referral chains are the parts of six main RDS assumptions (Heckathorn and Cameron 2017). Note that the other three RDS assumptions are only related to data collection issues—not referral chains. First, the smaller number of referrals from each node reduces the potential bias. Although only one referral is the best, since the small referral size yields some difficulty maintaining the chain-referral process, maximum 3-referrals in each sampling wave is recommended. Yet, this bias becomes marginal when the size of overall samples accounts for a small proportion of the population (Lu et al. 2012). Second, each referral must be random. When ego has 6-alters, each alters must have an equal chance to be referred by ego. If this is non-random, e_{ij} in P also changes, yielding biased estimation (Shi et al. 2019). Previous studies support that people tend to refer others randomly (Heckathorn 2007), but in some social groups, non-random referral happens significantly (Wejnert and Heckathorn 2008). Third, sampling without replacement yields bias due to the violation of the Markov Chain assumption that e_{ij} of P is constant. But this bias becomes marginal when the size of samples accounts for a small proportion of the population (Barash et al. 2016).

(2) RDS estimators: RDS estimators weight the initial sample proportions to control the sampling bias from the different topological characteristics of social groups. The initial sample proportions are called Naïve estimation (Heckathorn 1997; 2002).

Although no statistical weight is given for the estimation, the sample proportions are unbiased when network homophily is equal by groups. RDS-I estimator (Salganik and Heckathorn 2007) is based on the estimated ratio of e_{ij} to e_{ji} and each group's mean degree. When all nodes have an equal degree, $e_{ij} > e_{ji}$ means group j has more nodes than group i, and vice versa (i.e., each ego of group j (or i) has more (or less) alters of the same group than of different groups). RDS-II estimator (Volz and Heckathorn 2011) only uses each group's mean degree as the weight. The sample proportion of each group that has more mean degrees is less weighted, and vice versa. Heckathorn estimator (2007) uses sampling waves as the weight. Simply, when the two mean degrees of respondents at kth and k+1th sampling waves reach equilibrium, the samples are more weighted in the calculation of sample proportions.

MCMC estimation of network centrality through RDS simulation

In sum, RDS studies clarify that the sample proportions of “groups” by chain-referral sampling can be the MCMC estimate of the population proportions. They are unbiased when the conditions of referral chains are well controlled, and different network characteristics of groups are well reflected in estimators (or weights).

Here, focusing on the MCMC estimate of the population proportions of "nodes" in a network, I argue that RDS simulation can be a useful frame for constructing multiple *actor-based centrality* measures. One difference between actor-based centrality and existing RDS studies is that actor-based centrality mainly focuses on the biased estimation of population proportions—not the unbiased estimation. For example, in Figure 4.2, node A's sample proportion from an RDS simulation can be much larger than the population proportion (= 1/15) due to certain chain-referral conditions or network characteristics (e.g., more ties). While existing RDS studies consider it a "problem" to solve, actor-based centrality considers it a reflection of network centrality.

The strength of actor-based centrality is that researchers can customize the assumptions about flow processes by changing the assumptions about referral chains in an RDS simulation. This flexibility makes a clear distinction between actor-based centrality and existing centrality measures under fixed network flows—including PageRank (Page et al. 1999), which is similarly based on the Markov Chain process. Nevertheless, all actor-based centrality measures share the same evaluation assumption about a node's involvement in network flows and thereby have the same theoretical explanation for influential nodes. In turn, *a node more sampled by certain referral chains is considered influential with more access to resources that flow from other nodes.*

$\mathbf{P}$ =

	A	$B1$	$B2$	$B3$	$B4$	$B5$	$B6$	$C1$	$C2$	$C3$	$C4$	$D1$	$D2$	$D3$	$D4$
A	0	.33	0	0	0	0	0	.33	0	0	0	.33	0	0	0
$B1$	.25	0	.25	.25	0	0	0	0	0	0	0	0	0	0	0
$B2$	0	.25	0	0	.25	0	.25	0	0	0	0	0	0	0	.25
$B3$	0	.25	0	0	.25	.25	0	0	0	0	.25	0	0	0	0
$B4$	0	.2	.2	.2	0	.2	.2	0	0	0	0	0	0	0	0
$B5$	0	0	0	.5	.5	0	0	0	0	0	0	0	0	0	0
$B6$	0	0	.5	0	.5	0	0	0	0	0	0	0	0	0	0
$C1$	.33	0	0	0	0	0	0	0	.33	0	.33	0	0	0	0
$C2$	0	0	0	0	0	0	0	.33	0	.33	.33	0	0	0	0
$C3$	0	0	0	0	0	0	0	0	.5	0	.5	0	0	0	0
$C4$	0	0	0	.25	0	0	0	.25	.25	.25	0	0	0	0	0
$D1$	.33	0	0	0	0	0	0	0	0	0	0	0	.33	0	.33
$D2$	0	0	0	0	0	0	0	0	0	0	0	.33	0	.33	.33
$D3$	0	0	0	0	0	0	0	0	0	0	0	0	.5	0	.5
$D4$	0	0	.25	0	0	0	0	0	0	0	0	.25	.25	.25	0

Table 4.4 A Markov Chain transition matrix P for the network of Figure 4.2 (by nodes)

First of all, I suggest actor-based centrality measure under random-walks. Let R_i be the number of referrals to node i in an RDS simulation and $\overline{p_{\iota,m}}$ be the sample proportion of node i from the *m*th simulation of RDS in a network with N nodes (not groups). In each RDS simulation, seeds of referral chains are enough for each node, and every referral chain follows a random-walk with enough k-length (> 6). Then, when $\overline{p_{\iota,m}}$ is defined as the proportion of R_i in the total number of referrals, it will be the estimate of node i's population proportion, and the sample proportions of all nodes will be close to the stationary distribution X_n of an NxN Markov Chain transition matrix *P* under random-walks, such that $X_n = X_{n+1}$.

$$\overline{p_{\iota,m}} \approx \frac{R_i}{\sum_{i=1}^{N} R_i} \quad (1)$$

For example, from Figure 4.2, a 15x15 transition matrix *P* under random-walks can be formed, (Table 4.4). Suppose an RDS that sample nodes (not groups) is simulated in the network with many seeds for each node (= 100) and 6-length referral chains. Then, as with the example of RDS for groups (= 4x4 transition matrix in Figure 4.1), the RDS simulation will reproduce all possible 6-step random-walks under every P^k, such that 1 $\leq$ k $\leq$ 6, and the sample proportions (of nodes) will be close to the stationary distribution X_n of the *P*, such that $X_n = X_{n+1}$.

Additionally, suppose the RDS simulation is iterated M times under the same conditions, and $\overline{p_\iota}$ is the mean of $\overline{p_{\iota,m}}$ from M simulations of RDS. Then, $\overline{p_\iota}$ will be the bootstrap estimate of node i's population proportion with a low confidence interval. In other words, when this simulation is iterated with many times (= 100), the average sample proportions will be more close to X_n. Here, let C_i^{AB} be node i's actor-based centrality score under random-walks. When M is large enough, then.

$$C_i^{AB} = \overline{P_i} = \frac{1}{M}\sum_{m=1}^{M}\overline{p_{i,m}} \qquad (2)$$

$$C_i^{AB} > C_j^{AB} \equiv \overline{P_i} > \overline{P_j} \qquad (3)$$

Under this definition, every C_i^{AB} (under random-walks) will be different due to unequal topological characteristics of nodes (e.g., number of ties), and any pair of C_i^{AB} and C_j^{AB} in the same network can be robustly comparable with their lower confidence intervals. For example, in Figure 4.2, if nodes A and B1 are sampled 720 and 360 times among 3600 referrals in every RDS simulation, $\overline{p_A} = C_A^{AB}$ and $\overline{p_{B1}} = C_{B1}^{AB}$ will be .2 (= 720/3600) and .1 (= 360/3600), respectively, and $C_A^{AB} > C_{B1}^{AB}$ can be claimed (i.e., node A is more influential than node B1 due to more access to resources that flow through random-walks).

However, since the score of C_i^{AB} is largely affected by the number of nodes in each network, it is difficult to compare C_i^{AD} across different networks. For example, in a network with 100 nodes, C_i^{AB} = 0.02 could indicate a higher centrality score because each node's population proportion is 0.01. But in a network with 10 nodes, C_i^{AB} = 0.02 represents a very low centrality score because each node's population proportion is 0.1. Thus, normalization of actor-based centrality is required for the comparison of scores across different networks. Let $\tilde{C}_i^{AB}$ be node i's normalized actor-based centrality score, $\widehat{P_i}$ be node i's population proportion, and N be the number of nodes in a network. Then,

$$\tilde{C}_i^{AB} = \frac{C_i^{AB}}{\widehat{P_i}} = \frac{\overline{P_i}}{\widehat{P_i}} \ \ s.t \ \ \widehat{P_i} = \frac{1}{N} \quad (3)$$

$$Simply, \qquad \tilde{C}_i^{AB} = \frac{\overline{P_i}}{\widehat{P_i}} = \frac{\overline{P_i}}{1/N} = N\overline{P_i} = NC_i^{AB} \ (4)$$

When there are 100 nodes in a network, $\widehat{P_i}$ will be simply 0.01 (= 1/100). If C_i^{AB} = 0.02, the normalized centrality $\tilde{C}_i^{AB}$ will be 2 (= 0.02/0.01). This will be the same when the network has 10 nodes, and C_i^{AD} = 0.2 because $\widehat{P_i}$ = 0.1 and thus $\tilde{C}_i^{AB}$ will be 2 (= 0.2/0.1). The two scores equally reveal that the node i is sampled twice more than the population proportion and has that much of a centrality score. As proved in equation (4), the normalized centrality $\tilde{C}_i^{AD}$ is simply calculated by multiplying the number of nodes in a network (= N) to the unnormalized centrality C_i^{AB}.

Multiple measures of actor-based centrality within context-specific network flows

The scores of actor-based centrality measure under random-walks will be the unbiased Monte Carlo estimate of the stationary distribution X_n of a Markov Chain transition matrix *P*. Nodes more sampled by random-walks due to certain topological characteristics (e.g., more ties) will have higher actor-based centrality scores, and vice versa. The scores will identify influential nodes under non-context-specific flows (i.e., more access to resources that flow through random-walks).

The point is that since various assumptions about referral chains are customizable in the RDS simulation, by changing them, researchers can construct multiple actor-based centrality measures that reflect complex and diverse network flows in a flexible manner. In this case, the scores of each customized actor-based centrality measure will provide the "biased" estimate of the stationary distribution X_n of P. Thus, the comparison of the scores between two actor-based centrality measures—random-walk actor-based centrality vs. customized actor-based centrality—will clarify how much the estimation is biased due to the customized network flows, which can represent a non-Markovian process or another Markov Chain process under $P^{"}$, such that $P \neq P^{"}$. In other words, when C_i^{AB} is actor-based centrality measure under random-walks, the measure can be the reference for the customized actor-based centrality measures under context-specific flows (= $C_i^{AB\_bias}$).

Table 4.5 summarizes existing RDS assumptions about referral chains and relevant network flow assumptions that can be expressed with those assumptions. All assumptions about referral chains are proved well by previous RDS studies to generate a certain level of sampling bias (here, unequal network centralities).

Assumptions about referral chains for unbiased RDS	***Relevant assumptions about network flow***
Length (L): Referral chains need to have enough length (≥ 6), especially when seed-assignment is not uniform enough by groups.	Each flow has a different survival rate in terms of length; Some chains of transactions (e.g., trust-based exchanges) are short.
Seed assignment (S): Seed assignment needs to be uniform enough by groups, especially when the lengths of referral chains are not long enough.	Sources of resources (e.g., information) are unequally assigned to actors
Number of referrals (Z): When one refers others, the number of referrals needs to be minimized (≤ 3)	Exchange situations under inclusive/exclusive, multiple/singular, or non-zero-sum/zero-sum connection.
Differential Recruitment (R): One's referral must be based on random selection	Non-random network flow based on the characteristics of actors (e.g., flow under homophily or heterophily by class/race/gender)
Replacement (P): Sampling-with-replacement reduces sampling bias.	Walks or paths; Reciprocal or generalized exchange situations (i.e., direct or indirect rewarding)

Table 4.5 Assumptions about referral chains for unbiased RDS and relevant assumptions about network flow

A set of assumptions about referral chains represents an MCMC algorithm within an RDS simulation framework—and this MCMC algorithm represents a network flow algorithm for a customized actor-based centrality measure, which cannot be easily expressed as a transition matrix. Since many MCMC algorithms can be created by selecting a set of given assumptions, complex and diverse network flow algorithms can be constructed as well. Even the flow processes suggested in Figure 4.1 can be considered. If RDS is simulated with non-random referrals, this customized actor-based centrality measure could reflect the trust-based network flow circled within each group (= $C_i^{AB\_R}$). If the unequal number of referrals from each node is considered, this actor-based centrality measure could reflect the non-uniform diffusion of opinions through ties between homogeneous/heterogeneous nodes (= $C_i^{AB\_Z}$). These two assumptions can also be reflected in a single measure simultaneously (=$C_i^{AB\_R\&Z}$).

Multiple Measures of Power-Dependence Relations within Context-Specific Network Flows

The MCMC approach of actor-based centrality can also help to identify power-dependence relations in a network. By adding one more simple assumption to actor-based centrality, I argue that multiple measures of relative power (i.e., unequal dependence) and total power (i.e., mutual dependence) within context-specific network flows can be constructed, the concepts of which are in line with the power-dependence measures suggested by Casciaro and Piskorksi (2005).

Casciaro and Piskorksi (2005) focus on measuring resource-dependence relations between organizations and industry. Combining social exchange theories and Burt's (1983) market constraints measures, they suggest two measures of resource-dependence relations—power imbalance and mutual dependence—which are basically the same concepts of relative power and total power (Cook and Emerson 1978; Cook and Yamagishi 1992; Lawler and Bacharach 1986; Markovsky, Willer, and Patton 1988; Molm 1990; Willer 1992).

Let Z_{ij} be the total dollar value of goods and services industry i sell to industry j, and O_j be the concentration ratio of major four firms in industry i. Following Burt's (1983) measurement concept, Casciaro and Piskorski define the dependence of business units in industry i on business units in industry j, which is equal to the power of units in i over units in j (= $C_{j \to i}$), as below.

$$C_{j \to i} = \left(\frac{Z_{ji}}{\sum_q Z_{qi}} + \frac{Z_{ij}}{\sum_q Z_{iq}} \right) O_j \qquad (5)$$

Then, the power difference (= $PI_{i \leftrightarrow j}$) and mutual dependence (= $MD_{i \leftrightarrow j}$) between business units in industry i and j are defined below.

$$PI_{i \leftrightarrow j} = \left| C_{j \to i} - C_{i \to j} \right| \qquad (6)$$

$$MD_{i \leftrightarrow j} = C_{j \to i} + C_{i \to j} \qquad (7)$$

Equation (5) implies that when ego i industry's possessions (i.e., services and goods) flow *mainly* from $\left(= \frac{Z_{ji}}{\sum_q Z_{qi}}\right)$ or to $\left(= \frac{Z_{ij}}{\sum_q Z_{iq}}\right)$ a particular alter j industry, the dependence of business units in ego i industry on business units in alter j industry will increase. Additionally, when those services and goods in an industry are possessed by a few major business units (i.e., large O_j), the dependence will also increase as well. However, based on the idea of network centrality, this study assumes that ego i's dependence on alter j is affected only by the flow of transferable products from alter j to ego i $\left(= \frac{Z_{ji}}{\sum_q Z_{qi}}\right)$. Thus, the flow to alters $\left(= \frac{Z_{ij}}{\sum_q Z_{iq}}\right)$ is *not* considered for ego i's dependence. In addition, the concept of concentration ratios (= O_j), which is only necessary within the context of industrial relationships, is also not considered in this study.

Under these assumptions, when ego i's dependence on alter j is—which is equal to alter j's power over ego i—it will be simply $\frac{Z_{a_{ij}e_i}}{\sum_{j=1}^{n_{e_i}} Z_{a_{ij}e_i}}$. Then, this can be estimated through an RDS simulation by the proportion of referrals from alter j to ego I in the sum of referrals to ego i from alters $\left(= \frac{R\ a_{ij}e_i}{\sum_{j=1}^{n_{e_i}} R\ a_{ij}e_i}\right)$, such that n_{e_i} is the number of alters in ego i's network. In other words, the dependence score can also be considered as the ego-centric level of node i's actor-based centrality, which is generally estimated by the proportion of referrals to node i in the sum of referrals to every node $\left(= \frac{R_i}{\sum_{i=1}^{N} R\ i}, \text{see formula (1)}\right)$. Let $D_{e_i a_{ij}}(AB)$ be ego i's dependence on alter j estimated by an RDS simulation, and $P_{a_{ij}e_i}(AB)$ be alter j's power over ego i. Then,

$$P_{a_{ij}e_i}(AB) = D_{e_i a_{ij}}(AB) = \frac{Z_{a_{ij}e_i}}{\sum_{j=1}^{n_{e_i}} Z_{a_{ij}e_i}} \approx \frac{R_{a_{ij}e_i}}{\sum_{j=1}^{n_{e_i}} R_{a_{ij}e_i}} \quad (8)$$

Thus, the measures of ego i's relative power over (i.e., unequal dependence) and total power (i.e., mutual dependence) with alter j are formed below. Note that unlike the measure of power imbalance (= $PI_{i \leftrightarrow j}$) in Casciaro and Piskorksi's model, the relative power measure does not consider the concept of absolute value, assuming that a negative value implies ego i's weak relative power over alter j.

$$P_{e_i a_{ij}}(AB, R) = P(AB)_{e_i a_{ij}} - P(AB)_{a_{ij}e_i} \quad (9)$$

$$P_{e_i a_{ij}}(AB, T) = P(AB)_{e_i a_{ij}} + P(AB)_{a_{ij}e_i} \quad (10)$$

Since the measures are only about one's power over another, the mean of powers is considered ego i's power over alters. Thus, ego i's relative power and total power are defined below. In addition, the measures are only based on a single RDS simulation result. Therefore, as a final step, when M simulations of RDS are iterated, the average will be the bootstrapping estimate of ego i's relative/total power, the estimation approach of which is the same as actor-based centrality.

$$P_{e_i}(AB, R) = \frac{1}{n_{e_i}} \sum_{j=1}^{n_{e_i}} P(AB, R)_{e_i a_{ij}} \quad (11)$$

$$P_{e_i}(AB, T) = \frac{1}{n_{e_i}} \sum_{j=1}^{n_{e_i}} P(AB, T)_{e_i a_{ij}} \quad (12)$$

Compared to Casciaro and Piskorksi's measures, the power measures suggested here do not require empirical data on resource flow (e.g., transactions of services and goods between industries). Unlike existing measures, the new power measures theoretically estimate ego i's power over alters under certain assumptions about network flow. It is also noteworthy that the assumptions of network flow are flexible under the actor-based centrality approach. In turn, while existing measures are only based on a 1-step flow process, the new measures can consider multiple context-specific network flows by selecting RDS assumptions summarized in Table 4.5.

Theoretically, as pointed out in Chapter 3, ego i with a strong relative/total power is more likely to use hostile/conciliatory strategies for bargaining with alters. In this sense, it is assumed that ego i with a strong relative/total power—estimated by actor-based centrality—is advantageous to bargain for accessing resources that flow through a certain assumed way. This implies that the scores of actor-based centrality and power measures could have distinct meanings. For example, suppose some important rumors flow through random-walks. Then, ego i with higher C_i^{AB} is expected to have more chances to access those rumors when they are simply *given* (or provided) by other nodes. But if ego i's alters try to bargain about providing the rumors and ego i has weak $P_{e_i}(AB, R)$ and $P_{e_i}(AB, T)$, the chances would rapidly decrease.

Empirical Test: Centrality and Power-Dependence Relations of 15th Century Florentine Families

Applying customized measures of actor-based centrality and power dependence relations, I explore how network positions of 15th-century Florentine families in their marriage and business relations during 1394-1434 mattered to their power game. Note that all actor-based centrality and power-dependence measures are estimated using Netlogo, a widely used program for agent-based modeling.

The network datasets used in this chapter were created and explored well by Padgett and Ansell (1993; see also Breiger and Pattison 1986), which are widely used to test and apply newly invented centrality measures (Newman 2005; Bonacich and Lloyd 2001; Opsahl, Agneessens, and Skvoretz 2010). The previous study of Padgett and Ansell shows two major findings. First, the rise of the Medici family in the 15th century is largely related to their central position in both marriage and business networks (see Figure 4.3 and 4.4). Many elite families directly connected with the Medici in the networks tend to lack connections with other families, and thereby they could be connected with others *"only through the intermediation of the Medici family"* (Padgett and Ansell 1993), which is in line with the concept of betweenness centrality. Second, the fallen of the Strozzi and Peruzzi families—who had been as powerful as the Medici—is largely because of their equal status relationships with other elite families. In both business and marriage networks (see Figure 4.3 and 4.4), the Strozzi and Peruzzi—and other families connected with the two—tend to be *"densely interconnected,"* and no one can *"claim to leadership"* in terms of network positions (Padgett and Ansell 1993). Because of the structural condition, the two elite families could not be as influential as the Medici family in the marriage and business networks.

Yet, although the graphs seem to support their points, it is not quite clear whether those graph-theoretic network positions are still meaningful under the considerations of context-specific network flows potentially embedded in the marriage and business networks as well as the cultural meanings of social relations in the 15th century of Florentine. This chapter thus re-explores the two major findings of Padgett and Ansell, by utilizing multiple customized measures of actor-based centrality and power-dependence relations.

Florentine marriage network, 1394-1434

The marriage network graph of Florentine families is shown in Figure 4.3.

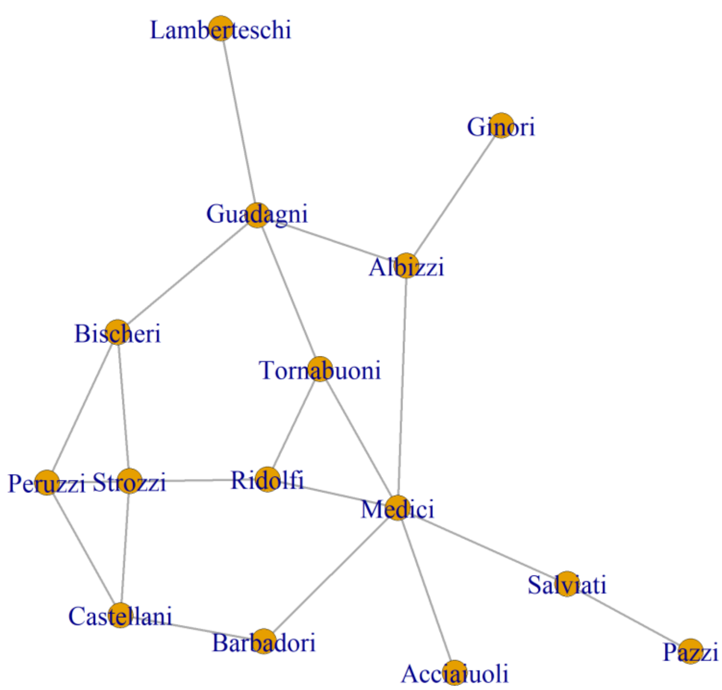


Figure 4.3 Florentine Marriage Network, 1394-1434

As the first step, I construct the reference actor-based centrality (= C_i^{AB}), which is purely based on random-walks. With enough seeds for each node (=40) and iterations (=100) for bootstrapping, this is measured under all chain-referral assumptions for unbiased sampling, which makes the referral chains close to random-walks. Thus, the assumptions are 1) all nodes have uniform seeds, 2) every chain has an equally 6-length during six sampling waves, 3) each node refers only one, 4) sampling-with-replacement, and 5) each referral is perfectly random. The scores of C_i^{AB} will reveal how much a node is more sampled by random-walks, representing the node's potential influence with more access to resources that flow through non-context-specific patterns.

In the second step, I suggest some context-specific flows that are potentially embedded in the marriage network and explain how those network flows can be reflected in actor-based centrality measures (= $C_i^{AB\_bias}$). Each $C_i^{AD\_bias}$ is measured under the same simulation conditions of C_i^{AB}, except for the customized assumptions about referral chains. In turn, the difference of centrality scores between C_i^{AB} and $C_i^{AB\_bias}$ will reveal which nodes can become much more influential when important resources flow through certain context-specific patterns.

Here, I propose two customized actor-based centrality measures. (1) *Longer chain of exchanges:* The marriage relations are often exceptionally strong. Thus, the chain of exchanges within the relations could survive much longer than that within other types of relations, generating longer flows of resources. For example, if the Pazzi family provides very important information to the Salviati family, this information is also likely to be shared with the Medici married with the Salviati—and so forth. To reflect this contextual flow process, I change each length of a chain from 6 to 12 (= $C_i^{AB\_L12}$) in the previous RDS simulation model for C_i^{AB}. (1) *Shorter chain of exchanges:* But at the same time, marriage relations are also trustworthy. Thus, when a referral is assumed as a way of sharing very important information, this will be less likely to flow through a network. For example, if the Medici provides very important information to the Ridolfi that must be kept secret, the information will not easily spread because sharing it with others could be considered by the Medici as the malfeasance of the Ridolfi. Considering this point, I change each length of a chain from 6 to 3 (= $C_i^{AB\_L3}$).

Under those assumptions of network flow, three different measures of actor-based centrality are constructed. Then, by adding the calculation assumption to the same simulation results, I also create three different measures of total power and relative power, respectively. The measures of ego i's total power under random-walks, longer chains, and shorter chains are formally expressed as $P_{e_i}(AB, T)$, $P_{e_i}(AB\_L12, T)$, and $P_{e_i}(AB\_L3, T)$, respectively. Similarly, the measures of relative are expressed as $P_{e_i}(AB, R)$, $P_{e_i}(AB\_L12, R)$, and $P_{e_i}(AB\_L3, R)$, as well.

Families	Betweenness Centrality		Closeness Centrality		Degree Centrality		Actor-based Centrality (Reference)		Actor-based Centrality with Longer Referral (=12)		Actor-based Centrality with Shorter Referral (=3)	
Acciaiuoli	0	(14)	.368	(12)	.071	(14)	.371	(14)	.375	(15)	.338	(15)
Albizzi	.212	(3)	.483	(4)	.214	(7)	1.260	(4)	1.195	(4)	1.299	(3)
Barbadori	.093	(8)	.438	(7)	.143	(11)	.720	(11)	.717	(11)	.670	(11)
Bischeri	.104	(6)	.4	(8)	.214	(7)	1.009	(8)	1.061	(7)	.969	(8)
Castellani	.055	(10)	.389	(10)	.214	(7)	1.021	(7)	1.043	(8)	1.014	(6)
Ginori	0	(14)	.333	(13)	.071	(14)	.404	(13)	.393	(13)	.427	(13)
Guadagni	.255	(2)	.467	(5)	.286	(3)	1.545	(2)	1.536	(2)	1.648	(2)
Lamberteschi	0	(14)	.326	(14)	.071	(14)	.367	(15)	.377	(14)	.351	(14)
Medici	**.522**	**(1)**	**.56**	**(1)**	**.429**	**(1)**	**2.424**	**(1)**	**2.359**	**(1)**	**2.551**	**(1)**
Pazzi	0	(14)	.286	(15)	.071	(14)	.485	(12)	.444	(12)	.526	(12)
Peruzzi	**.022**	**(11)**	**.368**	**(12)**	**.214**	**(7)**	**.991**	**(9)**	**1.039**	**(9)**	**.953**	**(9)**
Ridolfi	.114	(5)	.5	(2)	.214	(7)	1.040	(6)	1.085	(6)	.953	(10)
Salviati	.143	(4)	.389	(10)	.143	(11)	.949	(10)	.871	(10)	1.019	(5)
Strozzi	**.103**	**(7)**	**.438**	**(7)**	**.286**	**(3)**	**1.341**	**(3)**	**1.394**	**(3)**	**1.291**	**(4)**
Tornabuoni	.092	(9)	.483	(4)	.214	(7)	1.074	(5)	1.111	(5)	.992	(7)

Table 4.6 Centrality scores and ranks of Florentine families in the marriage network (normalized)

Families	Relative Power (Reference)		Relative Power with Longer Referral		Relative Power with Shorter Referral		Total Power (Reference)		Total Power with Longer Referral		Total Power with Shorter Referral	
Acciaiuoli	-.807	(15)	-.820	(15)	-.781	(15)	1.193	(4)	1.180	(4)	1.219	(4)
Albizzi	.142	(3)	.141	(3)	.139	(3)	.809	(6)	.808	(6)	.805	(6)
Barbadori	-.239	(11)	-.246	(11)	-.228	(11)	.761	(7)	.754	(7)	.772	(7)
Bischeri	-.068	(8)	-.062	(8)	-.067	(8)	.598	(12)	.605	(12)	.600	(12)
Castellani	.022	(6)	.020	(6)	.033	(6)	.688	(9)	.687	(9)	.700	(9)
Ginori	-.594	(13)	-.626	(13)	-.532	(13)	1.406	(2)	1.374	(2)	1.468	(2)
Guadagni	.253	(2)	.251	(2)	.248	(2)	.753	(8)	.751	(8)	.748	(8)
Lamberteschi	-.697	(14)	-.723	(14)	-.647	(14)	1.303	(3)	1.277	(3)	1.353	(3)
Medici	**.318**	**(1)**	**.326**	**(1)**	**.292**	**(1)**	**.651**	**(10)**	**.659**	**(10)**	**.626**	**(11)**
Pazzi	-.385	(12)	-.429	(12)	-.319	(12)	1.615	(1)	1.571	(1)	1.681	(1)
Peruzzi	**-.036**	**(7)**	**-.033**	**(7)**	**-.034**	**(7)**	**.630**	**(11)**	**.633**	**(11)**	**.633**	**(10)**
Ridolfi	-.098	(10)	-.089	(9)	-.106	(9)	.568	(14)	.577	(13)	.561	(13)
Salviati	.100	(4)	.094	(4)	.104	(4)	1.100	(5)	1.094	(5)	1.104	(5)
Strozzi	**.063**	**(5)**	**.071**	**(5)**	**.051**	**(5)**	**.563**	**(15)**	**.571**	**(15)**	**.551**	**(15)**
Tornabuoni	-.098	(9)	-.090	(10)	-.107	(10)	.569	(13)	.576	(14)	.560	(14)

Table 4.7 Power-Dependence scores and ranks of Florentine families in the marriage network

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Betweenness											
(2) Closeness	.807										
(3) Degree	.844	.825									
(4) ABC (Ref)	.929	.827	.977								
(5) ABC (Longer)	.902	.833	.991	.997							
(6) ABC (Shorter)	.946	.792	.955	.995	.985						
(7) R Pow (Ref)	.729	.695	.852	.863	.86	.856					
(8) R Pow (Longer)	.729	.71	.86	.867	.866	.857	.999				
(9) R Pow (Shorter)	.721	.667	.836	.852	.847	.848	.999	.996			
(10) T Pow (Ref)	-.433	-.758	-.766	-.649	-.696	-.578	-.687	-.709	-.655		
(11) T Pow (Longer)	-.429	-.756	-.764	-.646	-.694	-.575	-.686	-.708	-.654	1	
(12) T Pow (Shorter)	-.454	-.772	-.777	-.664	-.71	-.595	-.7	-.722	-.667	1	.999

Table 4.8 Correlation matrix of centrality and power-dependence measures in the marriage network

Tables 4.6 and 4.7 summarize the normalized scores and ranks of all actor-based centrality measures and power-dependence measures. The scores of three existing centrality measures—degree, betweenness, and closeness centrality—are also included for comparison. Table 4.8 shows the correlation matrix of all centrality and power-dependence measures. Each score's standard error (SE) is summarized in Appendix C. Every score has a lower SE (< .01), which means comparing the scores is available by their narrow confidence intervals. Note that SE can be much smaller when more seeds and iterations are assigned. The simulation running time to estimate the scores of each actor-based centrality measure was less than 20 seconds (by Netlogo).

The result of $\tilde{C}_i^{AB}$ supports that the Medici is more central than the Peruzzi and Strozzi, which is in line with the main argument of Padgett and Ansell's study. The Medici, who is ranked first in all three existing centrality measures, also has the highest $\tilde{C}_i^{AB}$. More specifically, the Medici family is sampled 2.4 times more than the population proportion (= 1/15) and is expected to be the most influential in the marriage network. On the contrary, the Peruzzi and Strozzi are ranked 3rd (= .991) and 9th (= 1.341) in $\tilde{C}_i^{AB}$, respectively, lower than the Medici. Yet, their ranks in $\tilde{C}_i^{AB}$ are higher than in existing centrality measures. The Peruzzi's ranks in betweenness and closeness centrality are 11th and 12th, respectively, and the Strozzi's ranks are equally 7th. This means that when important resources flow through random-walks, their influence could be improved than the shortest-path assumption.

The result of $\tilde{C}_i^{AB\_L12}$ is not interesting enough because the scores of $\tilde{C}_i^{AB\_L12}$ reveals no significant difference from the scores of $\tilde{C}_i^{AB}$. As shown in Table 4, most of the scores and their ranks in $\tilde{C}_i^{AB\_L12}$ did not change much, compared to $\tilde{C}_i^{AB}$, and the two measures have a very strong correlation (= .997). Although this result does not support the importance of a longer chain of exchanges, it supports the robustness of actor-based centrality. As an MCMC estimation, $\tilde{C}_i^{AB\_L12}$ is expected to be identical with $\tilde{C}_i^{AB}$ because $\tilde{C}_i^{AB}$ is the estimate of X_n of a Markov Chain matrix *P*, such that $X_n = X_{n+1}$. In other words, when the 6-length of referral chains is enough to estimate the stationary distribution X_n, the sampling result will not change much, even under 12-length. Thus, the similar centrality scores of $\tilde{C}_i^{AB}$ and $\tilde{C}_i^{AB\_L12}$ support that actor-based centrality is based on the MCMC estimation.

The result of $\tilde{C}_i^{AB\_L3}$ shows an interesting point. For the Medici, compared to $\tilde{C}_i^{AB}$, their $\tilde{C}_i^{AB\_L3}$ score increases from 2.242 to 2.551. On the contrary, the Peruzzi's and Strozzi's $\tilde{C}_i^{AB\_L3}$ scores decrease from .991 and 1.341 to .953 and 1.291, respectively. In other words, if the Medici's centrality in the marriage network had been crucial for their rise, it could have been not simply because of their graph-theoretic position but because of the shorter chain of exchanges that could be related to the contextual actions in the marriage network.

The power measures also reveal an interesting snapshot of their power game. It is clear that the Medich has much stronger relative power than the Peruzzi and Strozzi in bargaining. Under any flow assumption, Medich's relative power is around .3, whereas Strozzi's power is around .06. The Peruzzi even has weak relative powers; every relative power is less than 0. This result supports Padgett and Ansell's argument that the two families have equal status (or power) relationships with other families in the marriage network. But here, an unexpected part is that the two families even have lower total power scores. In three total power measures, the Peruzzi and Strozzi are ranked 11th and 15th, respectively. Their total power scores are even lower than the Medici, ranked 10th in every total power measure. This implies that the fallen of the two families was because of their lack of total power that could lead to cooperation (or conciliatory strategy), rather than the weak relative power for hostile strategy.

Florentine Business Network, 1394-1434

The business network graph of Florentine families is shown in Figure 4.4. I also add their net wealth information (unit = 1k of lira) because the assumptions about network flow in this part are related to their unequal wealth.

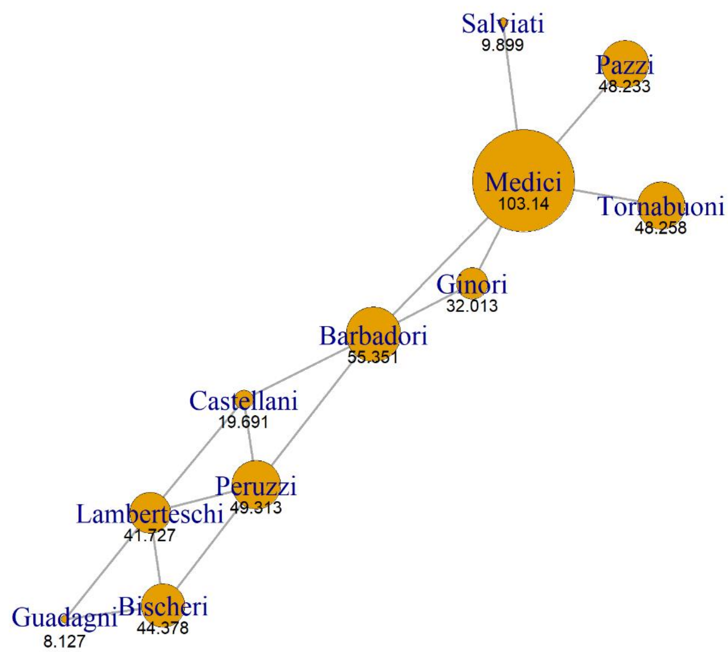


Figure 4.4 Florentine Business Network and their Wealth, 1394-1434

As the first step, the reference actor-based centrality (= C_i^{AB}) is measured. With the same way of constructing C_i^{AB} in the Florentine marriage network, this is estimated under all assumptions about referral chains for unbiased RDS with enough seeds (= 40) and iterations (= 100). Note again that those assumptions make the referral chains close to random-walks.

Based on the simulation conditions of C_i^{AB}, I suggest two customized actor-based centrality measures (= $C_i^{AB\_Bias}$) for the business network. (1) *Unequal Seeds by Wealth*: when one's first referral is considered as a way of helping other families with their own resources, the chances could be differentiated by their wealth. Families with more wealth will help other families more with enough resources, and vice versa. This assumption is reflected by unequally distributing the number of seeds for each node based on their wealth (= $C_i^{AB\_S}$). For example, in an RDS simulation, while 103 seeds are assigned for the Medici, the Guadagni has only 8 seeds. Note that the average number of seeds under this assumption is around 42, similar to the number of seeds (= 40) for C_i^{AB}. (2) *Non-Random Referral by Wealth*: similarly—but also dissimilarly—when one's referral is considered as a way of gifting for a future business relationship, the selection could be differentiated by the wealth of neighboring families. For example, suppose the Ginori has a piece of information for trading, which is beneficial for both the Medici and Barbadori. If this information must be given to one of them exclusively, the Ginori will not choose the partner randomly: they are more likely to choose the richer Medici than the Barbadori for a better future business relationship. Considering this point, I assume that ego is more likely to refer an alter who has more wealth[11].

Based on the assumptions, three different measures of total power and relative power are constructed as well, respectively. The measures of ego i's total/relative power under random-walks, unequal seeds (i.e., unequal distribution of wealth), and non-random referral (i.e., wealth-phily flow) are formally expressed as $P_{e_i}(AB, T)$, $P_{e_i}(AB\_NR, T)$, $P_{e_i}(AB\_S, T)$, $P_{e_i}(AB, R)$, $P_{e_i}(AB\_NR, R)$, and $P_{e_i}(AB\_S, R)$, respectively

[11] This is assumed with the simulation condition that alters are initially excluded in ego's referral with the prob = (1 - own wealth of alter j / max wealth of alters). For example, when the Ginori refers one of alters—Medici and Barbadori—they are initially excluded with probabilities 0 = (1 – 103.14/103.14) and 0.463 = (1 – 55.351/103.14) and after that randomly referred. Under this condition, the Medici is more likely to be refereed than the Babadori.

Families & Ranks of Wealth	Betweenness Centrality		Closeness Centrality		Degree Centrality		Actor-based Centrality (Reference)		Actor-based Centrality with Unequal Seeds		Actor-based Centrality with non-random Referral	
Barbadori (2)	**.556**	**(1)**	**.588**	**(1)**	**.4**	**(2)**	**1.466**	**(2)**	**1.512**	**(2)**	**1.752**	**(2)**
Bischeri (6)	.056	(6)	.4	(7)	.3	(5)	.972	(5)	.800	(7)	.889	(5)
Castellani (9)	.111	(5)	.5	(4)	.3	(5)	.959	(6)	.924	(5)	.418	(9)
Ginori (8)	.	(7)	.455	(5)	.2	(7)	.777	(7)	.878	(6)	.647	(8)
Guadagni (11)	.	(7)	.312	(11)	.2	(7)	.636	(8)	.540	(8)	.120	(11)
Lamberteschi (7)	.133	(4)	.417	(6)	.4	(2)	1.298	(4)	1.086	(4)	1.025	(4)
Medici (1)	**.533**	**(2)**	**.526**	**(2)**	**.5**	**(1)**	**2.272**	**(1)**	**2.525**	**(1)**	**3.130**	**(1)**
Pazzi (5)	.	(7)	.357	(8)	.1	(9)	.441	(9)	.521	(9)	.731	(6)
Peruzzi (3)	**.3**	**(3)**	**.526**	**(2)**	**.4**	**(2)**	**1.306**	**(3)**	**1.182**	**(3)**	**1.431**	**(3)**
Salviati (10)	.	(7)	.357	(8)	.1	(9)	.435	(11)	.520	(10)	.136	(10)
Tornabuoni (4)	.	(7)	.357	(8)	.1	(9)	.438	(10)	.514	(11)	.719	(7)

Table 4.9 Centrality scores and ranks of Florentine families in the business network (normalized).

Families	Relative Power (Reference)		Relative Power with Unequal Seeds		Relative Power with Non-Random Referral		Total Power (Reference)		Total Power with Unequal Seeds		Total Power with Non-Random Referral	
Barbadori (2)	**.053**	**(3)**	**.067**	**(3)**	**.027**	**(5)**	**.553**	**(10)**	**.567**	**(9)**	**.527**	**(10)**
Bischeri (6)	.003	(5)	-.001	(5)	.071	(4)	.670	(7)	.666	(7)	.737	(5)
Castellani (9)	-.097	(6)	-.107	(6)	-.208	(6)	.569	(9)	.560	(10)	.459	(11)
Ginori (8)	-.277	(8)	-.273	(8)	-.369	(8)	.723	(6)	.727	(6)	.631	(8)
Guadagni (11)	-.188	(7)	-.241	(7)	-.358	(7)	.812	(5)	.759	(5)	.642	(7)
Lamberteschi (7)	.092	(2)	.082	(2)	.153	(2)	.592	(8)	.582	(8)	.653	(6)
Medici (1)	**.573**	**(1)**	**.586**	**(1)**	**.636**	**(1)**	**.973**	**(4)**	**.986**	**(4)**	**1.036**	**(4)**
Pazzi (5)	-.773	(9)	-.752	(9)	-.771	(9)	1.227	(1)	1.248	(1)	1.229	(1)
Peruzzi (3)	**.024**	**(4)**	**.036**	**(4)**	**.105**	**(3)**	**.524**	**(11)**	**.536**	**(11)**	**.605**	**(9)**
Salviati (10)	-.774	(10)	-.814	(11)	-.914	(11)	1.226	(2)	1.186	(3)	1.086	(3)
Tornabuoni (4)	-.776	(11)	-.752	(10)	-.771	(10)	1.224	(3)	1.248	(2)	1.229	(2)

Table 4.10 Power-Dependence scores and ranks of Florentine families in the business network

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Betweenness											
(2) Closeness	.852										
(3) Degree	.829	.775									
(4) ABC (Ref)	.886	.759	.95								
(5) ABC (Seed)	.892	.75	.857	.973							
(6) ABC (Non-Random)	.877	.684	.778	.914	.949						
(7) R Pow (Ref)	.733	.666	.958	.924	.839	.725					
(8) R Pow (Seed)	.75	.689	.964	.936	.853	.753	.998				
(9) R Pow (Non-Random)	.744	.669	.97	.938	.847	.781	.985	.99			
(10) T Pow (Ref)	-.381	-.612	-.686	-.456	-.29	-.153	-.674	-.668	-.644		
(11) T Pow (Seed)	-.346	-.568	-.664	-.428	-.258	-.105	-.664	-.653	-.623	.996	
(12) T Pow (Non-Random)	-.247	-.505	-.517	-.289	-.145	.053	-.545	-.527	-.466	.95	.965

Table 4.11 Correlation matrix of centrality and power-dependence measures in the business network

Tables 4.9 and 4.10 summarize the scores and ranks of all actor-based centrality and power-dependence measures in the Florentine business network—as well as degree, closeness, and betweenness centrality. Table 4.11 shows the correlation matrix of all network measures. The standard error of each actor-based centrality score is summarized in Appendix D. Every score has a lower standard error (< .01). Note that the running time of each actor-based centrality measure was less than 30 seconds.

The results of actor-based centrality measures basically support the previous analysis of Padgett and Ansell; the Medici is more central—and thereby will be more influential—than the Peruzzi under any customized network flow (e.g., random-walks; unequal seeds; non-random referral). However, the measures also show that the Medici's influence in the business network could not have been simply because of their position. Compared to C_i^{AB} (= 2.272), both Medici's $C_i^{AB\_S}$ (= 2.525) and $C_i^{AB\_NR}$ (= 3.130) increase. Those results are expectable because Medici's wealth is ranked 1st.

In Medici's $C_i^{AB\_S}$, when more referrals happen from the Medici due to more seeds (or wealth), more returns happen as well, and thereby the family could eventually be more sampled than others. Similarly, in Medici's $C_i^{AB\_NR}$, the family will be more likely to be referred by neighboring families (e.g., neighboring families will provide important resources to the Medici for the future business relationship). On the contrary, although Peruzzi's wealth is ranked 3rd, their $C_i^{AB\_S}$ (= 1.182) even decreases compared to C_i^{AB} (= 1.306), and $C_i^{AB\_NR}$ also does not show a dramatic increase (1.306 $\rightarrow$ 1.431), unlike Medici's scores (2.272 $\rightarrow$ 3.130).

This is mainly because of the position and actions of the Barbadori. In $C_i^{AB\_S}$, when a referral is assumed as a way of helping, the Peruzzi could help their neighboring families with more wealth (or seeds). The expectation of reciprocal returning (i.e., referring the Peruzzi) is, however, may be lower. When the help from the Peruzzi is given to neighboring families and chained, the flows may head to the Barbadori due to the existence of multiple paths between the two families within the dense connections (e.g., Peruzzi $\rightarrow$ Castellani $\rightarrow$ Barbadori). The problem is that if the Barbadori uses the resources for helping the other side of the families—Medici and Ginori—it could be very hard to flow back to the Peruzzi's side. This means that without a strong norm of reciprocity, the Peruzzi cannot be influential with their wealth. On the contrary, the Medici's neighboring families tend to have exclusive connections with the Medici. Thus, when the Medici help those families (e.g., Pazzi, Salviati, and Tornabuoni), the returns are structurally enforced on them. Similarly, in $C_i^{AB\_NR}$, the Barbadori could easily access valuable resources from their neighboring families because of their wealth, which is similar with the Peruzzi's. However, when the Barbadori uses the resources, it could go to the Medici than the Peruzzi because of their wealth difference (103.14 vs. 49.313). In turn, although the Peruzzi and Barbadori could have had a good partnership, since the Medici is also so close to the Barbadori, their resources are more likely to flow to the Medici, instead of the Peruzzi—under the contextual assumption of non-random exchanges by wealth—and thereby it lowers the Peruzzi's influence.

The Barbadori's contribution for the Medici is not limited to lowering the Peruzzi's influence—they also weaken their bargaining powers. Peruzzi's relative powers (.24 ∼ .104) are much weaker than Medici's (.573 ∼ .636), and their total powers are ranked the lowest in the network. This is because the Barbadori's dependence on the Peruzzi—which is equal to the Peruzzi's power over the Barbarodi—becomes lower under the assumed network flows. Within the assumption of unequal seeds by wealth (AB_S), the Barbadosi will mainly earn resources from the Medici, which increases their dependence. Thus, their dependence on the Peruzzi (i.e., Peruzzi's power over the Barbadosi) will decrease, and thereby it weakens both $P_{e_i}(AB\_S, T)$ and $P_{e_i}(AB\_S, R)$ of the Peruzzi. Similarly, within the assumption of non-random referral by wealth (AB_NR), the Barbadosi will be more likely to provide valuable resources to the Medici than the Peruzzi. The point is that since the Barbadosi is the most wealthy family among the neighboring families of the Medici, the returns could easily come. Thus, the Barbadosi's dependence on the Medici will increase, and thereby their dependence on the Peruzzi will be relatively weaker. Therefore, both $P_{e_i}(AB\_NR, T)$ and $P_{e_i}(AB\_NR, R)$ of the Peruzzi cannot strong enough due to their weak powers over the Barbadosi.

Discussion

With the flexibility of network flows, actor-based centrality helps researchers to construct multiple centrality measures that identify influential nodes within multiple relational contexts. Moreover, this approach helps to identify power-dependence relations within context-specfic network flows, which are not available by existing power measures. But at the same time, in any network, those customized network measures share the same MCMC estimation approach (i.e., selecting a set of given assumptions about referral chains in an RDS simulation), score format, and theoretical explanation of influential or powerful nodes (i.e., nodes more sampled by certain referral chains can be more influential over other nodes or more dependent on particular alters).

Because of its MCMC estimation approach, actor-based centrality can consider complex and diverse network flows in a flexible manner, which cannot be easily expressed as a transition matrix. Then, why is RDS a useful frame to construct those Monte Carlo-based measures of centrality and power? I argue that because researchers do not need to create their own flow algorithms.

There are a few previous empirical studies that use a Monte Carlo approach to measuring centrality. For instance, Gao et al. (2013) apply several empirically encountered network flows into their own simulation model of betweenness centrality to explore the relationship between street network positions and traffic flow. They find that compared to Freeman's original measure, their revised betweenness centrality measures provide better explanations for their empirical case. The previous study implies that when empirical researchers successfully build their own flow algorithms and simulation models customized for their network data, some complex network flows within particular contexts can be reflected in existing centrality measures. With this approach, a comparison between the scores of original and revised centrality measures can provide meaningful explanations for a substantial research question.

This previous study implies that when empirical researchers successfully build their own flow algorithms and simulation models customized for their network data, some complex network flows within a particular context can be reflected in existing centrality measures. However, this Monte Carlo approach has limitations to deal with diverse network flows within multiple relational contexts. As noted earlier, due to the heterogeneity of nodes and ties, multiple relational contexts are diversely embedded in social networks, and there is no uniform complex pattern of actions (or flow) that can be applied to any network. In this sense, when there are *n*-networks, for the best analysis, *n*-flow algorithms and simulations are required. But it is not easy for researchers to create their own flow algorithms entirely based on heuristics without any clue. Moreover, creating own simulation models always has a risk of errors. It is noteworthy that many agent-based models, which are usually based on researchers' own programming, often yield some validation problems by programming errors (Rijt, Siegel, and Macy 2009; Will 2009; Macy and Sato 2010). In other words, with this empirically driven Monte Carlo approach, researchers may have difficulty creating their own flow algorithms as well as checking the validity of their own simulation models.

Applying RDS into the construction of Monte Carlo-based centrality measures helps to reduce those potential concerns. As noted, flow algorithms can be easily constructed by selecting a set of given assumptions about referral chains, which are demonstrated by previous RDS studies to reduce sampling bias (i.e., unequal centrality scores). Thus, researchers can efficiently create complex and diverse network flows. Moreover, when a single valid model of actor-based centrality is widely shared, the constructed measures under the model can have a lower risk of validation problems. This implies that the cost of checking validity in actor-based centrality is expected to be significantly lower than that of general Monte Carlo-based centrality measures.

It is also noteworthy that from a broad perspective, actor-based centrality can be in line with stochastic actor-based models, which focus on the dynamic of social networks (Snijders 1996; Snijders, Van de Bunt, and Steglich 2010; Snijders and Steglich 2015), and combining the two approaches could provide another theoretical or methodological contribution. In actor-based centrality, researchers can flexibly customize the assumptions about network flow to take a "snapshot" of positional influence. However, the network graph itself is fixed. Unlike actor-based centrality, stochastic actor-based models help researchers to assume certain dynamics of a network graph to take a "snapshot" of network structure. This means that when the two approaches are simultaneously applied in the same network, very different meanings of positional influence can be found under the dynamics of both network flow and structure. For instance, in a network, some nodes may be influential under certain context-specific network flows. But their influence may be very unstable when the network dynamic is assumed under a particular stochastic actor-based model. In other words, empirical studies based on the two approaches could reveal more "relational" aspects of social networks (e.g., the meaning of positions or structure), which are driven by agentic actors—not nodes.

REFERENCES

Alderson, Arthur S and Jason Beckfield. 2004. "Power and Position in the World City System." *American journal of sociology* 109(4):811-51.

Aral, Sinan, Lev Muchnik and Arun Sundararajan. 2009. "Distinguishing Influence-Based Contagion from Homophily-Driven Diffusion in Dynamic Networks." *Proceedings of the National Academy of Sciences* 106(51):21544-49.

Barash, Vladimir D, Christopher J Cameron, Michael W Spiller and Douglas D Heckathorn. 2016. "Respondent-Driven Sampling–Testing Assumptions: Sampling with Replacement." De Gruyter Open.

Bonacich, Phillip. 1972. "Factoring and Weighting Approaches to Status Scores and Clique Identification." *Journal of mathematical sociology* 2(1):113-20.

Bonacich, Phillip. 1987. "Power and Centrality: A Family of Measures." *American journal of sociology* 92(5):1170-82.

Bonacich, Phillip and Paulette Lloyd. 2001. "Eigenvector-Like Measures of Centrality for Asymmetric Relations." *Social networks* 23(3):191-201.

Bonacich, Phillip. 2007. "Some Unique Properties of Eigenvector Centrality." *Social networks* 29(4):555-64.

Borgatti, Stephen P and Martin G Everett. 1992. "Notions of Position in Social Network Analysis." *Sociological methodology*:1-35.

Borgatti, Stephen P, Candace Jones and Martin G Everett. 1998. "Network Measures of Social Capital." *Connections* 21(2):27-36.

Borgatti, Stephen P. 2005. "Centrality and Network Flow." *Social networks* 27(1):55-71.

Borgatti, Stephen P and Martin G Everett. 2006. "A Graph-Theoretic Perspective on Centrality." *Social networks* 28(4):466-84.

Borgatti, Stephen P and Daniel S Halgin. 2011. "On Network Theory." *Organization science* 22(5):1168-81.

Borgatti, Stephen P, Martin G Everett and Linton C Freeman. 2014. "Ucinet." *Encyclopedia of social network analysis and mining*:2261-67.

Breiger, Ronald L and Philippa E Pattison. 1986. "Cumulated Social Roles: The Duality of Persons and Their Algebras." *Social networks* 8(3):215-56.

Casciaro, Tiziana and Mikolaj Jan Piskorski. 2005. "Power Imbalance, Mutual Dependence, and Constraint Absorption: A Closer Look at Resource Dependence Theory." *Administrative Science Quarterly* 50(2):167-99.

Chai, Sun-Ki and Mooweon Rhee. 2010. "Confucian Capitalism and the Paradox of Closure and Structural Holes in East Asian Firms." *Management and Organization Review* 6(1):5-29.

Cook, Karen S and Richard M Emerson. 1978. "Power, Equity and Commitment in Exchange Networks." *American Sociological Review*:721-39.

Cook, Karen S and Toshio Yamagishi. 1992. "Power in Exchange Networks: A Power-Dependence Formulation." *Social networks* 14(3-4):245-65.

Everett, Martin G and Stephen P Borgatti. 2014. "Networks Containing Negative Ties." *Social networks* 38:111-20.

Freeman, Linton C. 1978. "Centrality in Social Networks Conceptual Clarification." *Social networks* 1(3):215-39.

Freeman, Linton C, Stephen P Borgatti and Douglas R White. 1991. "Centrality in Valued Graphs: A Measure of Betweenness Based on Network Flow." *Social networks* 13(2):141-54.

Friedkin, Noah E. 1991. "Theoretical Foundations for Centrality Measures." *American journal of sociology* 96(6):1478-504.

Friedkin, Noah E. 2006. *A Structural Theory of Social Influence*, Vol. 13: Cambridge University Press.

Gao, Song, Yaoli Wang, Yong Gao and Yu Liu. 2013. "Understanding Urban Traffic-Flow Characteristics: A Rethinking of Betweenness Centrality." *Environment and Planning B: Planning and Design* 40(1):135-53.

Gile, Krista J and Mark S Handcock. 2010. "7. Respondent-Driven Sampling: An Assessment of Current Methodology." *Sociological methodology* 40(1):285-327.

Goel, Sharad and Matthew J Salganik. 2009. "Respondent-Driven Sampling as Markov Chain Monte Carlo." *Statistics in medicine* 28(17):2202-29.

Gulati, Ranjay. 1999. "Network Location and Learning: The Influence of Network Resources and Firm Capabilities on Alliance Formation." *Strategic management journal* 20(5):397-420.

Heckathorn, Douglas D. 1997. "Respondent-Driven Sampling: A New Approach to the Study of Hidden Populations." *Social problems* 44(2):174-99.

Heckathorn, Douglas D. 2002. "Respondent-Driven Sampling Ii: Deriving Valid Population Estimates from Chain-Referral Samples of Hidden Populations." *Social problems* 49(1):11-34.

Heckathorn, Douglas D. 2007. "6. Extensions of Respondent-Driven Sampling: Analyzing Continuous Variables and Controlling for Differential Recruitment." *Sociological methodology* 37(1):151-208.

Heckathorn, Douglas D. 2011. "Comment: Snowball Versus Respondent-Driven Sampling." *Sociological methodology* 41(1):355-66.

Heckathorn, Douglas D and Christopher J Cameron. 2017. "Network Sampling: From Snowball and Multiplicity to Respondent-Driven Sampling." *Annual review of sociology* 43:101-19.

Hubbell, Charles H. 1965. "An Input-Output Approach to Clique dentification." *Sociometry*:377-99.

Ibarra, Herminia. 1993. "Network Centrality, Power, and Innovation Involvement: Determinants of Technical and Administrative Roles." *Academy of Management journal* 36(3):471-501.

Katz, Leo. 1953. "A New Status Index Derived from Sociometric Analysis." *Psychometrika* 18(1):39-43.

Krackhardt, David. 1990. "Assessing the Political Landscape: Structure, Cognition, and Power in Organizations." *Administrative Science Quarterly*:342-69.

Lawler, Edward J and Samuel B Bacharach. 1986. "Power Dependence in Collective Bargaining."

Lu, Xin, Linus Bengtsson, Tom Britton, Martin Camitz, Beom Jun Kim, Anna Thorson and Fredrik Liljeros. 2012. "The Sensitivity of Respondent-Driven Sampling." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 175(1):191-216.

Macy, Michael and Yoshimichi Sato. 2010. "The Surprising Success of a Replication That Failed." *Journal of Artificial Societies and Social Simulation* 13(2):9.

Markovsky, Barry, David Willer and Travis Patton. 1988. "Power Relations in Exchange Networks." *American Sociological Review*:220-36.

Molm, Linda D. 1990. "Structure, Action, and Outcomes: The Dynamics of Power in Social Exchange." *American Sociological Review*:427-47.

Neal, Zachary. 2011. "Differentiating Centrality and Power in the World City Network." *Urban Studies* 48(13):2733-48.

Newman, Mark EJ. 2005. "A Measure of Betweenness Centrality Based on Random Walks." *Social networks* 27(1):39-54.

Opsahl, Tore, Filip Agneessens and John Skvoretz. 2010. "Node Centrality in Weighted Networks: Generalizing Degree and Shortest Paths." *Social networks* 32(3):245-51.

Padgett, John F and Christopher K Ansell. 1993. "Robust Action and the Rise of the Medici, 1400-1434." *American journal of sociology* 98(6):1259-319.

Page, Lawrence, Sergey Brin, Rajeev Motwani and Terry Winograd. 1999. "The Pagerank Citation Ranking: Bringing Order to the Web." Vol.: Stanford InfoLab.

Sade, Donald Stone. 1989. "Sociometrics of Macaca Mulatta Iii: N-Path Centrality in Grooming Networks." *Social networks* 11(3):273-92.

Salganik, Matthew J and Douglas D Heckathorn. 2004. "Sampling and Estimation in Hidden Populations Using Respondent-Driven Sampling." *Sociological methodology* 34(1):193-240.

Shi, Yongren, Christopher J Cameron and Douglas D Heckathorn. 2019. "Model-Based and Design-Based Inference: Reducing Bias Due to Differential Recruitment in Respondent-Driven Sampling." *Sociological Methods & Research* 48(1):3-33.

Snijders, Tom AB. 1996. "Stochastic Actor-Oriented Models for Network Change." *Journal of mathematical sociology* 21(1-2):149-72.

Snijders, Tom AB, Gerhard G Van de Bunt and Christian EG Steglich. 2010. "Introduction to Stochastic Actor-Based Models for Network Dynamics." *Social networks* 32(1):44-60.

Snijders, Tom AB and Christian EG Steglich. 2015. "Representing Micro–Macro Linkages by Actor-Based Dynamic Network Models." *Sociological Methods & Research* 44(2):222-71.

Stephenson, Karen and Marvin Zelen. 1989. "Rethinking Centrality: Methods and Examples." *Social networks* 11(1):1-37.

Van de Rijt, Arnout, David Siegel and Michael Macy. 2009. "Neighborhood Chance and Neighborhood Change: A Comment on Bruch and Mare." *American journal of sociology* 114(4):1166-80.

Volz, Erik and Douglas D Heckathorn. 2008. "Probability Based Estimation Theory for Respondent Driven Sampling." *Journal of official statistics* 24(1):79.

Wasserman, Stanley and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications*, Vol. 8: Cambridge university press.

Wejnert, Cyprian and Douglas D Heckathorn. 2008. "Web-Based Network Sampling: Efficiency and Efficacy of Respondent-Driven Sampling for Online Research." *Sociological Methods & Research* 37(1):105-34.

Wejnert, Cyprian. 2010. "Social Network Analysis with Respondent-Driven Sampling Data: A Study of Racial Integration on Campus." *Social networks* 32(2):112-24.

Will, Oliver. 2009. "Resolving a Replication That Failed: News on the Macy & Sato Model." *Journal of Artificial Societies and Social Simulation* 12(4):11.

Willer, David. 1992. "Predicting Power in Exchange Networks: A Brief History and Introduction to the Issues." *Social networks* 14(3-4):187-211.

Xiao, Zhixing and Anne S Tsui. 2007. "When Brokers May Not Work: The Cultural Contingency of Social Capital in Chinese High-Tech Firms." *Administrative Science Quarterly* 52(1):1-31.

Yamanis, Thespina J, M Giovanna Merli, William Whipple Neely, Felicia Feng Tian, James Moody, Xiaowen Tu and Ersheng Gao. 2013. "An Empirical Analysis of the Impact of Recruitment Patterns on Rds Estimates among a Socially Ordered Population of Female Sex Workers in China." *Sociological Methods & Research* 42(3):392-425.

Yan, Erjia and Ying Ding. 2009. "Applying Centrality Measures to Impact Analysis: A Coauthorship Network Analysis." *Journal of the American Society for Information Science and Technology* 60(10):2107-18.

CHAPTER 5

POWER-DEPENDENCE RELATIONS IN CHAIN OF REMITTANCE FLOWS: HOW CAN MEXICAN LOCAL COMMUNITIES CONTRIBUTE TO THE SOCIAL CAPITAL OF THE U.S. FIRMS?

Introduction

The flow of remittances is widely accepted as a uni-directional flow of capital (or money) from more developed to less developed countries (Chami, Fullenkamp, and Jahajh 2005; Giuliano and Ruiz-Arranz 2009; Buch and Kuckulenz 2010; Garip 2014). Based on the theoretical frameworks of social exchange (Homans 1958; Blau 1964; Emerson 1976) and social meaning of money (Zelizer 1989; 1997), this chapter suggests an alternative explanation that the flow of capital in a remittance network can be bi-directional and a formal model of how the mechanism can produce power-dependence relations in social networks.

This chapter mainly consists of two parts. First, I propose a theoretical mechanism of how the currency of remittance money can be dynamic by its rewarding process from the recipient family to the donor migrant workers and how the changed currency could affect the workers' commitment to their jobs (e.g., more likely to stay in current jobs; willingness to take (or not change) lower-wage jobs). The suggested mechanism clarifies that the chain of remittances could yield not only the flow of money (from the host country to the home country) but also the flow of social rewards enhancing migrant workers' job commitments with no cost, which can be considered as the social capital of the firms in the host country. Based on this theoretical idea, I generate and test certain hypotheses with the Mexican Migration Project data set (MMP170) that contains 4154 cases of Mexican migrant workers in the U.S. whose detailed information about remittance behaviors is included. The results of multiple regression analysis support those hypotheses.

In the second part, I suggest a new theoretical model of power-dependence relations in social networks based on the proposed mechanism. I argue that the bi-directional flow of capital is not a unique phenomenon from remittances—it could also result from the interdependence structure of ordered exchanges in social networks (i.e., ego i's successful exchange with alter j is dependent on ego i's successful exchange with alter k). In turn, the chain of remittance flows can be expressed as a particular ordered exchange situation where a migrant worker i's successful remittance to the home country family j is dependent on the worker i's successful job-related tasks for his/her firm k. Within this assumption, the emergence of social rewards from j that leads to i's commitment to k (i.e., $j \rightarrow i \rightarrow k$) could be the consequence of the dependence structure (i.e., $k \rightarrow i \rightarrow j$), the direction of which is the reversal of the resource flow. Formalizing those mechanisms, I create several propositions of power and affective commitments testable in future studies

Remittance as Social Exchange of Meaningful Money

Pioneer exchange theorists (Homans 1958; Blau 1964; Emerson 1976) assume that any exchanges in social relations have the issues of reward and cost, similar to the economic transactions between buyer and seller. The main concepts they suggested can be summarized as the three features.

(1) Rewards and Costs: any exchangeable resources transferable for positive or negative values (e.g., the time for helping a friend; valuable information) can become rewards or costs to exchange actors. **(2) Commitment**: positive outcomes for an actor from an exchange relation (i.e., rewards – costs > 0) lead to the actor's commitment toward the exchange relation (i.e., repeated exchanges). The motivation of the commitment could be psychological (i.e., emotional attachment; satisfaction), and it prevents the actor from moving to another exchange relation, even if the alternative provides better rewards. **(3) Power-Dependence:** when ego's rewards from an exchange relation with an alter cannot be provided by other exchange relations (i.e., monopoly), ego becomes more dependent on the relation, and the alter becomes more powerful over ego in the relation, and vice versa.

Zelizer (1989; 1997) argues that the meaning of money is not a single dimension. Money has various meanings when used for certain types of social interactions, and thus its currency can be differentiated under certain relational circumstances. For example, the meaning of $10 for tipping a waiter (i.e., gratitude with social distinction) is not the same as $10 tipping a lawyer (i.e., disrespecting one's profession). Two major concepts are suggested by Zelizer.

(1) Earmarking: money can have different social meanings when it is earmarked for various social interactions. The money earmarked for a funeral is distinct from the money earmarked for rent. The different meaning of each earmarked money makes social actors have different attitudes toward the origin and purpose of money. The money from illegal jobs may be considered "dirty money," which cannot be earmarked for certain types of social interactions (e.g., gifts; donations). Parents may hesitate to use the money earmarked for their children to pay the fine for their fault. In other words, social actors may face very different meanings of money, which are not correlated with its amount. Zelizer also points out that the difference in meanings is affected by social structures (e.g., class/race/gender) and culture. **(2) Currencies:** the amount of money earmarked for a certain social interaction is not always correlated with the success of the social interaction. An expensive gift to a co-worker who is not a close friend may be inappropriate. The life insurance money from one's death used to be considered unacceptable by their family, especially when the amount was large (Zelizer 1994). This means that each money has a different currency for the success of a targeted social interaction. Even with the same amount of money, social actors may experience very different outcomes of social interactions.

The frameworks of social exchange theory and the social meaning of money are useful for characterizing remittances and their social consequences. Figure 5.1 shows the potential bidirectional flow of capital within the chain of remittances. The blue arrows reflect the previous idea that the flow of capital is uni-directional. When migrants work for firms in the host country, they earn some money and send it to their home country families. If money has only a singular meaning and function, the flow of capital within remittances is simply from the host county to the home country of migrant workers.

Yet, when money is assumed to have multiple meanings and is considered an exchangeable resource in social relations, the flow of red arrows—which is the reverse flow of blue arrows (or money)—could emerge in remittances.

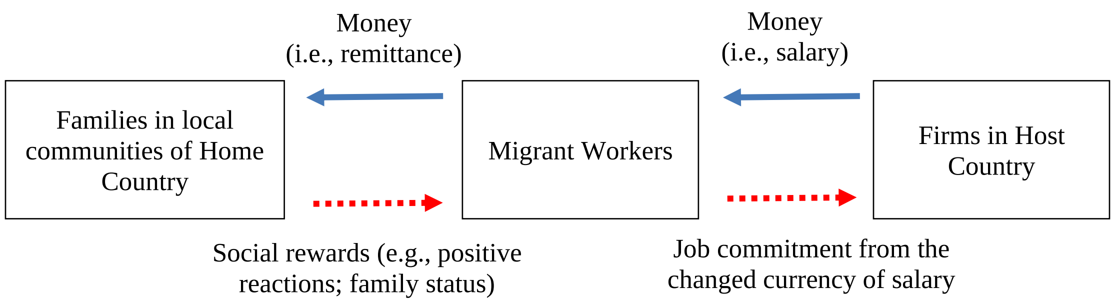


Figure 5.1 The bidirectional flow of capital between the home and host countries of migrant workers

Suppose a migrant worker **earmarks** some money for remittance. From Zelizer's point of view, this money will have a unique social meaning to the worker, which is different from any other earmarked money (e.g., money for rent; grocery shopping). When the migrant worker sends the money to their family in the home country, the family will **earmark** it for certain purposes, assigning various social meanings to the money. It could be a life saver when used for a family member's very important surgery. It could be a way of status gaining when the family spends it for ritual interactions with others in their community, pointing out the origin of the money. At the same time, it could be less meaningful when the remittance is considered a duty enforced by the norms of reciprocity between parents and children (Gouldner 1960).

Here, the key point is that, from a social exchange perspective, the different social meanings of remittances for the recipients (i.e., family in the home country) may lead them to provide different social **rewards** to the donors (i.e., migrant workers in the host country)—even if the amounts of the remittances are the same, which are **costs**. For example, suppose Jason sent $1000 as a remittance for his mother's urgent surgery. Then, his family will show their gratitude to Jason, sending all the words of how much they appreciate him for sending the meaningful money. On the contrary, suppose Kate sends $1000 to his parents, which is enforced by the norms of reciprocity between parents and grown-up children. Then, her parents will consider this money as her "repaying" for their investment in her, which does not produce very meaningful social interactions. In this case, the social rewards from them to Kate would not be as significant as the rewards Jason can receive from his family.

When a remittance guarantees certain social rewards, which are profitable compared to its cost (i.e., the amount of money), the exchange process changes the currency of the original money, which was earmarked for the remittance. From Zelizer's point of view, the right currency of some earmarked money depends on whether or not the money leads to successful social interactions. If $1000 of remittance is enough for the success of a particular social interaction, it could be the right currency and vice versa. This implies that even with the same amount of money, remittances could have very different currencies, which yield a good or bad exchange ratio for rewards. For example, $1000 of remittance for the successful reciprocity enforced by social norms could have a worse exchange ratio than $1000 of remittance for the successful gifting that guarantees the sender's higher status and influence in their home family. Thus, the currencies of remittances could be diverse based on their purposes and usefulness in certain social interactions.

The dynamic currency of remittance is important because it determines the worth (or satisfaction; fairness; value) of migrant workers' exchanges with their employers (or firms). This is because even if the same salary is given to them, the social rewards they can access through remittances could be differentiated largely by the rewards. For example, with a $5000 monthly salary and $1000 remittance per month, some migrant workers may earn enough social rewards from their home country families—but others may not. For the first group, the exchanges with their employers are worth it because of the utility of the salary that guarantees enough social rewards. Thus, they are likely to maintain and be committed to their exchanges (or jobs). On the contrary, for the second group, since the exchanges do not provide enough social rewards, they are less likely to be satisfied with their jobs. Thus, the different levels of commitment may emerge from the different rewards of remittance.

In sum, the chained process explains that the flow of capital by remittances could be bidirectional. The meaning of remittance is shaped by the process of earmarking the money in the home family, and it could lead to the emergence of job commitments of migrant workers (i.e., they may move to an alternative job place or be willing to take a lower rewarding job). This can be considered the social capital of the firms that employ the workers—the firms can possess those commitments with no cost of investment in it.

Hypotheses for Empirical Test

The theoretical prediction is testable by certain hypotheses about the relationship between migrant workers' remittance-related behaviors and their job-related choices. The first hypothesis is

Hypothesis 1: Migrant workers who send remittances are more likely to be committed to their jobs.

Compared to migrant workers who do not send remittances, those who send them will have more opportunities to earn social rewards from their home country family. Thus, they are more likely to be satisfied with their current job wages and thereby less likely to look for better rewarding jobs. In this sense, those migrant workers may stay longer in their current jobs even if the wages are lower than other alternative jobs they could find.

However, the meaning of remittance money could be differentiated by how the recipient uses (or earmarks) the money. This implies that the senders could earn very different social rewards from their remittances based on the remittances' meanings (or purposes) for the recipients. Thus, the second hypothesis is

Hypothesis 2: Only migrant workers who send remittances for certain socially meaningful purposes (e.g., health expenses) are more likely to be committed to their jobs.

The two hypotheses are in contrast to the individual perspective, on which many existing studies of remittances are based. When migrant workers send remittances, their amount of resources (or money) for their own utility is reduced. In this sense, it is expected that those are eager to find better jobs in terms of wages. Unlike this individual perspective idea, the hypotheses expect those workers to stay in their current jobs with the satisfaction or emotional attachment that comes from the social rewards of remittances. These hypotheses align with a structural perspective that considers migrant workers as social actors embedded in the networks of two different societies (i.e., relations with the family in the home country and the firms they work for).

Empirical Test

Data, Analysis, and Variables

Note that the empirical test part is based on the co-work of myself and Filiz Garip—the dissertation committee chair.

The data we use come from the MIG and MIGOTHER files of the Mexican Migration Project datasets (MMP170), collected from 170 local communities in Mexico. MIG contains information on migrants who were household heads (recorded in all communities 1-170). MIGOTHER contains information on migrants other than the household head if the household head was not a US migrant (recorded in communities 120-170). We combine the two data sets, which gives us information on 8,823 household heads and 938 other household members. We exclude 1,095 individuals whose last migration trip happened prior to 1965 (that is, too far in the past) and 25 individuals whose year of last migration is missing. This gives us a sample of 8,641 individuals. Among the sample, 4154 cases are finally selected for the empirical test of the two hypotheses after all missing cases for the test are excluded.

The empirical test is based on ordinary least squares (OLS) regression models with fixed effects for year and community. Table 5.1 summarizes the variables considered in the models, and Figures 5.2 and 5.3 show the histograms of one's trip year and community number.

N = 4184	Mean	SD	Min	Max
Relative-Z-Score of wage	-.021	.965	-2.564	9.319
Age	32.031	10.845	15	76
Gender (1 = male)	.95	.218	0	1
Education (years)	6.126	3.921	0	22
N of Children	2.93	3.159	0	17
Undocumented Migrants	.702	.457	0	1
Duration of the last U.S trip (months)	46.036	74.372	0	17
Owning Land	.125	.331	0	1
Owning House	.273	.446	0	1
Owning Business	.063	.243	0	1
Bringing Saving	.623	.485	0	1
Sending Remittance	.75	.433	0	1
----- for Food/Maintenance	.345	.475	0	1
----- for Health Expenses	.212	.409	0	1
----- for Building House	.058	.234	0	1
----- for Debt Payments	.026	.159	0	1
----- for Other Reasons	.065	.247	0	1
----- for Unknown Reasons	.044	.205	0	1

Table 5.1 Descriptive statistics of dependent and independent variables.

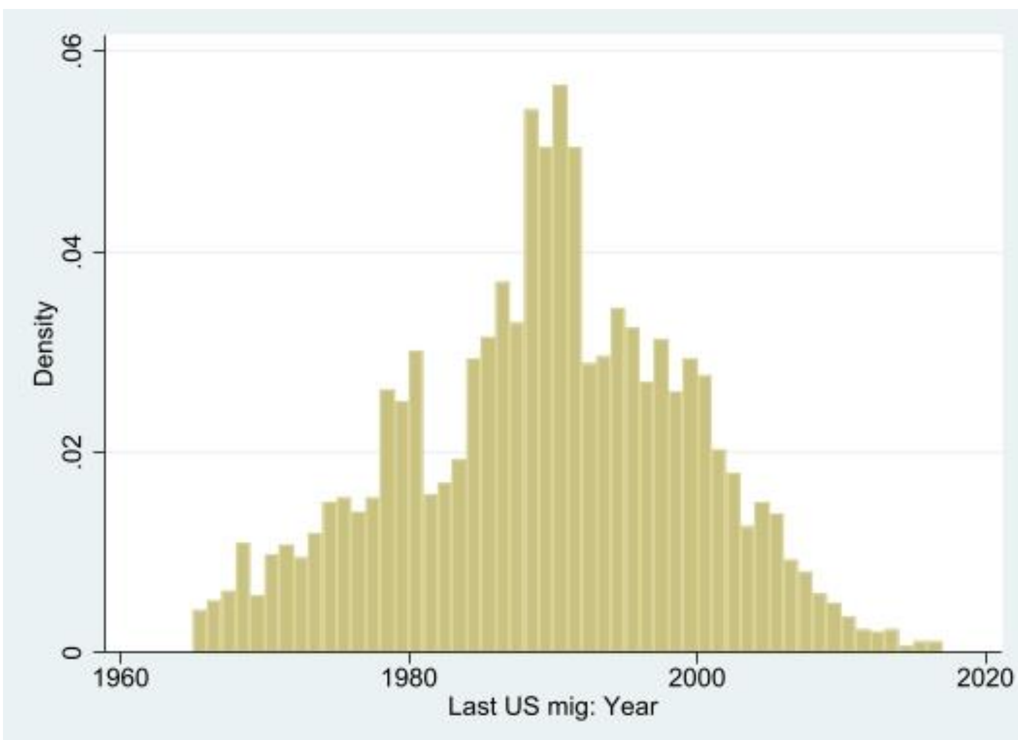


Figure 5.2 Histogram of the year of last U.S. migration (N=4184)

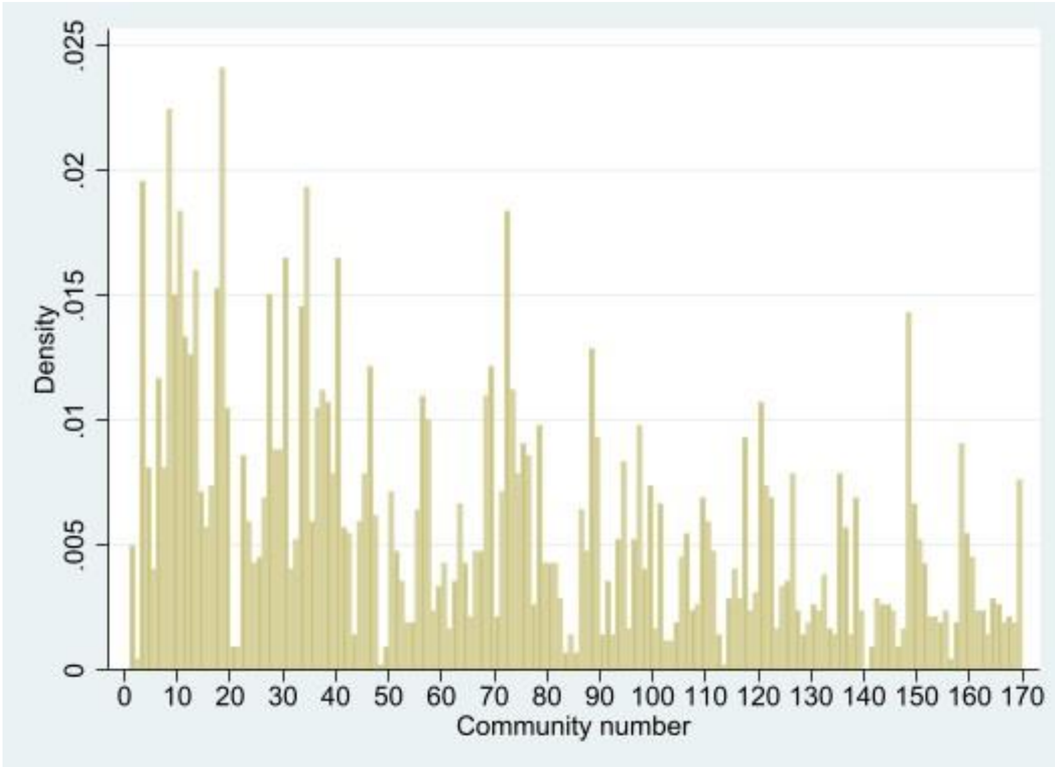


Figure 5.3 Histogram of the local community in Mexico (N=4184)

The dependent variable is one's z-score of the monthly wage on the last trip, which reflects the distance from the mean wage in that year measured in the standard deviation. This variable shows one's relative job position among all available jobs for Mexican migrant workers in terms of wage. Thus, when everyone's characteristics that affect their job selection and wage are controlled in the regression models (e.g., education; duration of stay; assets in the home country), one's lower z-score may imply that the individual has been more committed to their early job with a relatively lower wage, rather than switching to a better-wage job. Note that the z-scores are measured based on the wage information of all non-missing cases (= 5407) among the initial 8641 cases.

The main independent variables are whether one sent remittances (1 = yes) during the last U.S trip, which is measured by whether the amount of monthly remittance is > 0 or = 0, and the main reason for sending remittances, which we categorize as 6-reasons (1 = food/maintenance; 2 = health expenses; 3 = building house; 4 = debt payments; 5 = other reasons; 6 = sending remittances, but the main reason is unknown). The two variables are considered binary and multiple categorical variables, respectively, and in each variable, the reference group is equally the migrant workers who did not send remittances. Additionally, we also consider whether one brought savings (1 = yes) after the last U.S trip, which is measured by whether the amount of savings one brought is > 0 or = 0. Although this variable is not greatly appropriate to test the hypotheses, it could show how one's earmarking process is related to his/her job commitment.

The control variables mainly consist of individual characteristics and assets in the home country. Age, gender, education, number of children, migration status (documented or not), and duration of the last U.S trip are considered in the regression models to control the effect of individual characteristics on one's monthly wage position among migrant workers. Migrants who were younger, educated more, documented, and stayed longer are likely to have had better-wage jobs. Whether one owns the land, house, or business in Mexico is considered the variable of one's assets. More assets one owned in Mexico (i.e., home country), better wage jobs one can eventually find in the U.S (i.e., host country) because of their less dependence on the current job wage.

	Models				
	1	2	3	4	4-2
Individual Characteristics					
Age	-.004*	-.004*	-.004*	-.004*	-.004*
	(.002)	(.002)	(.002)	(.002)	(.002)
Gender (1 = male)	.366***	.369***	.368***	.370***	.371***
	(.061)	(.06)	(.06)	(.06)	(.059)
Education (years)	.018***	.018***	.018***	.018***	.018***
	(.004)	(.004)	(.004)	(.004)	(.004)
N of Children	-.011	-.011	-.011	-.011	-.01
	(.006)	(.006)	(.006)	(.006)	(.005)
Undocumented Migrants	-.320***	-.316***	-.318***	-.315***	-.318***
	(.04)	(.04)	(.04)	(.04)	(.041)
Duration of the last U.S trip	.005***	.005***	.005***	.005***	.005***
	(.0)	(.0)	(.0)	(.0)	(.0)
Assets in Home Country					
Owning Land	-.044	-.039	-.044	-.039	-.033
	(.044)	(.044)	(.044)	(.044)	(.041)
Owning House	.112**	.122**	.113**	.122**	.120**
	(.039)	(.039)	(.039)	(.039)	(.039)
Owning Business	.021	.024	.02	.023	.034
	(.048)	(.048)	(.047)	(.047)	(.048)
Remittance-related					
Bringing Saving		-.055		-.054	-.058
		(.036)		(.037)	(.036)
Sending Remittance			-.017	-.007	
			(.039)	(.04)	
----- for Food/Maintenance					.049
					(.048)
----- for Health Expenses					**-0.103***
					(.045)
----- for Building House					.032
					(.084)
----- for Debt Payments					**-0.122****
					(.047)
----- for Other Reasons					.094
					(.071)
----- for Unknown Reasons					.004
					(.073)
Constant	-0.502*	-0.475*	-0.496*	-0.473*	-.443
	-(.23)	-(.23)	-(.228)	-(.228)	-(.224)
N	4184	4184	4184	4184	4184
R^2	.213	.214	.213	.214	.217
Adj R^2	.201	.202	.201	.202	.204

Note: last US trip year and community number in Mexico are considered for fixed effects
$^{*}P < .05$; $^{**}P < .01$; $^{***}P < .001$ (two-tailed tests)

Table 5.2 OLS regression of migrants' standardized-monthly-wages on the last US trip

Table 5.2 shows the estimates from an OLS regression of z-scores of monthly wages (i.e., how many standard deviations away a migrant's wage is from migrants leaving the same year) on indicators of individual characteristics and home assets (Model 1), added indicators for whether migrant brings savings at the end of the trip (Model 2) or sends remittances regularly (Model 3), and both indicators with or without the main reason of remittance (Model 4-1 and 4-2). All models consider fixed effects for a migrant's last migration year and home community in Mexico.

Regarding the control variables, the results suggest that their relations with the dependent variable follow the expectations. Older migrants accept lower-than-average wages, as do female migrants. More educated migrants accept higher-than-average wages, as do migrants from relatively better-off households that own houses. Undocumented migrants are likely to accept lower-than-average wages, but migrants who stay longer are likely to accept higher-than-average wages.

Unlike the expectation, bringing savings or sending remittances is not significantly related to the migrants' acceptance of lower-than-average wages, which is considered the result of job commitment (Model 2 and 3). Even if the two variables are simultaneously considered, the result does not change (Model 4-1). Yet, when the main reason for sending remittances is considered in the model, the result supports that remittances of socially meaningful money can be significantly related to the senders' job commitment (Model 4-2). When migrants send money for health expenses or debt payments, which can be very meaningful to their home family, they are more likely to take or stay in relatively lower-wage jobs. On the contrary, when the money is used for food/maintenance, building a house, or other reasons, the senders are not significantly engaged in certain-wage jobs.

This result is especially meaningful because the duration of stay is controlled in the model. Bivariate analysis suggests that while migrants who remit to cover necessities (food and maintenance) or to build a house tend to stay long in their destination (median = 24 months), those remitting to cover debt or health expenses stay only briefly (median = 9 months). This implies that the relationship between migrants' remittance purposes and job wages may be simply because of their duration of stay—rather than their job commitments. Yet, the result of Model 4-2 supports that even if migrant workers stay in the same period, those relationships are still statistically significant—although the coefficients decrease from -.188 to -.103 (for health expenses) and from -.255 to -.122 (for debt payment), respectively. In other words, the result supports Hypothesis 2, implying that the meaning of money in remittance exchanges may matter for the migrants' affective commitments to their early nonoptimal jobs.

Modeling Power-Dependence relations in Chain of Remittance Flows

The empirical results support that the bidirectional flow of capital could exist within remittances due to its characteristics as a social exchange of meaningful money. Based on this flow mechanism, I develop a new theoretical model of power-dependence relations potentially embedded in social networks and suggest several propositions of bargaining and affective commitment in social exchanges.

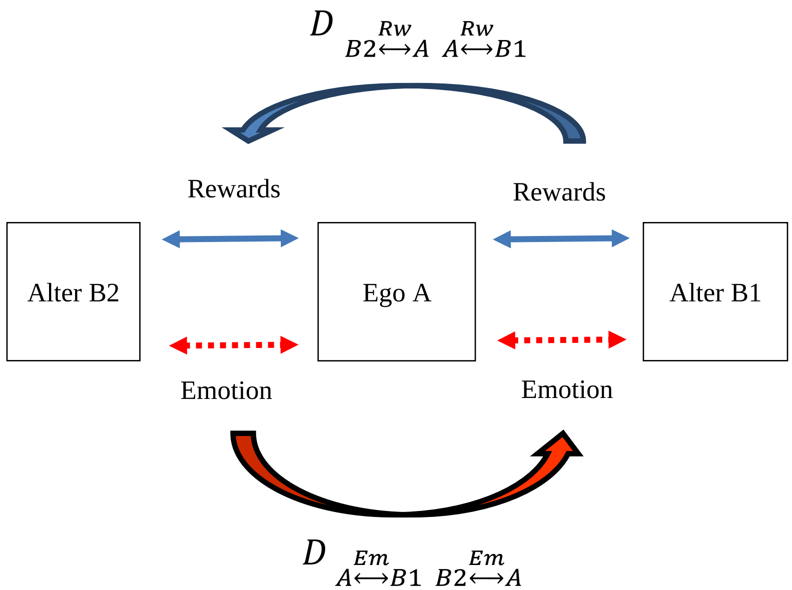


Figure 5.4 Interdependent structure of ordered exchanges and emotional chains

The theoretical model comes from the idea that the relationship between migrant workers' jobs and remittances is similar to an ordered exchange (Walker et al., 2000; Corra and Willer 2002). In other words, one's successful exchange (2^{nd} order; remittance) with someone is only available by one's successful exchange with another (1^{st} order; job). More formally, let $B2 \overset{Rw}{\leftrightarrow} A$ be the flow of exchange rewards between B2 and A. This can be the flow of A's remittance to B2 and B2's social rewards to A. Then, suppose this exchange is only available when A earns rewards from B1, which is embedded in $A \overset{Rw}{\leftrightarrow} B1$. This can be the flow of A's wage from the frim B1. Then, the two exchanges are ordered (i.e., $B2 \overset{Rw}{\leftrightarrow} A$ is available by $A \overset{Rw}{\leftrightarrow} B1$) and as shown in Figure 5.2, their interdependent structure can be defined as $D_{B2 \overset{Rw}{\longleftrightarrow} A \;\; A \overset{Rw}{\longleftrightarrow} B1}$ (i.e., successful $B2 \overset{Rw}{\leftrightarrow} A$ is dependent on successful $A \overset{Rw}{\leftrightarrow} B1$). In this framework, two theoretical conjectures are available.

$$\textbf{\textit{Conjecture 1}}.\ If\ \ \exists\, D_{B2\overset{Rw}{\longleftrightarrow}A\ \ A\overset{Rw}{\longleftrightarrow}B1},\ \ then\ \ \exists\, D_{A\overset{Em}{\longleftrightarrow}B1\ B2\overset{Em}{\longleftrightarrow}A}$$

$$\textbf{\textit{Conjecture 2.}}\ \ D_{B2\overset{Rw}{\longleftrightarrow}A\ \ A\overset{Rw}{\longleftrightarrow}B1} \equiv D_{A\overset{Em}{\longleftrightarrow}B1\ B2\overset{Em}{\longleftrightarrow}A}$$

The first conjecture assumes that when $B2 \overset{Rw}{\leftrightarrow} A$ is dependent on $A \overset{Rw}{\leftrightarrow} B1$, a reversal dependence structure emerges; A and B1's emotions to their exchange relation (= $A \overset{Em}{\leftrightarrow} B1$) is dependent on B2 and A's emotions to their exchange relation (= $B2 \overset{Em}{\leftrightarrow} A$). The second conjecture assumes that the two dependence structures are equivalent. For example, when $D_{B2\overset{Rw}{\longleftrightarrow}A\ \ A\overset{Rw}{\longleftrightarrow}B1}$ produce successful rewards for the actors, $D_{A\overset{Em}{\longleftrightarrow}B1\ B2\overset{Em}{\longleftrightarrow}A}$ will also produce positive emotions .

The two conjectures are based on Lawler's (2001) affect theory. Lawler argues that when exchange actors earn satisfactory rewards by being greatly involved in their tasks (i.e., jointness) and helping each other (i.e., interdependence), each actor's positive emotion from their rewards is attached to their exchange relation. The point is that this process comes from the non-separability between rewards and costs they percept. When jointness and interdependence in an exchange relation are strong, each actor will presume that their rewards cannot be available without cooperative work with their partner (or costs). Then, one's global emotion from rewards can develop as a specific emotion toward the exchange relation with the partner. When the emotion is positive, one is likely to be committed to the relationship (e.g., not trying to find alternative partners). In this sense, if $D_{B2\overset{Rw}{\longleftrightarrow}A\ \ A\overset{Rw}{\longleftrightarrow}B1}$ exist, A's emotion toward the exchange relation with B2 (= $B2 \overset{Em}{\leftrightarrow} A$) will affect A's emotion toward B1 (= $A \overset{Em}{\leftrightarrow} B1$) in a similar manner with $D_{B2\overset{Rw}{\longleftrightarrow}A \; A\overset{Rw}{\longleftrightarrow}B1}$ (e.g., if positive $A\overset{Rw}{\leftrightarrow}B1$ leads to positive $B2\overset{Rw}{\leftrightarrow}A$, it will produce positive $B2\overset{Em}{\leftrightarrow}A$ that affect positive $A\overset{Em}{\leftrightarrow}B1$).

Based on the conjectures, I suggest three propositions of power and affective commitment in exchange relations. The notations are based on the graph in Figure 5.2

Sign Proposition 1 (+): *When* $D_{B2\overset{Rw}{\longleftrightarrow}A \; A\overset{Rw}{\longleftrightarrow}B1}$ *is positive (> 0),* $D_{A\overset{Em}{\longleftrightarrow}B1 \; B2\overset{Em}{\longleftrightarrow}A}$ *is positive (> 0). Within this positive sign structure, A is more likely to be committed to the exchange relation with B, and thereby B's power over A becomes strong.*

Sign Proposition 2 (-): *When* $D_{B2\overset{Rw}{\longleftrightarrow}A \; A\overset{Rw}{\longleftrightarrow}B1}$ *is negative (< 0),* $D_{A\overset{Em}{\longleftrightarrow}B1 \; B2\overset{Em}{\longleftrightarrow}A}$ *is negative (< 0). Within this negative sign structure, A is more likely to be de-committed to the exchange relation with B, and thereby B's power over A becomes weak.*

Strength Proposition: *When* $D_{B\overset{Bn}{\longleftarrow}C \; B\overset{Bn}{\longleftarrow}A}$ *increases with a positive/negative sign,* $D_{B\overset{Em}{\longrightarrow}A \; B\overset{Em}{\longrightarrow}C}$ *increases with a positive/negative sign, respectively. Within this strength structure, the strength of A's commitment/de-commitment to the exchange relation with B correlates with the strength of* $D_{B\overset{Bn}{\longleftarrow}C \; B\overset{Bn}{\longleftarrow}A}$.

The two sign propositions explain how different structures of ordered exchanges can produce different chains of emotions that may affect one's commitment and power in exchange relations. For example, suppose parents (= A) can maintain their good status and respect from children (= B2) by their enough salary from current jobs (= B1) (i.e., successful $A\overset{Rw}{\leftrightarrow}B1$ leads to successful $B2\overset{Rw}{\leftrightarrow}A$). Then, the positive structure of $D_{B2 \overset{Rw}{\longleftrightarrow} A \; A \overset{Rw}{\longleftrightarrow} B1}$ will produce parents' positive emotions to exchange relations with their children, which affect their emotions toward the current jobs in a positive way (i.e., positive $D_{A \overset{Em}{\longleftrightarrow} B1 \; B2 \overset{Em}{\longleftrightarrow} A}$). In this case, as expected in Sign Proposition 1 (+), they will be committed to their jobs, not because of the amount of rewards but because of emerging positive emotions (i.e., affective commitment). Then, it will lead to A's more dependence on their jobs (= B1), which is equal to B1's power over A in bargaining.

On the contrary, suppose parents fail to earn good status and respect from children because of their jobs. It may be because their current jobs do not allow enough time to hang out with their children or do not guarantee social status (i.e., successful $A \overset{Rw}{\leftrightarrow} B1$ leads to unsuccessful $B2 \overset{Rw}{\leftrightarrow} A$). Then, parents and children will have negative emotions in their exchange relations (= negative $B2 \overset{Em}{\leftrightarrow} A$), and it will also change their emotions toward the jobs negatively (= negative $A \overset{Em}{\leftrightarrow} B1$). In this case, as expected in Sign Proposition 2 (-), the parents (= A) will be de-committed to their jobs (= B1), and B1's power over A—which is equal to A's dependence on B1—will become weaker.

The strength proposition explains how different strengths of dependence of $D_{B2 \overset{Rw}{\longleftrightarrow} A \; A \overset{Rw}{\longleftrightarrow} B1}$ can produce different strengths of $D_{A \overset{Em}{\longleftrightarrow} B1 \; B2 \overset{Em}{\longleftrightarrow} A}$— and thereby different strengths of commitment and power in exchange relations. For example, suppose a migrant worker (= A) is the only child of his/her parents in the home country (= B2). Then, A's remittances will be very meaningful to his/her parents that cannot be altered by any other exchanges with their neighbors. In turn, A's job (= B1) leads to a successful exchange relationship with his/her parents (= B2), producing greatly positive emotions ($B2 \overset{Em}{\leftrightarrow} A$). Thus, this strong dependence in $D_{B2 \overset{Rw}{\longleftrightarrow} A \; A \overset{Rw}{\longleftrightarrow} B1}$ will eventually contribute to A's very positive emotions toward his/her current job ($A \overset{Em}{\leftrightarrow} B1$), and thereby A's commitment and dependence on B1 will also greatly increase. Yet, this situation will become contrary when the sign of $D_{B2 \overset{Rw}{\longleftrightarrow} A \; A \overset{Rw}{\longleftrightarrow} B1}$ is negative with the same strength.

In sum, the three potentially testable propositions imply that the bidirectional flow of capital in remittances may not be a specific case, but a generalizable case that results from those interdependent structures potentially embedded in social networks. This means that the implications of the empirical findings are not limited to explaining the remittance-related behaviors, but extended to revealing an unexplored mechanism of interdependence and affective decisions.

Discussion

This chapter explores the interdependence between migrants' work choices in the U.S. and their remittance exchanges back home. Based on theoretical frameworks of social exchange and Zelizer's social meaning of money, I find that migrant workers who send remittances for certain purposes could be committed in their jobs—even if they are high-risk and low-premium jobs—which could be a 'capital' for the firms in the United States. This mechanism of work choices is also developed as a new theoretical model of power-dependence relations in social networks with certain testable propositions.

The main implication of the finding is that it could change the general perception that migrant workers and their families in the home country provide no benefits to the people in the host country. Usually, public opinions about migrant workers are that they take residents' jobs and money in the host country (Neal and Bohon 2003). Yet, as shown in this study, the flow of capital could be bi-directational. Although this study only focuses on job commitments, other social resources could also flow to the host country through the chained exchange processes embedded in remittances.

The limitation of the empirical test is that the models do not clarify whether the relation between job-related choices of Mexican migrant workers and their remittances is based on emotional attachment. This question can be explored by qualitative interview data that could reveal how they feel from the reactions of their home families when they receive remittances and how it changes the currency (or perception) of their wages. Additionally, it is also testable how the network structure of a local community can matter to the families' reactions to remittances, which could affect the senders' reactions and emotions. The studies of homophily, network externalities, or the norms in dense network connections could be helpful (McPherson, Smith-Loving, and Cook 2001; DiMaggio and Garip 2001; Piskorski and Gorbatâi 2017)

The suggested theoretical model of power-dependence relations imply that even within the structure of emotional dependence, some exchange actors could earn benefits from partners' commitment actions without spending its cost. More practically, it means an employer could save the cost of reducing the turnover rate of their employees. But does it guarantee the collective benefits of employees in the labor market? In other words, can employees be efficiently positioned in the labor market when the structure of emotional dependence is positive and strong? White (1970; 1981) points out that a market cannot be effective as predicted because the participants tend to find their niche places (i.e., companies try to be positioned in less competitive fields) instead of competing with each other. In turn, when all employees are positioned in the labor market due to the structure of emotional dependence, the market itself may have a lower efficiency because of the employees' easy settling down. This issue is also theoretically interesting and needs to be explored in future studies.

REFERENCES

Blau, Peter Michael. 1964. *Exchange and Power in Social Life*: Transaction Publishers.

Buch, Claudia M and Anja Kuckulenz. 2010. "Worker Remittances and Capital Flows to Developing Countries." *International Migration* 48(5):89-117.

Chami, Ralph, Connel Fullenkamp and Samir Jahjah. 2005. "Are Immigrant Remittance Flows a Source of Capital for Development?". *IMF Staff papers* 52(1):55-81.

Corra, Mamadi and David Willer. 2002. "The Gatekeeper." *Sociological Theory* 20(2):180-207.

DiMaggio, Paul and Filiz Garip. 2011. "How Network Externalities Can Exacerbate Intergroup Inequality." *American journal of sociology* 116(6):1887-933.

Emerson, Richard M. 1976. "Social Exchange Theory." *Annual review of sociology* 2(1):335-62.

Garip, Filiz. 2014. "The Impact of Migration and Remittances on Wealth Accumulation and Distribution in Rural Thailand." *Demography* 51(2):673-98.

Giuliano, Paola and Marta Ruiz-Arranz. 2009. "Remittances, Financial Development, and Growth." *Journal of development economics* 90(1):144-52.

Gouldner, Alvin W. 1960. "The Norm of Reciprocity: A Preliminary Statement." *American Sociological Review*:161-78.

Homans, George C. 1958. "Social Behavior as Exchange." *American journal of sociology* 63(6):597-606.

Jan Piskorski, Mikołaj and Andreea Gorbatâi. 2017. "Testing Coleman's Social-Norm Enforcement Mechanism: Evidence from Wikipedia." *American journal of sociology* 122(4):1183-222.

Lawler, Edward J. 2001. "An Affect Theory of Social Exchange." *American journal of sociology* 107(2):321-52.

McPherson, Miller, Lynn Smith-Lovin and James M Cook. 2001. "Birds of a Feather: Homophily in Social Networks." *Annual review of sociology* 27(1):415-44.

Neal, Micki and Stephanie A Bohon. 2003. "The Dixie Diaspora: Attitudes toward Immigrants in Georgia." *Sociological Spectrum* 23(2):181-212.

Walker, Henry A, Shane R Thye, Brent Simpson, Michael J Lovaglia, David Willer and Barry Markovsky. 2000. "Network Exchange Theory: Recent Developments and New Directions." *Social Psychology Quarterly*:324-37.

White, Harrison C. 1981. "Where Do Markets Come From?". *American journal of sociology* 87(3):517-47.

White, Harrison C. 2018. *Markets from Networks: Socioeconomic Models of Production*: Princeton University Press.

Zelizer, Viviana A. 1989. "The Social Meaning of Money:" Special Monies"." *American journal of sociology* 95(2):342-77.

Zelizer, Viviana A. 1994. *Pricing the Priceless Child: The Changing Social Value of Children*: Princeton University Press.

Zelizer, Viviana A Rotman. 1997. *The Social Meaning of Money*: Princeton University Press.

CHAPTER 6

CONCLUSION

The implications of the three studies about the social capital of power-dependence relations are mainly in two directions; they contribute to the explanatory power of both network theories of social capital and social exchange theories of power, bridging the gap between the two theoretical programs—not contrasting them.

From a perspective of social capital theories, the power propositions and measures suggested in the first chapter help explain the puzzle of success in certain industries and professional fields where networking crucially matters, but bargaining is still essential, such as joint venture partnerships, job markets for elite managers, and social relationships between firms and banks (Uzzi 1999; Inkpen and Beamish 1997; D'Aveni and Kesner 1993). It could also provide alternative explanations for some empirical cases known as the counterexamples of the network theories. Using ego-centric measures, many studies of social capital find that structural holes and network closure do not always provide expected benefits. To explain the exceptional cases, the studies mainly focus on non-network features, such as gender, culture, and roles (Burt 1998; Xiao and Tsui 2007; Gargiulo, Ertug and Galunic 2009). Indeed, those alternative explanations are strongly supported by empirical evidence. Nevertheless, as shown in the empirical tests of this study, the cases may still be explained by the theories of structural holes and network closure if the alter-centric (or power) measures are applied.

Useful predictions about strategic actions in social networks can be testable with the power propositions and measures. Social exchange theories have been widely applied in organizational and management studies. However, in most cases, the theories are often used as a framework or analytical tool in a *post hoc manner*—not to predict certain behaviors (Cropanzano and Mitchell 2005; Cropanzano et al., 2017). The power propositions of structural holes and network closre could provide certain predictions about hostile and conciliatory bargaining strategies in social networks. For example, the empirical findings of this study reveal that directors with strong relative power within network closure may potentially use the hostile bargaining strategy to their "structural" muses. This prediction is testable and falsifiable in future studies.

Similarly, the suggested approach to measuring centrality and power can also contribute to building a new network theory of social capital within context-specific network flows. Economic sociologists have explored what economic actions are embedded in social relations. Usually, they distinguish the embeddedness frame into two types—"relational" and "structural" embeddedness (Granovetter 1992; see also Rowley, Behrens, and Krackhardt 2000; Moran 2005). The studies on relational embeddedness focus more on the actions rooted in deep "relational" characteristics within a dyadic relation (e.g., mutual trust; strength of ties). On the contrary, the studies of structural embeddedness focus on how one's network position, which is differentiated by one's connections with others, generates certain economic actions. In general, network theories of social capital are mainly based on the structural embeddedness perspective, such as structural holes and network closure theories, overlooking cultural or social-psychological meanings of relations between heterogeneous actors. The key is that building a network theory of social capital based on various context-specifc network flows can be testable with actor-based centrality and following power measures. In other words, reducing the tension between two theoretical frameworks in economic sociology—relational vs. structural embeddedness (i.e., relationalism and formalism)— the suggested Monte Carlot approach could be a fine tool to lead the development of a new network theory of social capital.

More broadly, from a meta-theoretical perspective, actor-based centrality helps to reveal "relational" characteristics of a network with a "formalized" term of network analysis. This means that it bridges the two theoretical frameworks in social network analysis—formalism and relationalism—that need to be unified but are widely considered mutually exclusive or often mixed with logical inconsistences (Erikson 2013). When the scope of each centrality measure is to explain the relationship between positions (or central nodes) and roles (or influences) in a network, the tension between formalism and relationalism derives from the two values—generalization of its application and specification of its network flow assumptions. To achieve both, a centrality measure must be applied to various networks, representing various context-specific flows in each network. But this is difficult to achieve purely by either the previous graph-theoretic approach (only for formalism with formality) or empirically-driven Monte Carlo approach (only for relationalism with flexibility). Actor-based centrality can reduce the tension through its customizability to cover numerous "relational" flow assumptions and its robustness supported by the "formal" frame of identifying influential nodes in any network.

From a perspective of social exchange theories, the power propositions and measures can contribute to developing a network theory of social psychology. As noted, recent social exchange theories focus more on the psychological consequences of the bargaining process, which were central issues of classic exchange theories, instead of the distribution of rewards (Cook et al. 2013). For example, Lawler and his colleagues argue that when exchange actors have strong total power and equal relative power (or mutual and equal dependence), their successful bargaining promotes them to have psychological elements for social order, such as trust, positive emotion, and cohesion toward their exchange relationships (person-to-person) or social group (person-to-unit). Thus, with the generated psychological elements, exchange actors are likely to maintain their exchange relationships even if they have better alternative partners (i.e., committed behaviors) (Lawler, Thye, and Yoon 2000; 2008; 2009; Lawler 2001; Lawler and Yoon 1996; Kuwabara 2011). Molm and her colleagues also argue that unequal relative power in bargaining is harmful to developing the psychological elements for committed behaviors, but its negative effect significantly decreases in non-bargaining situations, including reciprocal and generalized exchanges (Molm, Takahashi, and Peterson 2000; Molm, Collett, and Schaefer 2007; Molm, Whitham, and Melamed 2012).

Although laboratory experiments strongly support these theories, it is unclear under what circumstances the specified dependence situations emerge in social networks. In other words, there is no mechanism (Hedström and Swedberg 1998) suggested between macro-structure (i.e., social networks) and micro-structure (i.e., dependence situations), which makes it challenging to test theose theories in real-life cases. The suggested power-dependence propositions and measures will help make the theories testable, clarifying a potential macro-micro mechanism. For example, within the network overlap and same network size, an ego will have strong total power and equal relative power with alters, and the network position could be related to the development of ego's psychological bonds (e.g., trust, emotion, and cohesion) toward his/her network or group. In turn, illuminating the black-box between social networks and inter-dependence situations, the power propositions and measures can contribute to explaining how some social ties, networks, or group memberships have strong bonds that can be related to certain actions.

The model of power-dependence relations in the chain of remittance flows can also contribute to building a network theory of social psychology. As noted, although the bidirectional flow of capital under remittance exchanges (the money from migrants to families back home vs. the motivation of migrants to accept worse jobs of the U.S firms) seems like a particular situation, this mechanism may be general in social networks. Suppose, in the C-A-B network, A's exchange with B is dependent on A's exchange with C. Then, A's emotion toward the exchange with C may be dependent on A's emotion toward the exchange with B. The point is that this mechanism can help to theorize how one’s specific emotion toward a particular relation can emerge. For example, many migrant women in developed countries, including Singapore, work as nannies (Hochschild and Russell 2011; Hochschild 2015). In this global care chain, migrant nannies care for their employees' children and send the money to their home country families to care for their own children. In turn, their caring for own children (= B) is dependent on caring for their employees' children (= C) (i.e., A's exchange with B is dependent on A's exchange with C). Within this interdependent structure of the C-A-B nanny chain, migrant nannies' emotional attachment toward their employees' children may largely depend on their successful/unsuccessful remittance exchanges for caring for their children in the home country. I argue that the test of this hypothesis could reveal different snapshots of the global care chain where the migrant nannies' emotional attachment toward their children is mainly studied.

As a final statement, I would like to note that the extension of network theories—from social capital to social psychology—is the essential next step to answer a question that may arise from this dissertation: if all individuals bargain for their benefits, what is the difference between social relationships and arm's length ties? The sources of social capital in existing network theories are instrumental rather than consummatory (Portes 1998). Alters are motivated to provide ego with resources, not because they feel the immediate satisfaction from the donating itself, but because they think its results help reach their desired goals. The sources of social capital in many propositions of power sound much instrumental because ego and alters are assumed to bargain for more exchange rewards with the same motivation of reaching desired goals. In this sense, exchange relationships in social networks seem no different from arm's length ties in transactions: they do bargaining and transactions only for their goals.

However, unlike arm's length ties, exchange relationships yield a change in social relationships. Mutual trust can be generated in some ties after bargaining or non-bargaining. Some actors may have positive emotions and cohesion in their social group after repeating exchanges. The point is that when social relationships change, it generates certain social actions shaping one's access to social capital, the motivations of which are not only instrumental (e.g., we trust each other. If I help him/her now, he/she will help me later), but also consummatory (e.g., I will keep helping our community because they are like my family). Therefore, the eventual goal of this approach—integrating network theories of social capital and social exchange theories—is not to simply consider a game-theoretic process of bargaining in social networks. Instead, it is more to develop a new theory of structure and action that helps to explore the "social psychology of social capital" (Cook 2005), potentially embedded in social networks.

REFERENCES

Burt, Ronald S. 1998. "The Gender of Social Capital." *Rationality and society* 10(1):5-46.

Cook, Karen Schweers. 2005. "Networks, Norms, and Trust: The Social Psychology of Social Capital 2004 Cooley Mead Award Address." *Social Psychology Quarterly*:4-14.

Cook, Karen S, Coye Cheshire, Eric RW Rice and Sandra Nakagawa. 2013. "Social Exchange Theory." *Handbook of social psychology*:61-88.

Cropanzano, Russell and Marie S Mitchell. 2005. "Social Exchange Theory: An Interdisciplinary Review." *Journal of management* 31(6):874-900.

Cropanzano, Russell, Erica L Anthony, Shanna R Daniels and Alison V Hall. 2017. "Social Exchange Theory: A Critical Review with Theoretical Remedies." *Academy of Management Annals* 11(1):479-516.

D'Aveni, Richard A and Idalene F Kesner. 1993. "Top Managerial Prestige, Power and Tender Offer Response: A Study of Elite Social Networks and Target Firm Cooperation During Takeovers." *Organization science* 4(2):123-51.

Erikson, Emily. 2013. "Formalist and Relationalist Theory in Social Network Analysis." *Sociological Theory* 31(3):219-42.

Gargiulo, Martin, Gokhan Ertug and Charles Galunic. 2009. "The Two Faces of Control: Network Closure and Individual Performance among Knowledge Workers." *Administrative Science Quarterly* 54(2):299-333.

Granovetter, Mark. 1992. "Problems of Explanation in Economic Sociology." *Networks and organizations: Structure, form, and action*:25-56.

Hedström, Peter and Richard Swedberg. 1998. *Social Mechanisms: An Analytical Approach to Social Theory*: Cambridge University Press.

Hochschild, Arlie Russell. 2011. "Love and Gold." *Family, Ties and Care: Family Transformation in a Plural Modernity*:177.

Hochschild, Arlie Russell. 2015. "Global Care Chains and Emotional Surplus Value." Pp. 249-61 in *Justice, Politics, and the Family*: Routledge.

Inkpen, Andrew C and Paul W Beamish. 1997. "Knowledge, Bargaining Power, and the Instability of International Joint Ventures." *Academy of management review* 22(1):177-202.

Kuwabara, Ko. 2011. "Cohesion, Cooperation, and the Value of Doing Things Together: How Economic Exchange Creates Relational Bonds." *American Sociological Review* 76(4):560-80.

Lawler, Edward J and Jeongkoo Yoon. 1996. "Commitment in Exchange Relations: Test of a Theory of Relational Cohesion." *American Sociological Review*:89-108.

Lawler, Edward J, Shane R Thye and Jeongkoo Yoon. 2000. "Emotion and Group Cohesion in Productive Exchange." *American journal of sociology* 106(3):616-57.

Lawler, Edward J. 2001. "An Affect Theory of Social Exchange." *American journal of sociology* 107(2):321-52.

Lawler, Edward J, Shane R Thye and Jeongkoo Yoon. 2008. "Social Exchange and Micro Social Order." *American Sociological Review* 73(4):519-42.

Lawler, Edward J, Shane R Thye and Jeongkoo Yoon. 2009. *Social Commitments in a Depersonalized World*: Russell Sage Foundation.

Molm, Linda D, Nobuyuki Takahashi and Gretchen Peterson. 2000. "Risk and Trust in Social Exchange: An Experimental Test of a Classical Proposition." *American journal of sociology* 105(5):1396-427.

Molm, Linda D, Jessica L Collett and David R Schaefer. 2007. "Building Solidarity through Generalized Exchange: A Theory of Reciprocity." *American journal of sociology* 113(1):205-42.

Molm, Linda D, Monica M Whitham and David Melamed. 2012. "Forms of Exchange and Integrative Bonds: Effects of History and Embeddedness." *American Sociological Review* 77(1):141-65.

Moran, Peter. 2005. "Structural Vs. Relational Embeddedness: Social Capital and Managerial Performance." *Strategic management journal* 26(12):1129-51.

Portes, Alejandro. 1998. "Social Capital: Its Origins and Applications in Modern Sociology." *Annual review of sociology* 24(1):1-24.

Rowley, Tim, Dean Behrens and David Krackhardt. 2000. "Redundant Governance Structures: An Analysis of Structural and Relational Embeddedness in the Steel and Semiconductor Industries." *Strategic management journal*:369-86.

Uzzi, Brian. 1999. "Embeddedness in the Making of Financial Capital: How Social Relations and Networks Benefit Firms Seeking Financing." *American Sociological Review*:481-505.

Xiao, Zhixing and Anne S Tsui. 2007. "When Brokers May Not Work: The Cultural Contingency of Social Capital in Chinese High-Tech Firms." *Administrative Science Quarterly* 52(1):1-31.

APPENDICES

Appendix A: Correlation Matrix of Network Measures from the Data for Empirical Test

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Structural Holes						
(2) Network Closure	-.452					
(3) Total Power SH	**.551**	-.479				
(4) Total Power NC	-.417	**.761**	-.499			
(5) Relative Power SH	.61	-.516	**.318**	-.252		
(6) Relative Power NC	.472	-.628	.369	**-.3**	**.891**	

Note: (1) The results are based on 90 different project-based networks in 1929-2019. (2) The measure of structural holes (= effective network size) has weaker correlation with total power within SH (=.551) than expected. But the correlation becomes strong when the structural holes measure is logged (=.853).

Appendix B: Factor Analysis with Varimax Rotation Method for Genres

	Factor 1 Thriller/Horror /Mystery/Sci-fi	**Factor 2** Action /Adventure	**Factor 3** Comedy /Western	**Factor 4** History /Doc/Bio	**Factor 5** Family /Ani/Fantasy
Thriller	0.6				
Horror	0.65				
Mystery	0.47				
Sci-fi	0.32				
Action		0.75			
Adventure		0.64			
Comedy	-0.36	-0.41	0.32	-0.31	
Western			0.33		
History				0.55	
Doc				0.62	
Bio				0.53	
Family					0.65
Ani					0.55
Fantasy					0.52
Crime			-0.38		
Drama			-0.82		
Romance	-0.38	-0.33			
Musical		-0.31			
Music					
News					
War					

Note: Only component values >.3 are written in the table. Film-noir, reality-TV, Talk-show, Short, Game-show, and sport genres are initially considered the reference genres. Musical, music, news, and war genres are also considered the reference genres due to lower component values. Crime, Drama, and romance are considered distinct genres.

Appendix C: Standard Errors of Actor-Based Centrality (normalized) and Power-Dependence scores of Florentine families in the marriage network

	ABC (Ref)	ABC (Long)	ABC (Short)	R Pow (Ref)	R Pow (Long)	R Pow (Short)	T Pow (Ref)	T Pow (Long)	T Pow (Short)
Acciaiuoli	.004	.003	.005	.001	.001	.002	.001	.001	.002
Albizzi	.008	.006	.007	.001	.001	.001	.001	.001	.001
Barbadori	.006	.004	.007	.002	.001	.002	.002	.001	.002
Bischeri	.006	.005	.008	.001	.001	.002	.001	.001	.002
Castellani	.007	.005	.008	.002	.001	.002	.002	.001	.002
Ginori	.005	.004	.006	.002	.002	.003	.002	.002	.003
Guadagni	.008	.006	.009	.001	.001	.001	.001	.001	.001
Lamberteschi	.004	.003	.005	.002	.001	.002	.002	.001	.002
Medici	.009	.008	.011	.001	.001	.001	.001	.001	.001
Pazzi	.004	.004	.006	.003	.002	.004	.003	.002	.004
Peruzzi	.007	.006	.007	.002	.001	.002	.002	.001	.002
Ridolfi	.007	.005	.009	.001	.001	.002	.001	.001	.002
Salviati	.006	.006	.006	.001	.000	.001	.001	.000	.001
Strozzi	.006	.006	.009	.001	.001	.002	.001	.001	.002
Tornabuoni	.006	.005	.009	.001	.001	.002	.001	.001	.002

* Seeds per each node = 40; Iterations = 100

* The running time of each measure was less than 10 seconds

Appendix D: Standard Errors of Actor-Based Centrality (normalized) and Power-Dependence scores of Florentine families in the business network

	ABC (Ref)	ABC (Seed)	ABC (Non-Random)	R Pow (Ref)	R Pow (Seed)	R Pow (Non-Random)	T Pow (Ref)	T Pow (Seed)	T Pow (Non-Random)
Barbadori	.007	.007	.007	.001	.001	.001	.001	.001	.001
Bischeri	.005	.005	.006	.002	.002	.003	.002	.002	.003
Castellani	.005	.006	.004	.001	.001	.001	.001	.001	.001
Ginori	.006	.005	.006	.001	.001	.001	.001	.001	.001
Guadagni	.005	.005	.002	.002	.002	.001	.002	.002	.001
Lamberteschi	.006	.005	.006	.002	.002	.003	.002	.002	.003
Medici	.008	.008	.008	.001	.001	.001	.001	.001	.001
Pazzi	.004	.004	.006	.001	.001	.001	.001	.001	.001
Peruzzi	.007	.007	.007	.001	.001	.002	.001	.001	.002
Salviati	.004	.005	.002	.002	.002	.001	.002	.002	.001
Tornabuoni	.004	.004	.005	.001	.001	.001	.001	.001	.001

* Seeds per each node = 40 (except R Pow (Seed) and T Pow (Seed); Iterations = 100
* The running time of each measure was less than 10 seconds