Title of dissertation:

Social Capital as a Multilevel Phenomenon: A Cross-Level and Mixed-Determinant Network Study from the Emerging Micro-Power Field

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Abstract (short version)

Most studies that explicitly or implicitly address the concept of social capital either emphasize the focal actor's external relations or examine relational characteristics for collectives. This dissertation addresses both these approaches by conducting a cross-level and mixed-determinant network study on the emerging hydroelectric micro-power field in Western Norway. The focal actor's position in the organizational field comprises his external relations, and the study shows a curvilinear relationship with the shape of a negative 2^{nd} degree polynomial between network distance to the center of the field at start-up and electricity production per financial capital invested. With regard to relational characteristics for collectives, the dissertation shows that structurally equivalent start-ups in densely connected niches are likely to outperform their colleagues in a sparsely connected niche. In particular, this seems to be the case if the focal actor accesses non-redundant information. Finally, the dissertation addresses issues from population ecology theory and institutional theory and questions whether the start-up success/failure of either an early or late adopter in an emerging field is a possible outcome of population density or mimetic behavior. Analyses show a curvilinear relationship with the shape of a positive 2^{nd} degree polynomial, indicating partial support for both arguments, but when this is controlled for network predictors of social capital, the effect turns negative. Implications of the findings and avenues for further research are discussed.

Sammendrag (abstract in Norwegian)

De fleste studier som eksplisitt eller implisitt behandler begrepet sosial kapital belyser enten den fokale aktørs eksterne relasjoner eller studerer relasjonelle karakteristika for kollektiver. Denne doktoravhandlingen behandler begge disse tilnærmingene ved å foreta en kryssnivå- og miksdeterminant nettverksstudie av det fremvoksende organisatoriske feltet hydroelektrisk mikrokraft på Vestlandet. Den fokale aktørs posisjon i det organisatoriske feltet tilsier hans eksterne relasjoner, og studien viser en kurvlineær sammenheng som tar form som et negativt andregrads polynom mellom nettverksavstand til feltets senter ved oppstart og strømproduksjon per investert kapital. Hva gjelder karakteristika for kollektiver så viser avhandlingen at strukturelt ekvivalente aktører i nisjer med tette nettverksstrukturer er tilbøyelige til å ha høyere produksjon enn sine kolleger i en nisje hvor det er løsere nettverksstruktur, og spesielt synes dette å være tilfellet dersom den fokale aktør har tilgang til ikke-redundant informasjon. Avhandlingen belyser også elementer fra populasjonsøkologi samt institusjonell teori og stiller spørsmål ved om hvorvidt grad av suksess ved å etablere seg tidlig eller sent som mikrokraft produsent kan tilskrives populasjonstetthet eller etterlignende adferd. Analyser viser en kurvlineær sammenheng som tar form som et positivt andregrads polynom, men ved å kontrollere for nettverksmål for sosial kapital blir sammenhengen negativ. Implikasjoner fra funnene og retninger for ny forskning diskuteres.

Abstract (extended version)

Most studies that explicitly or implicitly address the concept of social capital either emphasize the focal actor's external relations or examine relational characteristics for collectives. Contributions that comprise external relations investigate, for instance, the possible effects on parameters of performance from the focal actor's configuration of direct or indirect inter-firm links (e.g. Ahuja 2000a; Baum, Calabrese and Silverman 2000; Baum and Oliver 1991; Choonwoo, Lee and Pennings 2001; Shan, Walker and Kogut 1994; Smith-Doerr, Owen-Smith and Powell 1999; Stuart 2000; Stuart, Hoang and Hybels 1999). Burt's (1992a) structural hole theory also belongs to this camp, arguing that the optimal strategy for the player is to construct an ego-network with disconnected alters (for a review, see Burt 2000).

On the other hand, contributions that focus on collectives investigate the influence of relational characteristics and abilities for given subsets of actors (Adler and Kwon 2000; Gittel and Vidal 1998; Putnam 2000). For instance, Walker, Kogut et al. (1997), discovered that structurally equivalent biotech firms had a larger propensity to establish ties within their own subset of actors than to ally with organizations on the outside. Unfortunately, the authors did not measure how the emerging structure affected performance. However, in a study of Norwegian pulp and paper mills, Greve, Golombek et al. (2001) found that actors who were structurally equivalent with universities and research institutions had lower pollution levels than mills outside these subsets. This latter contribution indicates that certain relational characteristics for collectives seem to have explanatory power in portraying whether social capital is present or not.

In this dissertation, I have studied the concept of social capital on the emerging hydroelectric micro-power field in Western Norway by simultaneously investigating the focal actor's external relations and relational characteristics for collectives. This implies that I have conducted a cross-level and mixed-determinant network study. Cross-level models describe relationships between independent and dependent variables at different levels, while mixed-determinant models suggest that predictors at a variety of levels may influence a criterion of interest (Klein, Danserau and Hall 1994; Rousseau 1985). Whereas methodological approaches normally require a researcher to choose one particular level of analysis as the primary focus of study, Gabbay and Leenders (1999: 5) argue that the very nature of social capital runs through various levels of analysis and a *"full study of social capital should thus*

incorporate structure... *at multiple levels of analysis."* The concept of social capital is defined as *"resources embedded in social networks that are accessed and used by actors for actions."* (Lin 2001: 25)

Data for this study was gathered from hydroelectric micro-power start-ups in Western Norway during the fall of 2002 and early January 2003. The plants were established throughout the region between 1994-2001. The sample of network data on start-up was 23, representing a response rate of 92% from the relevant actors. I identified a total of 115 network ties between these entrepreneurs and other actors (i.e. vendors and consultants), which I dichotomized and symmetrized. The focal actor's network position comprises his external relations, and by applying Freeman's (1979) concept of closeness centrality, the study showed a curvilinear relationship with the shape of a negative 2nd degree polynomial between network distance to the center of the field at start-up and electricity production per financial capital invested (discounted in real terms). This indicates that the actors in intermediate network positions were superior in venture success, whereas their colleagues at the core or at the margins of the field were inferior.

Regarding relational characteristics for collectives, I examined if density of contacts within subsets of structurally equivalent niches (Burt and Talmud 1993) would affect outcome for the same actors. By applying the so-called Concor (convergence of iterated correlations) technique – developed by White and colleagues (White, Boorman and Breiger 1976; White, Breiger and Boorman 1976) – I identified 3 different niches into which micro-power start-ups are embedded. Structural-equation approaches can indicate roles distributed among actors according to similarity in communication structures (Greve and Salaff 2001) and identify groups of actors with shared cognitions (Carley 1986; Galaskiewicz and Burt 1991). Niche density is defined as the number of relations *(l)* among *(n)* actors that exist compared to the maximum possible number of relations, $l/[n(n-1)/2]$, and analyses show that structurally equivalent start-ups in densely connected niches are likely to outperform their colleagues in a sparsely connected niche. By conducting interaction effects between the nominal niche variable and the focal actor's access to non-redundant information – operationalized by applying Freeman and colleagues' (1991) centrality measure of flow betweenness – I observed that non-redundant information is positive for start-ups in densely connected niches, whereas it is actually negative in a sparsely connected niche. The findings thus revealed that the concept of social capital could be inferred as both a cross-level and mixed-determinant phenomenon.

The dissertation moreover hypothesizes that late adopters will outperform early adopters as a result of increased density and legitimacy in the emerging field (Aldrich 1999; Hannan 1986). An alternative hypothesis suggests that the relationship might be the reverse due to mimetic behavior among late adopters (DiMaggio 1991). Initial analyses give partial support for both hypotheses; between 1995 and 1998 the trend is negative, which supports the argument behind mimetic behavior (DiMaggio 1991). From this year on, however, the curve becomes positive, indicating support for the density argument (Hannan 1986). We accordingly observed the contours of a non-linear relationship with the shape of a positive 2^{nd} degree polynomial between start-up year and venture success, where 1998 is the turning point. The most likely interpretation of these findings is that both of these opposite causal forces are at play. In the early years, it seems that the negative effect of mimetic behavior is superior in predictive power, whereas the increased competence and learning that is developed throughout the field more than outweighs this negative trend beyond 1998.

However, when I controlled for network predictors of social capital, the positive polynomial effect is faded away and a genuine negative linear trend between start-up year and venture success appeared. My interpretation of this finding is that in order to gain from the increased level of organizational learning that has taken place in the emerging field, it is essential to acquire this competence through access to social capital. In other words, despite an overall increased knowledge base throughout the field, this asset does not benefit late adopters per se, but has to be gained by the specific network constellations that this dissertation has uncovered.

Acknowledgements

First of all, I would like to thank the committee-members Profs. Sven A. Haugland, Arent Greve, and Howard A. Aldrich for all their help and advice during the completion of this dissertation. Thanks also to Mario Benassi for his willingness to be part of my dissertation committee. Valuable feedback from Drs. Iver Bragelin and Daniel McFarland was furthermore highly regarded. I am also indebted to all the respondents who provided valuable data and made this study possible. Seming Skau at The Norwegian Water Resources and Energy Directorate provided me helpful information about small scale hydropower in Norway, whereas Gudmund A. Dalsbø at The Norwegian Institute of Meteorology accessed me data on yearly precipitation from a number of weather stations in Western Norway. I am indebted to both of them. Furthermore I will give thanks to two experts in small-scale hydropower for granting me valuable knowledge about the sector. The administrative staff at the Norwegian School of Economics and Business Administration, Department of Strategy and Management, has provided the best working conditions possible and are accordingly highly regarded. Thanks also to Prof. Walter Powell and Barbara Beuche at the Scandinavian Consortium for Organizational Research (Scancor), Stanford University, for making my time there as a visiting scholar both smooth and efficient. Janet Iversen is highly regarded for her assistance in correcting and editing the text in the dissertation. This research was supported by grant number F015/2001, provided by the Norwegian School of Economics and Business Administration.

Table of Contents

List of Figures

List of Tables

1. Introduction

Positioning and Contribution

Practically no organization stands on its own. Ongoing exchange relationships with suppliers and buyers, as well as other interactions among stakeholders within and across industries, are translated into more or less stable inter-organizational networks that one way or another will affect the actors. Over the last decades, scholars in the area of strategy and organization theory have attempted to explain this phenomenon (for reviews, see for instance Grandori and Soda 1995; Gulati 1998; Gulati, Nohria and Zaheer 2000), and in the 1990s the concept of social capital gained prominence as a potential answer to researchers' call for *"a good network theory of organization"* to describe *"how structures of interactions enable coordinated interaction to achieve collective and individual interests"* (Salancik 1995: 348).

Most studies that explicitly or implicitly address the concept of social capital emphasize either the focal actor's external relations or examine relational characteristics for collectives (Adler and Kwon 2000; Gittel and Vidal 1998; Putnam 2000). A number of contributions that comprise external relations investigate, for instance, the possible effects on parameters of performance from the focal actor's configuration of direct or indirect inter-firm links (Ahuja 2000a; Baum, Calabrese and Silverman 2000; e.g. Baum and Oliver 1991; Choonwoo, Lee and Pennings 2001; Shan, Walker and Kogut 1994; Smith-Doerr, Owen-Smith and Powell 1999; Stuart 2000; Stuart, Hoang and Hybels 1999). Burt's (1992a) structural hole theory also belongs to this camp, arguing that the optimal strategy for the player is to construct an ego-network with disconnected alters (for a review, see Burt 2000).

On the other hand, contributions that focus on collectives investigate the influence of relational characteristics and abilities for given subsets of actors (Adler and Kwon 2000; Gittel and Vidal 1998; Putnam 2000). An example of such a study is Walker, Kogut et al.'s (1997) investigation of the formation of an industry network among young biotech firms. They discovered that structurally equivalent actors had a larger propensity to establish ties within their own niche or subset than to ally with organizations on the outside. Unfortunately, the authors did not measure how the emerging structure affected performance, but in a study of Norwegian pulp and paper mills, Greve, Golombek et al. (2001) found that actors in niches who were structurally equivalent with universities and research institutions, had lower pollution levels than mills outside these subsets. This latter contribution indicates that certain relational characteristics for collectives seem to have explanatory power in portraying whether social capital is present or not.

In this dissertation, I have studied the concept of social capital on the emerging hydroelectric micro-power field in Western Norway by simultaneously investigating the focal actor's external relations as well as examining relational characteristics for collectives; i.e. niches of structurally equivalent actors (Burt and Talmud 1993). This implies that I have conducted a cross-level and mixed-determinant network study. Cross-level models describe relationships between independent and dependent variables at different levels, while mixed-determinant models suggest that predictors at a variety of levels may influence a criterion of interest (Klein, Danserau and Hall 1994; Rousseau 1985). Whereas methodological approaches normally require a researcher to choose one particular level of analysis as the primary focus of study, Gabbay and Leenders (1999: 5) argued that the very nature of social capital runs through various levels of analysis and a *"full study of social capital should thus incorporate structure... at multiple levels of analysis."*

DiMaggio (1986: 341) held that there are instances in which causes of organizational outcomes may have different consequences for organizations that occupy different niches in a field, *"...[and] many of our theories, explicitly or implicitly, lead to expectations about relations among sets of organizations, rather than single organizations."* Research on emerging fields, however, has been scarce (for exceptions, see DiMaggio 1991; Galaskiewicz 1991), and to my knowledge so far no study has undertaken the task of concurrently examining the actor's network position and niche characteristics within a field. Organizational field has been defined as *"those organizations [or corporate actors] that, in the aggregate, constitute a recognized area of institutional life..."* (DiMaggio and Powell 1991: 64-65).

The start-up's network position comprises his external relations, and I studied how such connections – bringing the plant close to either the center, the margins, or intermediate positions of the field – may enable him to overcome its "liability of newness" (Stinchcombe 1965). Regarding relational characteristics for collectives, I examined if the density of contacts within subsets of structurally equivalent niches (Burt and Talmud 1993) affects the outcome for the same actors. Next, I studied if the effect from non-redundant network ties is contingent upon the plant's ecological niche into which it is embedded, and this implies that I simultaneously addressed focal actor's external relations and characteristics for collectives. Embeddedness has both a relational and a structural aspect, and Granovetter (1992: 33) emphasized that ignoring the social structure only gives a partial picture, warning that one can easily slip into *"dyadic atomization"*, a type of reductionism. Drawing upon the embeddedness perspective (Granovetter 1985; 1992), the dissertation thus examines if the intensity of contacts within niches moderates the value of accessing information from disparate sources. Accordingly, here I study how the structure of relationships in these subsets is expected to influence outcomes from the focal actor's relational ties that are considered to provide non-redundant information. The primary contribution in this dissertation can be summed up in the following research question:[1]

Research Question: Do we observe unique effects or interaction effects on focal actor outcome from his external relations in the field and niche characteristics? Thus, to what extent do we observe cross-level or mixed-determinant network predictors of social capital?

The dissertation furthermore addresses issues from population ecology theory and institutional theory and questions whether the start-up success/failure of either an early or late adopter in an emerging field is a possible outcome of population density and learning (Aldrich 1999; Hannan 1986) or mimetic behavior (DiMaggio and Powell 1991). Statistical analyses reveal a curvilinear relationship with the shape of a positive 2nd degree polynomial on venture success, but when controlling for network predictors of social capital the effect becomes genuinely negative. The way I interpreted this finding is that in order to gain from the increased level of organizational learning that has taken place in the emerging field, it is essential to acquire this competence through access to social capital. In other words, despite an overall increased knowledge base throughout the field, this asset does not benefit late adopters per se, but has to be gained by the specific network constellations that this dissertation has uncovered. These findings thus indicate that the inclusion of both network methodology and institutional- and ecological approaches can enrich researchers' understanding of social phenomena by revealing a conceptually interesting interplay between different structural levels. I discuss these issues in length in Chapters 5 and 6.

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[1] In chapter 2 I elaborate this research question in length.

Social Capital and Informal Network Ties in an Emerging Field

Lin (2001: 25) defined social capital as *"resources embedded in social networks that are accessed and used by actors for actions."* The concept has two important components: First, it represents resources embedded in social relations rather than individuals. In my empirical context, this implies the start-up's network position through its external ties in the emerging field, *and* characteristics of the ecological niche into which it is embedded. It is important to note that we do not capture the concept by its effects or outcomes, which implies that we avoid a functionalist view. Lin (2001: 28) warns that such a view *"may implicate a tautology...It would be impossible to build a theory in which causal effectual factors are folded into a singular function...... [and] incorrect to allow the outcome variables to dictate the specification of the causal variable."*

He emphasizes, however, *"[t]his is not to deny that a functional relationship may be hypothesized..."* (Lin 2001: 28), which shifts the focus to the latter part of the definition. Social capital *"should explain how access to social resources can be mobilized for gains – the process of activation"* (Lin 2001: 29), and if we apply this aspect to corporate life, a logical implication is emphasizing the attainment of gains from what has been implemented in a given project. Accordingly, the dependent variable in this study is average yearly electricity production at the focal plant per units of financial capital invested, discounted in real terms. Hence, the intention is to reveal how network predictors of social capital at different levels of analyses are expected to be reflected in gains (or losses) for (mostly) novel entrepreneurial actors in the emerging micro-power field.[2]

It is furthermore important to note that this dissertation emphasizes "informal" ties among the actors. This is in contrast to most other network studies on start-ups, which one way or another examined formalized relationships like contractual agreements or strategic alliances (e.g. Baum, Calabrese and Silverman 2000; Baum and Oliver 1991; Choonwoo, Lee and Pennings 2001; Shan, Walker and Kogut 1994; Stuart, Hoang and Hybels 1999; Walker, Kogut and Shan 1997). A liability of these contributions is that very few start-ups have any formalized alliances prior to, or around incorporation (or later). With the exception of Baum,

[2] Only two respondents in this study reported that they had any prior experience with small-scale hydroelectricity before building their present plant.

Calabrese et al.'s (2000) study of start-ups in the Canadian biotech industry, these contributions accordingly missed essential information of how contacts among actors in a very early stage affect later outcome.

Moreover, by examining informal network ties I captured relationships that would otherwise never have been discovered. When W. Powell presented the CEO of Centocor – a dedicated biotech firm – with a list of the firm's formal agreements, the CEO's reaction was: *"[This is just] the tip of the iceberg – it excludes dozens of handshake deals and informal collaborations, as well as probably hundreds of collaborations by our company's scientists with colleagues elsewhere"* (Powell, Koput and Smith-Doerr 1996: 120). Beneath most formal ties then, lies a sea of informal relations, and if researchers ignore these, I argue that valuable information of corporate life will be lost. It is important to note, however, that this study focuses on the very structure of the ties that make up the social network, rather than focusing on the content of these ties. Hinde (1976: 8) referred to the term structure *"as a patterning of relationships that is independent of the particular individuals concerned."* He furthermore stated that *"[i]n moving to this more abstract level we focus on aspects of the content... that show regularities across individuals and across societies..."*

Finally I expected that actors' access to social capital through informal network ties is particularly essential in young fields, where entrepreneurs have to learn new roles without the benefit of role models to discover and create effective routines and competencies. Whereas entrepreneurs in mature industries can benefit from already established templates and adopt those that are more preferable, well-developed templates are less tangible in emerging fields, and pioneering entrepreneurs must accordingly learn new schemata from a less developed and more fragmented knowledge base (Aldrich 1999; Barron 1998; Spender 1989; Stinchcombe 1965; Walsh 1995). A certain level of know-how is established, or at least in the process of being established, but it is probably not evenly distributed among the actors throughout the field. What can be gained by the means of approaching the "right" players with the "right" knowledge at the "right" time, or being part of a niche with the highest competence level will therefore particularly be reflected on start-ups in an emerging field, I argue.

Motivation for Empirical Setting and Applied Methodology

The Rise of the Micro-Power Field in Norway and Internationally

There is no agreed upon, international definition of what constitutes a hydroelectric micro-power plant. The Norwegian Water Resources and Energy Directorate (NVE), however, uses following definitions: Micro-power stations (maximum capacity up until 100 kWh [kilowatts produced per hour]), miniature-power stations (maximum capacity between 100-1,000 kWh), and small power stations (maximum capacity between 1,000-10,000 kWh). The micro-power stations are exempted from paying six øre (almost one cent) in consumption tax (in Norwegian: forbruksavgift) for each kWh they sell.

If we look at the dynamics of the start-ups in the sector between 1985 and 1999, the distinction of the different size classes in Figure 1.1 reveals an interesting picture (Based upon data from NVE 2000).

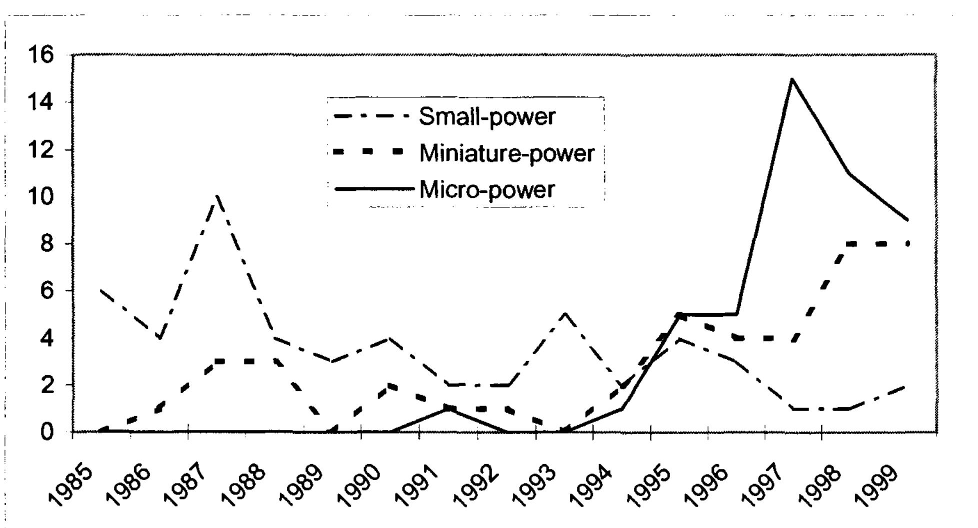

Figure 1.1 Start-ups of small-power, miniature-power and micro-power plants in Norway.

We observe that for small-power plants there has been a steadily decreasing establishment rate since 1985. For miniature power stations there were relatively few entrants between 1985 and 1994, but they took off somewhat in 1995. Regarding micro-power, there were practically no start-ups between 1985 and 1994, but we see a dramatic increase from 1995.

Moreover, the figure reflects a conservative illustration of the contrast between miniature- and micro-power start-ups. A number of the start-ups in the late 1990s reported a size of 100 kWh maximum capacity, and I have modeled these "borderline" cases (between what is considered to be miniature- and micro-power) as miniature plants. If these had been identified as micro-power plants, the contrast between the two categories would have been even more marked. Another issue, which possibly masks the distinction in the "take off" of micro-power compared to miniature-power, is that it is more difficult to gather reliable data on smaller plants compared to larger ones. Regarding micro-power, there is thus a stronger likelihood to expect a bias in underreporting than for the larger start-ups. Therefore, it is likely to assume that the marked shift in start-ups for micro-power plants has been considerably stronger than what we observe in Figure 1.1.

The potential for hydroelectric small power electricity production in Norway is estimated to be around 7 billion kWh, and for micro- and miniature plants about 3 billion kWh. The total yearly hydroelectric production in the country has been between 120 and 140 billion kWh over the last few years, so the potential is considerable. In 2000, the total production from micro- and miniature hydroelectric generators was roughly estimated to be 235 million kWh, which implies that even now only a marginal fraction of the estimated capacity has been built out (NVE).

Another central issue regarding micro-power is that these plants are considered extremely environmentally friendly – not only in the aspect that they produce renewable, practically clean and emission free energy compared to their larger siblings. The smaller the plant the less visible it is. Whereas large hydroelectric stations most often require the construction of large dams, smaller generators in many cases can be adapted to rivers that require few or no modifications, and they can also be easily removed with practically no permanent damage to nature. Hydroelectric micro-power plants are also established close to the end-user. This reduces the transmission costs and also adds to depressing the demand for extension of the grid-capacity, which entails both large investments and environmental degradation.

Finally, the emergence of micro-power stations is a typically rural phenomenon, and a number of the entrepreneurs are farmers who have property rights to a nearby river. Over the recent years there has been increasing political pressure towards reducing subsidies to rural farmers living on marginal farmland, and accordingly, many of these are striving to survive economically. In addition, a great number have already abandoned their land. The possibility of gaining some extra income (and also of saving money on the electricity bill for both the household and the farm) might enable a number of actors to avoid giving up their farm, and even encourage others to breathe new life into abandoned farms and rural community areas. In a country that highlights the importance of constraining pressure towards urbanization and encourages efforts that keep alive local communities, the rise of hydroelectric micro-power therefore has positive effects beyond what can be gained and measured in macroeconomic terms, I argue. Personal conversation with a representative of the technical department in a local municipality (in Norwegian: kommune) also revealed that they considered the emergence of efficient small hydroelectric plants as a potential for new economical growth in the area.

Despite that per capita consumption of electricity in Norway, for instance, is roughly twice as large as per capita consumption in the U.S., domestic demand seems to be constantly increasing (Encyclopedia Britannica Online 2003; NVE). In a country that gets 99% of its production from hydroelectricity (Microsoft Encarta Encyclopedia 2002), with limited capacity of import, and where public opinion to a large extent is skeptical about building large scale gas-fired power stations, it seems that the overall production of electricity in the future has to come also from hydro turbines. This, however, may represent a great challenge. Figure 1.2 illustrates yearly total investments in hydroelectricity in Norway between 1960 and 1999 (in 1997 kroner [crowns]). We observe a peak in 1980 and a steady decline in the following years. Since 1993, the investments have been relatively low. The major reason for reduced investments is that the remaining two-fifths of economically exploitable hydroelectricity is totally or partly constrained from being built on as result of increased concern for environmentalism (Encyclopedia Britannica Online 2003; Stortingsmelding [Parliamentary Report] nr. 37, 2000-2001). Thus, the period of large-scale investments in hydroelectricity definitely seems to be over.

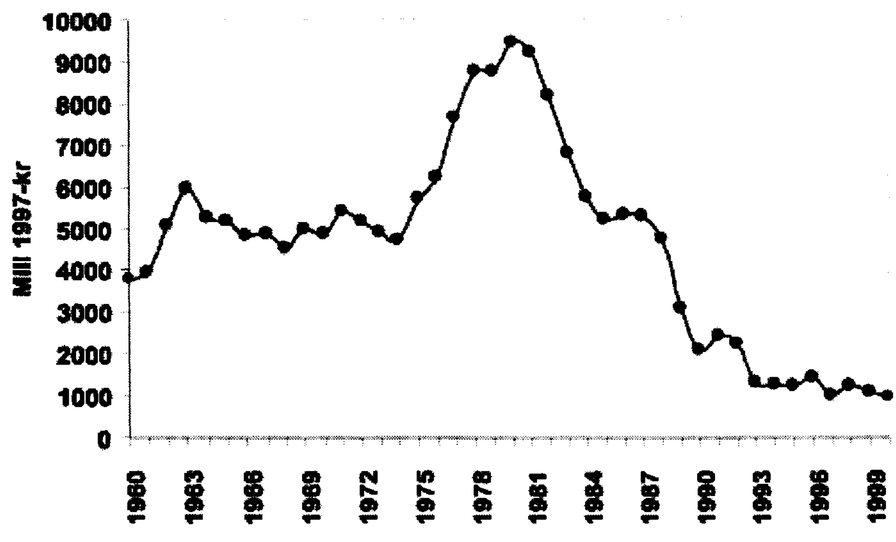

Figure 1.2 Investments in hydroelectricity in 1997 million kroner between 1960 and 1999. Adapted from the web-edition of Stortingsmelding (Parliamentary Report) Nr. 37 (2000-2001).

Altogether, the development of new technology enabling small power plants to become economically feasible, the ever increasing demand for electricity, the limited capacity for import, the constraints on large scale domestic investments, and a general enhanced interest in renewable and environmental friendly energy have paved the path for the appearance of hydroelectric micro-power in Norway. The take off that I have described above reflects the emergence of a new organizational field. A web search indicates that in addition to start-up plants, we now have an array of vendors and consultants of micro-power systems nationwide, and interest groups have been established as well. Sintef, a Norwegian technological research institute, is also involved in developing efficient and economically feasible hydroelectric micro-power generators.

Micro-Power in Norway as Part of an International Trend. It is moreover worth noting that the rise of micro-power in Norway is part of an international trend. Figure 1.3 portrays a marked shift in U.S. venture capital investment in micro-power technology from 1996 – about the same time that it took off in Norway – and within the next 7-8 years the market for such equipment may be estimated at more than $60 billon a year (The Economist 2000).

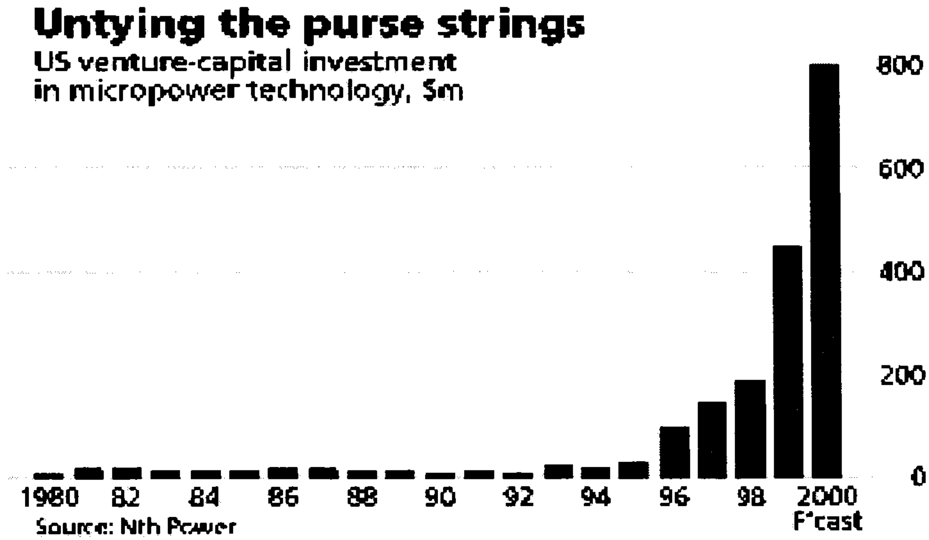

Figure 1.3 U.S. venture- capital investment in micro-power technology, $m. Adapted from the web-edition of The Economist (2000).

According to The Economist (2000), there are three reasons for the increased interest in micro-power. One is market liberalization. About half of America's state governments have now forced their electricity monopolies to face competition. In the European Union, a directive that took effect in 1999 ordered member governments to face competition in their wholesale market for electricity. Many developing countries as well, from India to Argentina, have embraced deregulation and privatization. Small, local plants offer a cheap way into such markets. New micro-power plants – using either natural gas or renewable energy – are not only smaller, nimbler and cleaner than older and larger plants, they are also closer to the end-user. Even if the power they produce is more costly at the source – which it often is – they do not suffer huge transmission losses when sending it to consumers. On top of that, the surplus heat they generate can be employed for useful purposes, such as warming buildings, whereas the excess from big generators located in the middle of the countryside is usually wasted.

When Thomas Edison set up his first heat-and-power cogeneration plant near Wall Street more than 100 years ago, he thought the best way to meet customers' needs would be to set up networks of decentralized power plants in or near homes and offices. Now, after a century of power stations becoming ever larger, transmission grids spreading ever wider and central planners growing ever stronger, this may change. Local generation for local consumption is back in fashion and Edison's dream is being revived (The Economist 2001).[3]

A second reason for the rise of micro-power is environmentalism. Ever-higher emission standards have made it unattractive to build new coal-fired plants in the rich world. America still gets more than half of its electricity from coal, but only because many older plants have been "grandfathered", and do not have to meet strict new emission standards. Europe has been more aggressive than America in pushing industry to adopt cleaner forms of power generation. In addition, micro-generators are extremely clean. The worst of them burn natural gas – a reasonably benign fuel. Others use hydrogen, wind, sunlight, manpower, and some produce renewable hydroelectricity.

A third reason is the demand for reliable, uninterrupted power. Karl Stahlkoph, the head of the Electric Power Research Institute (EPRI), an industry-financed, American research body, reckons that micro-power will take off in the U.S., where brownouts and blackouts are an ever-increasing problem (The Economist 2000). These issues have altogether stimulated the search for small, clean, reliable and above all, relatively cheap generating technologies that now are emerging.

The dawn of decentralized micro-power means that society at large no longer has to depend of the vagaries of the grid to the same extent, and it is more responsive to the needs of the consumer. This is a compelling advantage in rich countries, where the digital revolution is fuelling the thirst for high-quality, reliable power that the antiquated grid seems unable to deliver. California provides the best example: although the utilities have not built a single power plant over the last decade, individuals and companies have added 6 billion kWh of non-utility of micro-power over that period, roughly the equivalent of the state's installed nuclear capacity (The Economist 2001).

The argument in favor of micro-power is even more persuasive in developing countries, where the grid has largely failed the poor and 3 billion people are without reliable access to

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[3] It is, however, also necessary to mention that Edison's dream of small decentralized micro-power plants was conceived at a time when the transformer technology had not yet been developed. 100 years ago it was impossible to transport large amounts of electricity over long distances.

electricity (The Economist 2000). Gary Mittleman, the boss of Plug Power, estimates that it costs between $1,000 and $1,500 per kWh to build or replace electricity grids in developing countries. In such places, micro-power is already an attractive option, and international agencies such as the World Bank, as well as private sector operators and non-governmental groups, are devising "microfinance" schemes to help bring electricity to the poor in such countries as Mongolia and India (The Economist 2000).

Nevertheless, the rise of micro-power does not mean that grid power is dead. On the contrary, argues CERA, a robust grid may be an important part of micro-power future. In poor countries, the grid is often so shoddy and inadequate that distributed energy could well supplant it. However, in rich countries, where nearly everyone has access to power, micro-power is much more likely to grow alongside the grid. Not only can the owners of distributed generators tap into the grid for back-up power, but utilities can install micro-power plants close to consumers to avoid grid bottlenecks (The Economist 2001).

Micro-power may also change the way electricity grids operate – turning them from dictatorial monopolies into democratic marketplaces. Add a bit of information technology to a micro-generator and it will be able to both monitor itself and to talk to other plants on the grid. Visionaries see a future in which dozens, even hundreds, of disparate micro-power units are linked together in so-called "micro-grids". These networks could be made up of all sorts of power units, from solar cells to micro-turbines to fuel cells, depending on the needs of individual users and the abilities and comparative advantages of different producers (The Economist 2000).

The Western Region of Norway

As mentioned in the beginning of the chapter, this study addresses the concept of social capital on the emerging hydroelectric micro-power field in Western Norway. The region constitutes the four counties (in Norwegian: fylker) Rogaland, Hordaland, Sogn & Fjordane, Møre &Romsdal. There are three reasons why I have limited the study to start-ups in this area.

First, data provided from NVE (2000) on the development of the micro-power field clearly shows that this is a phenomenon that predominantly has taken place in this region. With the exception of Nord-Trøndelag (the northern part of Mid-Norway), there have by and large only been sporadic startups in other counties. In Nord-Trøndelag, however, the startups have not reached the same number as in any county in the Western Region of Norway. Thus, the four counties Rogaland, Hordaland, Sogn & Fjordane, and Møre & Romsdal compose a geographically connected area with the largest numbers of start-ups.

Second, the western region of Norway constitutes a relatively homogenous climatic zone where temperature and westerly winds create abundant precipitation. The eastern region, on the other hand, receives comparably little rain, due to the range of mountains that separates the regions and has a much colder climate in the winter. Other regions in Norway also represent different climatic zones. In this study, I have controlled for deviations in precipitation, yet by gathering data from micro-power start-ups only in Western Norway, I avoided disturbances in the dataset created from possible complex interaction effects between average rainfall, deviation in precipitation and other climatic conditions such as the amount of snow and ice. The latter issue here is of great importance since temperature and hence the snow and ice partake in predicting the distribution of the flow of river water throughout the year. Other things being equal, there will be little water in the river as long as the ground temperature in the catchment area of the water system is below 0°C, whereas melting snow increases the level. Personal communication with entrepreneurs has also taught me that in many occasions, ice complicates the intake of water into the production systems, and this is likely to affect total electricity production.

Third, regarding geological ground conditions, Western Norway represents a comparatively homogenous area. The soil is barren in this region, which implies that the terrain absorbs relatively little rainfall. This makes the level of flowing water in the rivers vulnerable to variations in precipitation. In the eastern part of Norway, on the other hand, the soil absorbs a larger percentage of the rainfall, and a consequence of this is that the water level in the rivers is less vulnerable to such variations. In other words, the western region of Norway lacks a natural water regulation mechanism for the level of flow of water in the rivers due to the overall barren soil in this area (personal communication with an engineer and expert in small-scale hydroelectricity).

Summed up, the growth of hydroelectric micro-power plants in Norway has predominately taken place in the Western region of the country, and this is the major reason for why I have constrained the empirical setting in this study to the four counties Rogaland, Hordaland, Sogn & Fjordane, Møre & Romsdal. In addition, this area represents a relatively homogenous zone for both climatic and geological conditions.

A Short Introduction to Applied Methodology in this Study

I conducted a network study on social contacts among actors within the emerging hydroelectric micro-power field in Western Norway. The phrase "social network" refers to a set of actors and the ties among them, which implies that theories, models and applications within this perspective are to be expressed in terms of relational concepts or processes (Wasserman and Faust 1994). Relations defined by linkages among units are considered fundamental. Wasserman and Faust (1994) emphasized that actors and their actions are to be viewed as interdependent rather than depicted as independent autonomous units, and relational ties between actors are channels for transfer of information or material assets.

Thus, what characterizes a social network approach is the sharing of tangible or intangible resources on relationships among the units. This perspective differs in fundamental ways from standard social and behavioral science research. Rather than merely focusing on the attributes of autonomous individual units, this approach views characteristics of the social units as arising out of structural processes where relational ties among actors are primary and attributes of actors are secondary (Wasserman and Faust 1994). Given a relevant collection of actors, social network analysis can then be used to study the structural variables measured for actors in the set.

Network data for this study was gathered from hydroelectric micro-power start-ups in Western Norway between September 2002 and January 2003. The plants from which I gathered data were established in the region between 1994-2001. I applied a so-called "snow-ball" sampling procedure where previously unrecognized candidates were captured by indications from already identified and approached actors. The total sample of start-ups from which I have network data is 23, representing a response rate of 92% from relevant actors.

Network variables at actor level and niche level represent predictors of social capital and comprise independent variables in this study. I also gathered data on autonomous actor attributes such as total financial investments at the plant and yearly electricity production, which was modeled as the dependent variable. Details about how I modeled network variables and the dependent variable are given in Chapter 4. There I also depict a number of control variables that I have applied in the study.

Outline

The outline of the dissertation is as follows: In the next chapter, I first discuss the concepts of organizational field (DiMaggio and Powell 1991) and ecological niches (Burt and Talmud 1993; DiMaggio 1986). Next, I present a general overview of the term social capital and describe how the concept can emphasize either the focal actor's external relations or relational characteristics for collectives. I furthermore argue how cross-level and mixed-determinant models possessing both these approaches to social capital can enhance a researcher's understanding of the concept. For illustrative purposes, I address level issues by analyzing two different networks. One is artificial, whereas the second is adapted from Padgett's (1987) study on marital relationships between 15 prominent Florentine families during Italy's renaissance. The last section, which concludes the chapter, is intended to explain in particular what the two approaches to social capital – focal actor's external relations and relational characteristics for collectives – entail. I also clarify limitations of the scope of the study, and finally address a research question.

In Chapter 3 I elaborate a number of hypotheses where I first apply each start-up's network position in the field (i.e. focal actor's external relations) and niche characteristics (i.e. relational characteristics for collectives) as the independent variables. This accordingly implies cross-level and mixed-determinant approaches to the concept of social capital. Next, I shift the focus outward from network variables and address issues from population ecology theory and institutional theory. Here, I question whether the start-up success/failure of either an early or late adopter in an emerging field is a possible outcome of population density (Hannan 1986) or mimetic behavior (DiMaggio and Powell 1991).

Chapter 4 addresses the research methodology that I have applied in this dissertation. I describe in detail how I gathered the data and modeled the dependent variable, independent variables and control variables.

The hypotheses are empirically tested in Chapter 5. In addition to presenting and discussing the results, I also give emphasis to other potentially interesting findings that are not necessarily reflected in the proposed hypotheses.

Chapter 6 concludes the dissertation. Here, I highlight the study's contribution to the field of organization studies in general and social capital theory in particular. I portray a few practical implications from the findings in this study, address some limitations, and finally point out avenues for further research.

2. Theory, Conceptual Clarifications, and Research Question

In this chapter, I elaborate the concept of organizational fields within the social network perspective first. I also argue that a convenient approach to study subsets of organizational actors in a field is to conduct block-modeling techniques to distinguish structurally equivalent actors, defined as ecological niches (Burt and Talmud 1993). Next, I present a brief overview of the very concept of social capital, and describe how a focus on focal actor's external relations and relational characteristics for collectives entail different approaches to the term. I furthermore illustrate how cross-level and mixed-determinant models possessing these forms of social capital represent metaphors of focal actor's network position in the field and niche characteristics, respectively. For illustrative purposes, I address level issues in the study of two different networks. The first is artificial, whereas the second is adapted from Padgett's (1987) study on marital relationships between 15 prominent Florentine families during Italy's renaissance. The last section, which concludes the chapter, is intended to explain in particular what the two approaches to social capital – focal actor's external relations and relational characteristics for collectives – entail. I also clarify limitations of the scope of the study, and finally address a research question.

Organizational Fields and Ecological Niches

Organizational Fields and the Social Network Perspective

Organizational Fields. The emergence of the organizational field paradigm in organization and political studies has challenged scholars throughout the research community about how to approach and uncover corporate and political issues within this framework. The concept is defined as *"those organizations [or corporate actors] that, in the aggregate, constitute a recognized area of institutional life: key suppliers and product consumers, regulatory agencies, and other organizations [or corporate actors] that produce similar services and products"* (DiMaggio and Powell 1991: 64-65).

Lauman, Galaskiewicz et al. (1978: 456) held that functional differentiation of organizational roles, reliance of individuals on bureaucratic organizations, and increasing rates of individual mobility all create situations where corporate actors are the most stable and efficacious participants in community life. According to DiMaggio and Powell (1991), the virtue of the field approach is that it directs the attention not simply to competing firms, as does the population approach (Hannan and Freeman 1977), but to the totality of relevant actors. At the national level, Scott and Meyer (1983) observed a trend toward "societal sectorialization," whereby the key actors in functional areas such as health, communications, or education are national systems of organizations coordinated through potent but fragmented network ties.

Studies of organizational fields, thus, promise to reconstitute large portions of macro-sociology at the inter-organizational rather than the societal level (DiMaggio and Powell 1991). For instance, if earlier work on education tended to regard the structure of schools as "emerging" out of macro-social changes in value systems (Dreeben 1968), or the needs of corporate elites (Bowles and Gintis 1976), later research located changes in the organization of schools in the specific structure of relations between federal, state, district, and school-level educational authorities (Meyer 1979). Furthermore, more recent research has focused on the market and inter-organizational factors that affect market-segmentation strategies of specific media organizations (DiMaggio 1977), and political scientists have focused on the specific relationships between state agencies and external organizational constituencies as determinants of public policies (Block 1977; Skocpol and Finegold 1982; Useem 1984).

The Social Network Perspective. In order to get a better understanding of the organizational field paradigm, it is helpful to give a brief presentation of what the social network perspective implies. Compared with the organizational field paradigm, I hold that the two lines of thinking complement one another. Whereas the former portrays conceptual content, the social network perspective establishes a methodological framework (which – in addition to organizational fields and ecological niches – can be applied to numerous other theoretical approaches within the area of social science). The phrase "social network" refers to a set of actors and the ties among them (Wasserman and Faust 1994). This implies that theories, models and applications within this perspective are to be expressed in terms of relational concepts or processes. Accordingly, relations defined by linkages among units are considered fundamental. Wasserman and Faust (1994) emphasized that actors and their actions are to be viewed as interdependent rather than depicted as independent autonomous units, and relational ties between actors are channels for transfer of information or material assets. Thus, what characterizes the social network approach is the sharing of tangible or intangible resources on relationships among the units, illustrated in the following example:

> Let us suppose we are interested in corporate behavior in a large, metropolitan area, for example the level of types and monetary support given to local non-profit and charitable organizations (see, for example, Galaskiewicz 1985). Standard social and economic science approaches would first define a population of relevant units (corporations), take a random sample of them (if the population is quite large), and then measure a variety of characteristics (such as size, profitability, level of support for local charities or other non-profit organizations, and so forth). The key assumption here is that the behavior of a specific unit does not influence any other units. However, network theorists take exception to this assumption. It does not take much insight to realize that there are many ways that corporations decide to do things they do (such as support non-profits with donations)... ...In order to get a complete description of this behavior, we must look to corporate relationships, such as shared board of director members, mutual acquaintances of corporate officers, joint business dealings, and other relational variables (Wasserman and Faust 1994: 7).

Thus, the network perspective differs in fundamental ways from standard social and behavioral science research. Rather than merely focusing on attributes of autonomous individual units, or – as described above – emphasizing "something" emerging out of macrosocial changes in value systems (Dreeben 1968), this approach views characteristics of the social units as arising out of structural processes where relational ties among actors are primary and attributes of actors are secondary. Given a collection of actors, social network analysis can then be used to study the structural variables measured on actors in the set. The concept of a network thus emphasizes the fact that each individual actor has tie(s) to other actor(s), each of whom in turn is tied to one or a number of others.

An analyst using this approach would seek to model these relationships to depict the structure of actors, and next he could study how this structure evolves over time or investigate the impact of the structure on actors in the network. To be more precise: Structural variables are measured on pairs of relations/ties among actors. Examples of such ties can be individual evaluations such as friendship, liking and respect, transactions of material resources, strategic alliances between otherwise independent firms, exchange of information and advice, direct interactions, etc. A variety of different measurements can be applied in order to uncover network properties for the network as whole, subsets of actors, or individual units within the observed structure. Statistical methods can, in turn, be exercised to model relationships between different network properties, or relationships between network properties and actor attributes (Wasserman and Faust 1994).

Ecological Niches

The outline above describes how the social network perspectives can be applied to the study of organizational fields. Thus, if a researcher is interested in conducting research in a given field, this line of attack proposes (among other things) careful examination of structural relations between recognized and relevant actors. Of course, the research question and motive of the study should serve as primary guidelines in how to undertake such tasks, yet one recommended technique – which I also implicitly mentioned above – is to somehow partition the field into subsets of actors. Aldrich (1978), Knoke and Rogers (1979) refer to the tendency of inter-organizational networks to develop "stable action sets" or "central cores" of dominant organizations, whereas DiMaggio and Powell (1983: 471) refer to *"the emergence of sharply defined interorganizational structures of domination and patterns of coalition"* in the development of organizational fields. Thus, partition is often desirable on practical grounds as a means of representing complex relational patterns with clarity (Aldrich and Whetten 1981: 385).

A central issue is *how* to conduct proper partitions of organizational fields into sets of corporate actors, and a number of approaches have been suggested. Below, I briefly illustrate partition based on the naturalistic approach, partition based on classification of attributes, partition based on structural cohesion, and finally emphasize why partition based on structural equivalence is perceived to constitute the better option.

The simplest way to partition an organizational field is on the basis of a priori commonsense, to categorize organizational forms such as distinction between firms in manufacturing, finance, or extraction field. This has been called the naturalistic approach. Yet in a number of cases *"researchers who use naturalistic definitions of subgroups run the risk of missing aspects of structure that should be central to analysis – as when...a population of organizations that share a simple nominalist label (e.g. universities) contains subsets of organizations that behave in systematically different ways with respect to some outcome with which the investigator is concerned"* (DiMaggio 1986: 341-342).

Classification on the basis of attributes can imply using bimodalities in percentage of industry sales to partition industry leaders from other firms, or more complex; partition on the basis of discriminant analysis of organization scores on a battery of variables. However, such partitions are likely to confound relational concepts with attribute measures that are more appropriately treated as variables that can explain the formation of relational networks, or dependent variables resulting from firms' structural position (DiMaggio 1986: 342).

Partition methods based on cohesion use matrices or graphs to represent presence or absence of ties between pairs of actors in order to partition those who interact maximally with one another, and minimally with other members in the field. Such methods range from informal approaches to clique detection techniques (Alba 1973), and N-dimensional space (Galaskiewicz 1979; Laumann and Pappi 1976). DiMaggio (1986) argued that such partitions are far superior to naturalistic attribute-based classification, in that they permit assignment of organizations to subgroups independent of factors thought to affect or be affected by the structure of group relations. Nonetheless, cohesion-based partitions do not fully exploit the data available in sociomatrices (Burt 1982), and are consequently often unable to discern sets of corporate actors that share similar relations to other actors without necessarily interacting with one another (Arabie, Boorman and Levitt 1978).

The alternative means of partitioning a field based on observed relations among the members is to divide it into structurally equivalent positions; actors in each subset share similar relations with actors in other subsets, whether or not they are connected to another. Imagine a field of organizational actors connected by flows of information. Subset A shares information with subset B, yet neither A nor B share information with one another. An attempt to partition this population based on cohesion would be unlikely to discern any cliques; it would instead yield a picture of an amorphously structured field consisting of no center and a large periphery. By contrast, structural-equivalence analysis would yield two clearly defined structural positions, occupied by the actors in subsets A and B, respectively (DiMaggio 1986).

Structural-equation approaches are thus more likely than cohesion approaches to identify sets of non-cliquing patterns familiar to scholars conducting research on inter-organizational fields. Among other things, they can indicate roles distributed among actors according to similarity in communication structures (Greve and Salaff 2001), discern patron-client patterns at the subpopulation level, identify occupants of positions in center-periphery structures, where outliers transact only with dominant actors (Meyer 1979), and elucidate brokerage or agency structures (White 1983). Structural equivalence also indicates groups of actors with shared cognitions (Carley 1986; Galaskiewicz and Burt 1991).

A clique is ordinarily a special case of structurally equivalent positions. Consequently, where cliquing patterns are present in the data, analyses based on structural-equivalence criteria will converge with cohesion approaches in the identification of subgroups (except the special case in which clique members' relations are so systematically different as to outweigh their shared mutual ties) (DiMaggio 1986). Cohesion analysis is consistent with Homans's (1958) version of exchange theory, particularly the proposition that interaction creates liking and liking creates interaction. Structural-equivalence analysis, on the contrary, is akin to (and in fact, theoretically derived from) role theory, where the premise is that actors with similar patterns of relations to other units are more similar even if they do not interact with one another directly (White, Breiger and Boorman 1976).

Burt and Talmud (1993) defined an ecological niche as a subset of structurally equivalent actors, and block model techniques can be applied to identify such partitions (White, Breiger and Boorman 1976). A block-model splits actors in the network into discrete ecological niches, and each such pair states the presence or absence of ties within or between them (Wasserman and Faust 1994). Previously, I have referred to tendencies of inter-organizational networks to develop "stable action sets" or "central cores" of dominant organizations (Aldrich 1978; DiMaggio and Powell 1983; Knoke and Rogers 1979) as motivating factors of somehow partitioning organizational field into subsets. Moreover, there are many instances in which structural causes of organizational outcomes may have different consequences for organizations that occupy different partitions in an organizational field, *...[and] many of our theories, explicitly or implicitly, lead to expectations about relations among sets of organizations, rather than single organizations"* (DiMaggio 1986: 341). Partitions of fields are particularly important for research on flows of innovation (DiMaggio and Powell 1983), personnel (Baty, Evan and Rothermel 1971), or information (Boorman and Levitt 1983). Accordingly, a block-model approach to study such patterns should serve as a viable option to uncover complex issues regarding ecological niches.

Later I describe how statistical techniques can be applied in order to perform block-modeling tasks. Armed with the outlines of fields and niches above, I also elaborate how these concepts are congruent with approaches to social capital that emphasize either focal actor's external relations or relational characteristics for collectives. First, however, I present a brief and general overview of the very concept of social capital.

The Concept of Social Capital

A Brief Historical Overview

The first appearance of the concept of social capital in the scientific literature was in Marshal's (1890) book on the "Principles of Economics". Yet, he used the term to refer to different kinds of physical capital. Hanifan (1920) was the first scholar who employed the concept in its present meaning to describe how people get help and support from those in their social network. Yet it would take a period of more than 40 years before the term reappeared in a similar context on community studies (Hannerz 1969; Jacobs 1965).[4] Loury (1977; 1987) used social capital in the area of child psychology, whereas Bourdieu (1972; 1980) developed the term in reference to cultural capital. Wellman (1981) applied the concept in his network study on social support. The first researchers who explicitly used social capital in studies of organizations were Flap and De Graf (1986) in their investigation of job mobility.

Seminal works of Coleman (1988; 1990), Burt (1992a), and Putnam (1993; 1995; 2000) have further pioneered the proliferation of social capital in the social sciences. Coleman developed a general wide-scale theory of social capital in relation to the study of actors who are pursuing interest driven goals, in describing how "closed" and dense networks may create normative sanctioning mechanisms, finely grained information sharing, higher levels of trust, and consequently decreased fear of opportunism. It is probably to date the most widely used framework by organizational scholars (Gabbay and Leenders 1999).

The work of Burt (1992a) was important in its wide visibility among researchers along with his explicit emphasis on actors who are described as competing players in the market place. In his study of managerial mobility in a high technology firm, he was also the first to introduce a quantitative measure for social capital. Whereas White, Boorman et al. (1976) suggested that the absence of ties could provide an advantage, Burt (1992a) showed that actors who were connected to disconnected others (i.e. spanned structural holes) advanced faster in the corporation under study. The causal motor behind this pattern, he argued, is the advantage of playing the role as gatekeeper, in addition to accessing non-redundant information from different sources.

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[4] Before this, use of concept reappeared in Hicks (1942) but with the same interpretation as Marshal (1890).

Putnam (1993) has been influential in his application of social capital to macro development policy issues, some of which are used by macro world-bank policy makers. In another influential contribution, "Bowling alone", he argued that social capital has declined in the United States since the population is now far less likely to become members of community organizations, clubs or associations than they were in the 1950s. Putnam (1995; 2000) illustrated his thesis by charting the decline of bowling leagues.

A number of network studies that did not explicitly employ the term social capital, have also been important in the discussion of the concept. Laumann (1973) presented a comprehensive overview of the form and substance of plural urban networks, whereas Granovetter (1973) in his seminal paper, "The strength of weak ties", greatly influenced the framework when he proposed that weak ties enable the focal actor to access non-redundant information from disparate parts of the system.[5] Lin and colleagues (Lin 1982; Lin, Ensel and Vaughn 1981) have shown how the status and information availability of an alter positively influenced the attainment of occupational status. Scholars have also argued that possessing a central network position is most likely expected to be positive for the focal actor. It is interpreted to represent efficiency, visibility, independence, more alternatives available, and avoidance of relying on mediating positions for access to vital information (Brass and Burkhardt 1992; Freeman 1979; Stephenson and Zelen 1989).

Central Aspects

Social capital has now gained increasing attention in a variety of disciplines and schools of thought, such as economics, political science, management science, and sociology. This is also reflected in an increasing body of literature that discusses the term (for reviews, see for instance Adler and Kwon 2000; Adler and Kwon 2002; Burt 2000; Foley and Edwards 1999; Lin 1999; Lin 2001; Portes 1998; The Economist 2003; Woolcock 1998; Woolcock and Narayan 2000). Moreover, the concept has achieved prominence as a potential answer to researchers' call for *"a good network theory of organization"* in describing *"how structures*

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[5] Granovetter's (1973) "weak ties" argument has been criticized by Burt (1992b: 73) who stated that the causal agent in the phenomenon is not the tie itself, but rather the structural hole it spans. *"The weakness is a correlate, not a cause"*, he asserted. But after controlling for "redundancy effects", Hansen (1999) still found that weak interunit ties helped project teams to search for useful knowledge in other subunits. This effect he attributed to the low cost of maintaining non-binding relationships.

of interactions enable coordinated interaction to achieve collective and individual interests" (Salancik 1995: 348).

However, despite its popularity, or perhaps even because of it, until recently social capital has not been uniformly defined and scholars have argued that lack of conceptual consistency may risk the term being used as a metaphor per se (Burt 1992a; Gabbay and Leenders 2001). Skeptics have characterized social capital, for instance, as *"a wonderfully elastic term"* (Lappe and Du Bois 1997: 119), a notion that means *"many things to many people"* (Naryan and Prichett 1997: 2), and that has taken on a *"circus tent quality"* (De Souza Briggs 1997: 111).

In a recent influential contribution on social capital, Lin (2001) tried to provide an answer to such critical voices by building a coherent and explicit theory of the concept. One of his major concerns was to explain what the term "capital" entails. After taking the reader through the classic Marxian view of capital, followed by a discussion of human capital along with cultural capital, he addressed a thesis of social capital as capital captured through social relations. In this perspective, he argued, *"capital is seen as a social asset by virtue of actors' connections and access to resources in the network or group of which they are members"* (Lin 2001: 19).

He also strongly emphasized that scholars must avoid a functionalist view of the term as adopted by Coleman (1990: 302), who stated that *"social capital is defined by its function"*. Lin (2001: 28) warned that such a view *"may implicate a tautology...It would be impossible to build a theory in which causal effectual factors are folded into a singular function...... [and] incorrect to allow the outcome variables to dictate the specification of the causal variable."* He defined social capital as *"resources embedded in social networks that are accessed and used by actors for actions"* (Lin 2001: 25). The concept has two important components: First, it represents resources embedded in social relations rather than individuals, and this implies that we are avoiding a functionalist view by not capturing the concept by its effects or outcomes.

Nevertheless, Lin (2001: 28) emphasized, *"[t]his is not to deny that a functional relationship may be hypothesized..."*, which shifts the focus to the latter part of the definition. Social capital *"should explain how access to social resources can be mobilized for gains – the process of activation"* (Lin 2001: 29). With regard to empirical evidence of network predictors of the concept, however, empirical findings are largely inconclusive. For instance, whereas a number of studies support Granovetter's (1973) weak tie argument (for a review, see Granovetter 1982), Krackhardt and Stern (Krackhardt 1992; Krackhardt and Stern 1988) posited and illustrated empirically that the pattern of strong friendship ties within a firm is critical to an organization's ability to deal with crises and radical challenges. Findings from a large electronics company have furthermore revealed that weak inter-unit ties helped project teams to search for useful knowledge in other subunits, but impeded the transfer of complex knowledge, which tended to require a strong tie between the two parties to a transfer (Hansen 1999).

A number of studies have also indicated support for Burt's (1992a) structural holes argument (for a review, see Burt 2000), whereas other contributions have showed opposite results (Ahuja 2000a; Hansen 1999). Ahuja (2000a) found that spanning of structural holes from strategic alliances among firms in the chemical industry depressed innovative output in terms of patents issued, while a similar inter-unit network pattern increased project completion time at the unit level in an electronic company (Hansen 1999). These latter findings are accordingly in line with Coleman's (1988; 1990) "closure" argument rather than Burt's "structural holes" theory.

Numerous studies seem to support arguments of the benefits from possessing a central network position (Ahuja 2000a; Baum, Calabrese and Silverman 2000; e.g. Baum and Oliver 1991; Choonwoo, Lee and Pennings 2001; Shan, Walker and Kogut 1994; Smith-Doerr, Owen-Smith and Powell 1999; Stuart 2000; Stuart, Hoang and Hybels 1999). Greve, Golombek et al. (2001), however, revealed a curvilinear relationship with the shape of positive 2nd degree polynomials between pulp and paper mills' centrality in the field and pollution levels. The same study also showed that the interaction effect between education level and centrality depressed pollution level, and other contributions have also revealed interaction effects on the outcome between inter-firm links and organizational characteristics such as age, technological capabilities, and financial resources (Baum and Oliver 1991; Choonwoo, Lee and Pennings 2001; Smith-Doerr, Owen-Smith and Powell 1999; Stuart 2000; Stuart, Hoang and Hybels 1999).

Altogether, the review suggests that both weak and strong ties may induce positive outcomes; the spanning of structural holes seems to be beneficial in some circumstances and negative in others, network centrality can predict linear and non-linear effects on outcome and moreover seems to be contingent upon firm characteristics. The divergences of the findings thus indicate that contextual issues appear to be involved in explaining outcomes and accordingly must be taken into consideration in social capital studies.

Lin's (2001: 25) definition of social capital portrayed the term as *"resources embedded in social networks..."*, and in my empirical context this implies the start-up's network position in the emerging field through his external ties *and* characteristics of the ecological niche into which he is embedded (i.e. relational characteristics for collectives). I did not explicitly conduct research on Granovetter's (1973) "weak tie" theory or Burt's (1992a) "structural hole" approach, yet access to non-redundant information is a part of the development of two hypotheses. Moreover, I hold that redundancy issues are contextually dependent on niche characteristics, so I intend to show how both dense network ties (Coleman 1988; 1990) within niches and contacts to disparate parts of the system (Burt 1992a; Freeman 1979; Granovetter 1973) share in expanding our understanding of the concept of social capital.

In order to conduct such tasks, I present below two approaches to social capital, namely focal actor's external ties *and* relational characteristics for collectives. Moreover, I intend to illustrate how these perspectives represent metaphors of different levels of analysis in the study of the concept.

Actor's External Relations, Relational Characteristics for Collectives, and Level Issues

Two Different Approaches to Social Capital

Most studies that explicitly or implicitly address the concept of social capital either emphasize the focal actor's external relations or examine relational characteristics for collectivities (Adler and Kwon 2000; Gittel and Vidal 1998; Putnam 2000). These different approaches to social capital can best be explained, I argue, through the illustration of a simplistic and hypothetical network as shown in Figure 2.1.

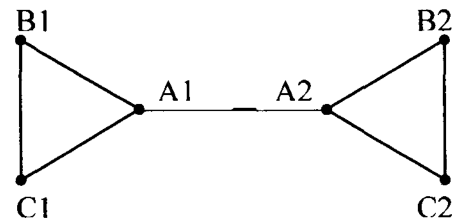

Figure 2.1 Social network structure of a hypothetical organizational field.

Here I portray a structural network or an organizational field consisting of six actors, A1, B1, C1, A2, B2, and C2. The lines illustrate symmetric and dichotomous network ties between pairs of actors. Intuitively we observe two subsets of actors, namely the "ones" and the "twos". A block-modeling technique such as Concor (Convergence of iterated correlations) (Breiger, Boorman and Arabie 1975; White 1983; White, Boorman and Breiger 1976) also makes a similar split, so these subsets can be identified as two distinct ecological niches. For curiosity's sake, we furthermore observe the niches are cohesive with maximum contact or density within them, whereas the tie between A1 and A2 is the only contact between the niches in the field.

If we denied the existence of niches and merely hypothesized that each actor's external relations would be reflected in outcome, we would be likely to expect identical results for A1 and A2, B1 and B2, C1 and C2, due to their equal network positions in the field. For instance, A1 and A2 are able to reach each actor to whom they are not directly connected in fewer steps than the other nodes; whereas A1 only has to pass through A2 in order to reach B2, B1 has to pass through both A1 and A2 in order to reach the same node. Thus, for B1 the distance is twice as long as it is for A1. A1 also has two indirect contacts (B2 and C2) whereas B1 has only one indirect contact (A2). We furthermore observe that A1 and A2 have direct contact with three nodes, whereas the other actors are directly connected to only two nodes. Summed up, this approach is congruent with the approach to social capital that studies the focal actor's external relations, which intends to explain the differential success (or failure) of individuals and firms by their configuration of direct and indirect links to other nodes (Adler and Kwon 2000; Gittel and Vidal 1998; Putnam 2000).

A great number of contributions – that either implicitly or explicitly address the concept of social capital, and where the dependent variable is attainment of gains for the focal actor – comprise the focal actor's external relations. Studies have discovered that organization configurations of direct and indirect inter-firm links predict performance on a variety of parameters such as chance of survival, patenting activity, revenues, time to IPO, stock-market value at IPO, etc. (Ahuja 2000a; Baum, Calabrese and Silverman 2000; e.g. Baum and Oliver 1991; Choonwoo, Lee and Pennings 2001; Shan, Walker and Kogut 1994; Smith-Doerr, Owen-Smith and Powell 1999; Stuart, Hoang and Hybels 1999).

Burt's (1992a) structural hole theory also belongs to the same camp. If we again look at Figure 2.1, we observe that A1 and A2 are the only nodes having direct access to information from both niches. These actors can, according to Burt's argument, gain access to information from disparate parts of the system through their external relations, and play the role of gatekeeper to other actors within their respective niche.

Concerning the investigation of relational characteristics for collectives, the conceptual content is somewhat ambiguous in my opinion. The major issue is the lack of a clear precision of what constitutes a set of collective actors, and the best way to illustrate this is to present a number of definitions that capture this approach to the concept of social capital. In Table 2.1, we see a variety of descriptions such as *"citizens"* (Brehm and Rahn), *"social structure"* (Coleman), *"groups and organizations", "members of a group"* (Fukuyama), *"a culture"* (Inglehart), *"social organization"* (Putnam), and *"civil society"* (Thomas). In this regard, it is essential to bear in mind that a definition is neither right nor wrong, only more or less useful (Grønhaug and Kaufmann 1988). Depending on the research question and purpose of study, such a variety of what constitutes a "collective" is accordingly defendable. Yet at the same time, focus can be lost in order to uncover underlying processes that one way or another are expected to produce some kind of (hopefully) positive outcome for members of an identified collective.[6]

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[6] Other relevant approaches to study collective forms of social capital are to conduct comparisons between identified collectives or comparisons between actors inside or outside a given collective. For an excellent discussion of how to compare relationships between structurally equivalent niches, see Wasserman and Faust (1994: 417-423).

Brehm and Rahn (1997: 999)	"the web of cooperative relationships between citizens that facilitates resolution of collective action problems."
Coleman (1990: 302)	"Social capital is defined by its function. It is not a single entity, but a variety of different entities having two characteristics in common: They all consist of some aspect of social structure, and they facilitate certain actions of individuals who are within the structure."
Fukuyama (1995: 10)	"the ability of people to work together for common purposes in groups and organizations."
Fukuyama (1997)	"Social capital can be defined simply as the existence of certain sets of informal values or norms shared among members of a group that permit cooperation among them."
Inglehart (1997: 188)	"a culture of trust and tolerance, in which extensive networks of voluntary associations emerge."
Portes and Sensenbrenner (1993: 1323)	"those expectations for action within a collectivity that affect the economic goals and goal-seeking behavior of its members, even if these expectations are not oriented toward the economic sphere."
Putnam (1995: 67)	"features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit."
Thomas (1996: 11)	"those voluntary means and processes developed within civil society which promote the collective whole."

Table 2.1 Definitions of "collective" forms of social capital. Adapted from Adler and Kwon (2002: 20).

Previously, I have argued that a preferable way to partition an organizational field into subsets of actors is to apply block-modeling techniques in order to identify ecological niches. This also represents a consistent approach to capturing different collectives within a larger network structure. Among the few studies I have found that apply such an approach is Walker, Kogut et al.'s (1997) study of the formation of an industry network among young biotech firms. They discovered that structurally equivalent actors had a larger propensity to establish ties within their own niche than with organizations on the outside. Unfortunately, the authors did not measure how the emerging structure affected performance, but in a study on pulp and paper mills in Norway, Greve, Golombek et al. (2001) discovered that mills structurally equivalent with universities and research institutions had lower pollution levels compared to mills outside these niches. Thus, this latter contribution indicates that certain relational characteristics for collectives seem to have explanatory power in portraying whether social capital is present or not.

If we apply the collective approach of social capital to Figure 2.1, this perspective does not emphasize the network configuration of each actor's external relations, but rather examines differences in organizational outcome as an effect of belonging to either the niche of "ones" or "twos". In order to do this, we have to dig a little deeper than merely examine issues such as the node's position in the field.

To my knowledge, there are no empirical studies where the focal actor's external ties and relational characteristics for collectives have been simultaneously examined. Nor have I observed contributions examining possible interaction effects between these two approaches. Later I argue the importance of conducting such research, yet since this approach implies a cross-level and multi-determinant line of attack, I elaborate in general what these level issues imply first.

Cross-Level and Mixed-Determinant Models

Cross-level models *"describe the relationship between independent and dependent variables at different levels"* (Rousseau 1985: 20). If, for instance, a model predicts that individual group members respond to a characteristic of the group in a comparably homogenous fashion, this cross-level model predicts within group homogeneity. That is, it predicts that both the group characteristic (the independent variable at a higher level aggregate) and individual behavior or outcome (the dependent variable at a lower level aggregate) is homogenous within groups. Instead, some cross-level models predict, implicitly or explicitly, that individual group members respond to a group-level characteristic in a disparate, rather than homogenous fashion. Here, the model's independent variable is homogenous within groups, but the dependent variable is not; it varies both within and between groups (Klein, Danserau and Hall 1994).[7] A theorist might furthermore posit that the independent characteristic of group members moderates the relationship of the group characteristic to individual behavior

[7] It can also imply that the independent variable is heterogeneous, i.e. the model focuses on individual attributes relative to the group average for this attribute. This has been described as "frog pond effects" (Firebaugh 1980), "within-group effects" (Glick and Roberts 1984), or "parts effects" (Danserau, Alutto and Yammarino 1984). Within one context or higher level aggregate (e.g. group), a given value at a lower level aggregate (e.g. individual characteristic or outcome) may be relatively large. Within a second context, the same value at a lower level aggregate may be relatively small. In this dissertation, however, I do not discuss this issue any further, but for more details and examples, see Klein, Danserau et al. (1994).

or outcome. Group members for whom the moderator is high, respond to the group characteristic in one way, whereas group members for whom the moderator is low, respond in a different fashion (Bedeian, Kermery and Mossholder 1989; Bryk and Raudenbush 1992; Danserau, Alutto and Yammarino 1984; Tate 1985). Thus, the interaction term expressing the combined effects of the homogenous group characteristic and the independent individual characteristic varies both within and between groups (Klein, Danserau and Hall 1994).

Mixed-determinant models suggest that predictors at a variety of levels may influence a criterion of interest. For instance, market characteristics (e.g. the availability of jobs), group characteristics (e.g. diversity within the group), and individual characteristics (e.g. job satisfaction) have all been hypothesized to influence employee turnover (Hulin, Roznowski and Hachiya 1985). Thus, whereas the interaction term in cross-level models produces combined effects on individual behavior or outcome from the homogenous group characteristic and the independent individual characteristic, mixed determinant models generate additive effects from the same (or other) levels.

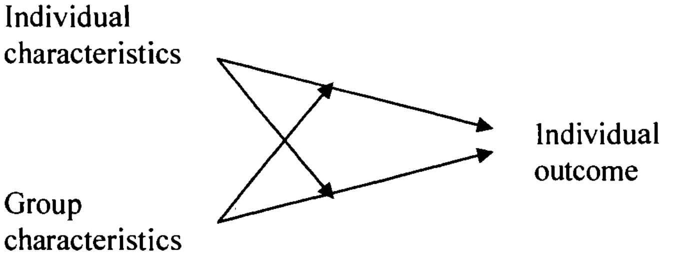

Figure 2.2 A cross-level and mixed-determinant model.

Figure 2.2 illustrates a cross-level and mixed-determinant model. Individual outcome in this stylistic example can be work satisfaction, which varies among employees both within and between groups, for instance. The independent variable at a lower level aggregate – individual characteristic – can be the employee's educational level, which is also likely vary both within and between groups. And finally, independent variable at a higher level aggregate – group characteristic in our example – can be high or low level of pressure to group conformity. Thus, this simple model illustrates cross-level effects by exemplifying interaction effects between educational level and level of pressure to group conformity on work satisfaction. We can, for instance, assume that for highly educated employees, pressure to group conformity will have a stronger negative impact on work satisfaction than for less educated employees.

Moreover, the arrows illustrate that the same independent variables have an additional effect on work satisfaction, and this shows that we also have a mixed-determinant model. Thus, even after controlling for interaction effects (and level of pressure to group conformity), a researcher might discover that highly educated employees report overall higher work satisfaction than less trained members of staff. At the same time – after controlling for both interaction effects and education level – pressure to group conformity can have a negative effect on the dependent variable.

The suggested cross-level and mixed-determinant effects on job satisfaction can be illustrated in Figure 2.3. In Figure 2.3a, we see that high pressure for group conformity depresses reported job satisfaction. Yet, we also observe that for employees within the group of high pressure to conform, educational level still positively predicts the dependent variable, but at a lower degree compared to the other group. Thus, we have both an interaction effect and additional effects for both independent variables at different level aggregates. Altogether, this implies that we are dealing with a model that is both cross-level and mixed-determinant. For curiosity, I have also included Models b and c. In Model b, we only observe additional effects from the independent variables at different levels on the dependent variable (but no interaction effects), indicating a purely mixed-determinant model. In Model c, on the other hand, we find cross-level effects, but no additional effects.

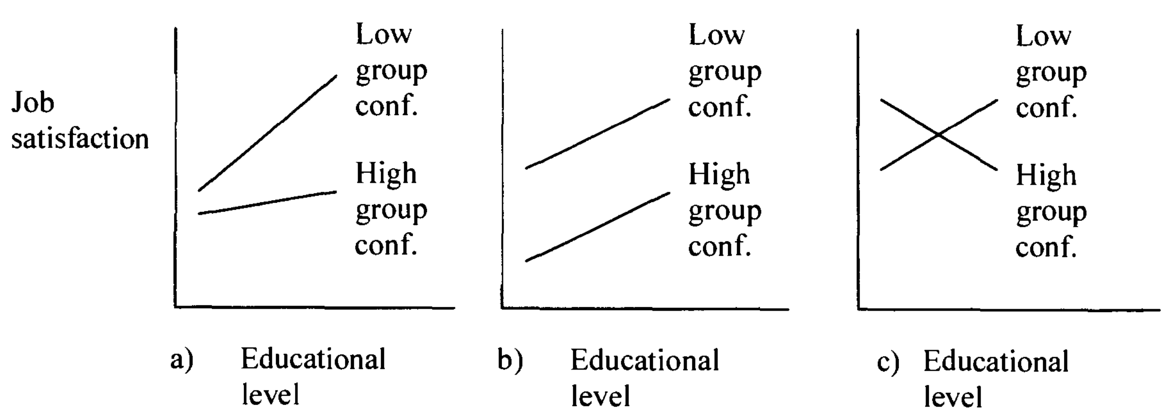

Figure 2.3 Examples of prediction effects from cross-level and mixed-determinant models.

This simple illustration accordingly shows that a careful examination of predictors at different levels of analysis can enhance researchers' understanding of social phenomena. Given that Model 2.3a is the correct one, if we had only studied the relationship between educational level and job satisfaction, knowledge of interaction effects with group characteristics, such as pressure to conformity, would have been foregone. Furthermore, we would have missed the insight that educational level still predicted the dependent variable, even after controlling for both group level characteristics and interaction effects. Moreover, we would fail to notice that pressure to group conformity not only interacts with educational level, but also has a unique (negative, I assume) effect on job satisfaction, even after controlling for the independent variable at a lower level aggregate. In the worst case, researchers who did not address level issues such as those in our example would have observed merely insignificant effects in their regression analyses by not taking into account that what influences job satisfaction (possibly) implies multi-level determinants. This would be case if Model 2.3c appeared to be the "true" one.

Level Issues in Network Research. If we turn back to the hypothetical network shown in Figure 2.1, I would like to now describe how level issues may have impact on the focal actor in the field. Previously I have explained how each actor's external relations capture individual network characteristics and to quantify each node's position within the system, a number of measures have been developed, such as network centralities (e.g. Freeman 1979) or constraints (Burt 1992a). In turn, these measures can be applied to uncover how they affect individual behaviour or outcome. In the methodological chapter, I describe these issues in detail, but for the time being, I maintain that each actor's network position in the field through his external relations is analogue to individual characteristics, i.e. lower level aggregate.

Let us now assume that prior research has taught us that within niche "one" in Figure 2.1 there is a high level of pressure for group conformity, whereas in niche "two" such pressure is low or absent. This is exactly the same higher-level aggregate variable as described above. Let us furthermore assume that each actor or node has been assigned individual tasks that can be characterized as complex and novel. In order to highlight the importance of high or low pressure to group conformity, the outcome for each node would have to benefit the niche as a whole. Thus, each actor has an incentive to achieve the highest possible outcome for him, as well as for the rest of the niche. Actors can exchange information on pairs of relations as illustrated in Figure 2.1.

If we only considered each node's network position through his external relations – i.e. analogue with lower level aggregate – it would be likely to expect that A1 and A2 would be in equally advantageous positions, compared to the other nodes. They have more direct and indirect access to information, and receive non-redundant feedback from disparate parts of the system. We would accordingly expect similar results for A1 and A2, and the rest of the nodes (B1, C1, B2, C2), respectively, in terms of individual outcome. Yet, contextual features may complicate such a pattern. A high level of pressure for group conformity in niche "one" would most likely suppress open discussion, which in turn would depress the accumulation of novel ideas, considered essential in solving complex tasks. Thus, each node in niche "one" is likely to suffer from this attitude, which would probably lead to lower individual outcome (and for the niche as a whole). In niche "two", the situation would probably be the other way around, since open discussion encouraging a high degree of diversity of inputs would play a part in solving complex and novel tasks.

Altogether, I expect that the node's network position in the field and niche characteristics matters in solving novel and complex tasks, but we do not know how the different level aggregates work together. Nevertheless, I expect that we would achieve results similar to either models a) or b) in Figure 2.4, implying a combined cross-level and mixed-determinant model (a), or a pure mixed-determinant model (b). Thus, being a central actor helps, but niche characteristics (such as level of pressure to group conformity) have a unique negative effect, I argue (models a & b), and possibly depress the advantages of being a central actor (model a).[8]

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[8] Depending on type of task, we could also assume that the situation would be the other way around. If, for instance, the actors were assigned routine tasks with low level of complexity and novelty, a high degree of pressure to group conformity could help to focus on the task at hand and speed up the process.

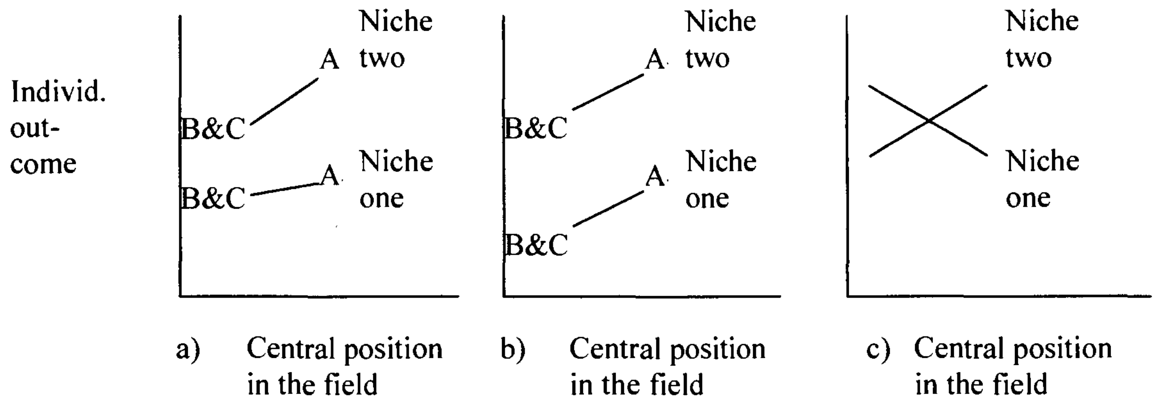

Figure 2.4 Revised examples of prediction effects from cross-level and mixed-determinant models.

Two Illustrations of Level Issues in Network Analysis

Illustration One. A slightly modified network in Figure 2.5 illustrates more comprehensively how the understanding of causal mechanisms in network studies can be lost if we do not carefully consider level issues.[9] Here one actor, D1 and D2, respectively has been added to each niche. As before, the network structure is symmetric, dichotomous, and the "ones" and "twos" possess equal individual positions through their external relations. From the figure, we furthermore observe that A1&2, B1&2, and C1&2 represent core players of each niche, whereas D1&2 are distant actors. A1&2 are still the most central actors in the field, bridging the two niches. C1&2 are the second most central actors through their connection to D1&2. B1&2 are the third most central actors, and finally D1&2 are the least central players.

[9] I acknowledge DiMaggio (1986: 339-340) for the idea of this illustration.

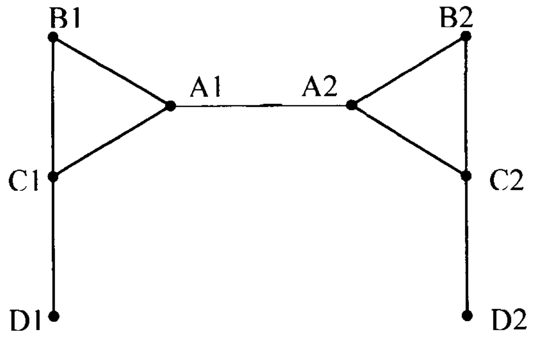

Figure 2.5 A modified network.

Let us furthermore suppose that the propensity for each actor to comply with the pressure of group conformity is contingent upon how close he is to the core-players in niche "one". We see that D2 is the most distant actor from the niche (he has to pass through C2 and A2 before reaching A1), B2 and C2 the second most distant actors (they have to pass through A2 before reaching A1), and A2 and D1 the third most distant actors (they have direct contact with core-players in niche one, A2 with A1, and D1 with C1, respectively). Thus, D2 will be negatively affected by conformity pressure to a very low degree, but at the same time, he possesses a distant position, constraining him to reduced input from the other parts of the network in solving novel and complex tasks. A1 is in the opposite situation. Belonging to a niche where conformity pressure constrains output, at the same time, he holds a central position in the network.

If a researcher overlooked how niche characteristics (i.e. higher level aggregate) interacted with the players' network position through their external ties, he could merely have obtained insignificant results if he conducted analyses on actors in this field, and the following illustration exemplifies this issue. For simplicity, I have granted the nodes in the network with the following centrality scores: A1&2 = 3, C1&2 = 2, B1&2 = 1, and D1&2 = 0. I moreover gave the actors following distance scores from the core-players in Niche 1: D2 = 3, C2&B2 = 2, and A2&D1 = 1. Since A1, B1, and C1 make up the core in Niche one, I gave them distance score 0. The individual task at hand is as complex and novel as before, with equal sharing of outcome within each niche.

Altogether, individual outcome is a function of network position and the distance from core-actors in Niche one. More formally:

$$F(\text{network position, distance from the core in niche one}) = \text{Individual outcome} \quad (1)$$

We know that, with everything else being equal, possessing a central position is positive for individual outcome and distance from core-players in Niche one is also positive, and the equation below suggests such a relationship:

$$\text{Individual outcome} = \text{network position} + (\text{distance from the core in Niche one})^2 \quad (2)$$

If we apply the centrality scores and the distance scores to the core players in niche "one", and furthermore assume Equation 2 to be the "true" one, individual outcome will be as follows: A1 = 3, B1 = 1, C1 = 2, D1 = 1, A2 = 4, B2 = 5, C2 = 6, and D2 = 9. Let us furthermore suppose that a researcher – lacking any prior knowledge of our "true" model (Equation 2) – intends to uncover the underlying mechanisms behind the observed results.

a)

	Mean	Std Dev	Outcome
Outcome	3.875	2.748	
Centrality	1.500	1.195	-.152

	Skewness	Kurtosis
Outcome	.884	.277
Centrality	0	-1.456

b)

	Model 1	Model 2	Model 3	Model 4
Intercept	4.400	3.875	4.400	4.400
	(2.535)	(6.560)	(4.221)	(7.012)
Centrality	-.350		-.350	-.350
	(-.377)		(-.628)	(-1.043)
Niche1		-2.125*	-2.125*	-2.125**
		(-3.597)	(-3.411)	(-5.667)
Centr*Niche1				1.050*
				(-3.13)
R^2	.023	.683*	.706*	.915*
R^2Adj	.140	.630*	.589*	.851*

Dep. var: Outcome; n =8; § p<.10; *p <.05; **p <.01 (two tailed tests)

Table 2.2 Correlation matrix and regression analyses.

The correlation matrix (Table 2.2a) indicates an insignificant effect between actor centrality and the dependent variable, and ordinary least square regression analyses in Table 2.2b (t-values in parentheses) reveals a similar picture in all models. Thus, if a researcher only emphasized the actor's external relations he would (wrongly) conclude that individual network position does not matter. Model 2, on the other hand, reveals that the dummy variable for niche significantly predicts the outcome, indicating that relational characteristics for collectives have causal power. As expected, actors in Niche 1 – allowing open discussion in solving novel and complex tasks – are likely to outperform their colleagues in Niche 2. The parameter moreover remains stable in Model 3, which investigates possible mixed-determinant effects (i.e. combined effects from the focal actor's network position and niche effects). Yet if we now look at the interaction term between actor centrality and niche effects in Model 4, we observe that individual network position does matter, but is contingent upon to which niche the actor belongs. The adjusted R-square is also considerably higher here compared with the previous models.

Altogether, from this particular case we can conclude that social capital appears to be a mixed-determinant and cross-level phenomenon, where both the focal actor's network position along with the relational characteristics for collectives are predictors of outcome. The above outline can also be shown in Figure 2.6 (adapted from Model 4 in Table 2.2b), which illustrates interaction effects between niche characteristics and network centrality. In Niche 2, being a central actor is negative, whereas the opposite is the case in Niche 1. If the lines had crossed each other as they do in Figures 2.3c and 2.4c, we would have a purely cross-level model. Thus, broadly spoken we can say that our model "approaches" such a model.

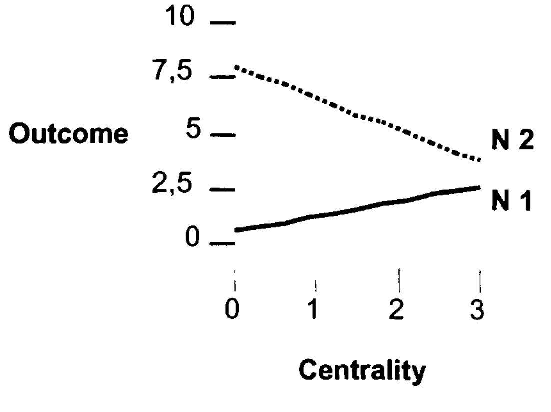

Figure 2.6 Mixed determinant and cross-level effects. Adapted from Model 4, Table 2.2b.

Even after conducting interaction effects between the actor's network positions in the field and dummy for which niche he belongs to, the researcher would still lack complete information about our "true" model. Yet, by also including Model 4 in the analyses, I argue that he is now in a much better position to start unearthing better and more comprehensive network predictors of actor outcome.

Illustration Two. Nevertheless, the above illustration of a cross-level and mixed-determinant model is admittedly utterly artificial. It is therefore defendable to include another illustration, this time with real data, compiled by Padgett (1987) and based on Kent's (1978) history of families in 15th Century Florence, Italy. The original dataset includes both marriage and business ties for 116 leading Florentine families of this period, but in this illustration, I chose marital ties for a collection of 15 families because of their historical prominence.[10] The family was an important economic and political unit at this time (Breiger and Pattison 1986), and in the early 1430s a political battle was waged in Florence for control of the government, primarily between the Medici and the Strozzi families (Padgett 1987). A marital tie exists between a pair of families if a member of one family marries a member of the other. Figure 2.7 illustrates the structural network on these relationships and the numbers in parentheses portray the families' net wealth in 1427, as taken from government records. The wealth variable thus depicts autonomous characteristics (Wasserman and Faust 1994).

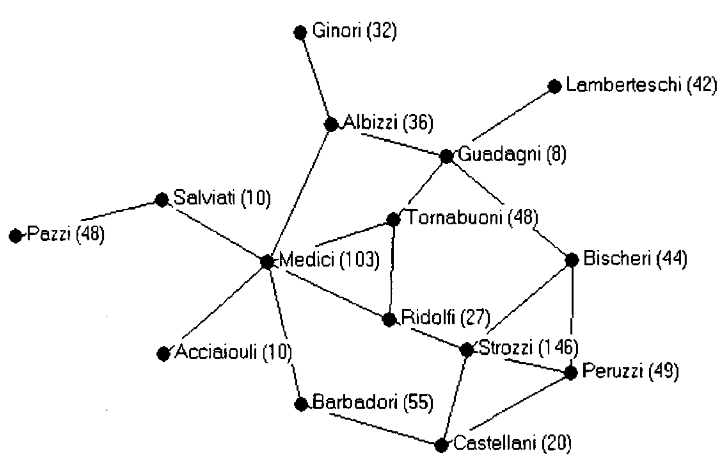

Figure 2.7 Marital ties between 15 Florentine families.

[10] The reduced dataset – presented in both Wasserman and Faust (1994) and Borgatti, Everett et al (2002) – contained 16 families, but since one of them is an isolate I deleted this node from the analyses.

Concor (Breiger, Boorman and Arabie 1975; White 1983; White, Boorman and Breiger 1976) identifies four ecological niches as shown in Table 2.3, whereas Table 2.4 illustrates densities within and between each block (all network analyses are calculated in Ucinet 6.12, Borgatti, Everett and Freeman 2002). An important issue to consider when using Concor is to decide how fine the partition should be. Wasserman and Faust (1994: 378) held that *"[t]heory and interpretability of the solution are the primary considerations in deciding how many... [partitions] to produce."* They furthermore argued that making too many splits can lead to unstable correlations, due to the small number of elements. I have therefore used Concor to divide the network into 4 niches, i.e. I conducted two splits, and this is also interpretable. Moreover, in unreported analyses I changed the number of splits, but the change in R-square indicates no other specific saturation point.

Network density is a measure of how many relations *(l)* among *(n)* actors (in this case marital ties among Florentine families) exist compared to the maximum possible number of relations, $l/[n(n\text{-}1)/2]$. The overall density (block alpha) in this network is .191. Density levels larger than the block alpha (presented in bold) are considered to be large, portraying niches that are either densely connected within themselves and/or with other niches. Thus, the matrix in Table 2.4 reveals how members are connected within and between niches.

Niche 1	Niche 2	Niche 3	Niche 4
Acciaiouli (10)	Pazzi (48)	Bischeri (44)	Guadagni (8)
Albizzi (36)	Ginori (32)	Peruzzi (49)	Lamberteschi (42)
Barbadori (55)	Medici (103)	Castellani (20)	
Ridolfi (27)		Strozzi (146)	
Salviati (10)			
Tornabuoni (48)			

Table 2.3 A block model of structurally equivalent actors.

	Niche 1	Niche 2	Niche 3	Niche 4
Niche 1	.067			
Niche 2	**.444**	.000		
Niche 3	.083	.000	**.833**	
Niche 4	.167	.000	.125	**1.000**

Table 2.4 Density matrix. Block alpha = .191

Figure 2.8 displays graphically the density structures in the field within and between niches and sums up what Table 2.4 tells us. We observe low density (indicated by the dotted arrow) within Niche 1, high density between Niches 1 and 2 (indicated by the lined arrow), absent density within Niche 2 (absent arrow), low density between Niches 1 and 4, low densities between Niches 1 and 3, and finally low density between Niches 3 and 4. The density is high within both Niches 3 and 4. Finally, there is no direct contact between Niches 2 and 3, and 2 and 4, respectively.

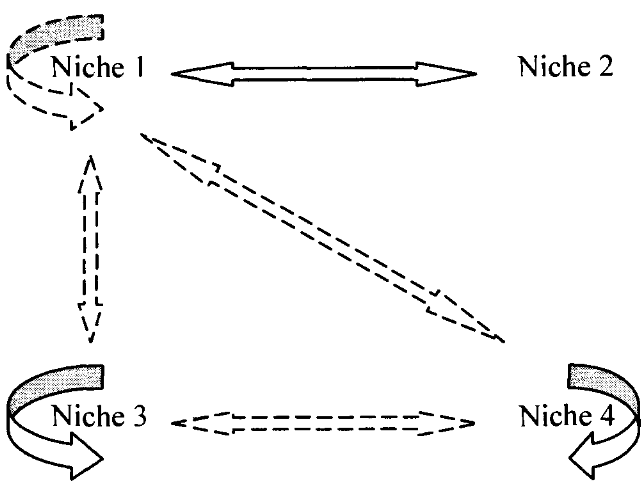

Figure 2.8 Graphical display of densities in relations within and between niches.

Table 2.5 introduces the measure of information centrality, derived from information theory and developed by Stephenson and Zelen (1989). It indicates the amount of information at each node in the network, calculated from the flow of communications through all paths of a network from all other nodes. Long paths contain less information than short ones due to the loss of information at each node. Thus, this measure of centrality uses all paths in a network, but gives them relative weighting as a function of the information they contain (for further details, see Stephenson and Zelen 1989). The correlation matrix (Table 2.5a) indicates a positive but insignificant relationship between this centrality measure and family wealth (I used the natural logarithm of wealth, WealthLn, due to kurtosis), and Models 1 and 3 in Table 2.5b show a similar picture (t-values in parentheses). Models 2 and 3 furthermore suggest that the niche the families belong to has no relationship with wealth.[11] Thus, given that a

[11] In JMP (2003), the nominal variables were expanded to all levels implying that the estimate for Niche 4 is the negative mean for the estimates of the other niches. In this way it is illustrated how each nominal factor deviates from the average of the other factors. In this particular case, it measures to what extent families in a given niche

researcher conducted no further analyses, he would accordingly (wrongly) have rejected any relationships between the described network parameters and family wealth.

a)

	Mean	Std Dev	WealthLn
WealthLn	3.520	.824	
InfoCentr	.747	.193	0.269

	Skewness	Kurtosis
Wealth	1.777	3.598
WealthLn	-.290	-.180
InfoCentr	-.433	-.775

b)

	Model 1	Model 2	Model 3	Model 4
Intercept	2.664	3.510	2.562	.249
	(3.038)	(15.800)	(2.936)	(.171)
InfoCentr (IC)	1.147		1.290	3.996§
	(1.007)		(1.123)	(2.232)
Niche1		-.283	-.312	-.052
		(-.886)	(-.987)	(-.215)
Niche 2		.481	.594	.903*
		(1.222)	(1.479)	(3.084)
Niche 3		.404	.293	-.393
		(1.127)	(.797)	(-.896)
Niche 4		-.601	-.575	-.457
		(-1.321)	(-1.275)	(-1.414)
Niche1*IC				.132
				(.063)
Niche2*IC				-2.544
				(-1.322)
Niche3*IC				10.489§
				(2.073)
Niche4*IC				-8.077**
				(-3.687)
R^2	.072	.268	.350	.806*
R^2Adj	.001	.068	.090	.612*

Dep. var: WealthLn; n =15; § p<.10; * p<.05; ** p<.01 (two tailed tests)

Table 2.5 Correlation matrix and regression analyses.

Model 3 is purely mixed-determinant, omitting possible cross-level effects between actor centrality and the niche parameter, while Model 4 includes interaction terms between them. With other words, in Model 4 we also allow for possible cross-level effects and the analyses definitely show a different picture. First, explained variance has increased dramatically – the

(e.g. Niche 1) are different in wealth as compared to the totality of families in the other niches (e.g. Niches 2, 3 and 4). Despite insignificant results in Models 2 and 3, contrast effects in JMP (2003) showed that the combined wealth for Niche 2 and 3 was significantly higher than the combined effect for Niches 1 and 4. In Model 2, t-value = 1.99 (p<.10) and in Model 3 t-value = 2.02 (p<.10).

adjusted R-square jumps from 9.0% in Model 3 to 61.2% in Model 4 – and is now also significant. We furthermore see that information centrality significantly predicts wealth ($p<.10$), and that Niche 2 is significantly wealthier than the other niches.[12] This piece of empirical evidence thus indicates that cross-level models can increase our understanding of social phenomena in general and network predictors at different level aggregates in particular.

The Medici's' wealth was possibly a result of possessing an overall central position in the network, both indicated by the highest centrality score (Table 2.6) and the "star" position in Figure 2.7. The family's success can partly be explained by not being connected at all within its own niche but strongly connected to Niche 1 – which is loosely tied within itself and to the other blocks in the field. In this case, it seems that wealth (intentionally or unintentionally) was created through mechanisms at different level aggregates, indicating that mixed-determinant mechanisms were also present.

It is beyond the scope of this dissertation to discuss in detail the possible driving forces behind the observed pattern, yet plausible explanations might be that Burt's (1992a) structural hole theory or Granovetter's (1973) weak tie argument could be manifest at different levels of analyses. The first explains how access to valuable non-redundant information can be achieved by connections with disconnected others throughout the field, whereas the latter predicts that such resources can be achieved by being weakly connected to distinct social circles (which is the case when densities within and between niches are low).

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[12] Despite low sample size and relatively many parameters, the lack of fit function in JMP (2003) gave no warning about loss in degrees of freedom. Furthermore, visual inspection of the data plots in the statistical program did not indicate multicollinearity problem.

Family	Inf. Centr.
Pazzi (48)	.394
Ginori (32)	.483
Lamberteschi (42)	.511
Acciaiouli (10)	.554
Salviati (10)	.598
Barbadori (55)	.763
Peruzzi (49)	.779
Castellani (20)	.794
Albizzi (36)	.830
Bischeri (44)	.832
Strozzi (146)	.878
Ridolfi (27)	.901
Tornabuoni (48)	.902
Guadagni (8)	.917
Medici (103)	1.064

Table 2.6 Information centralities for the Florentine families.

For the Strozzi family in Niche 3, the picture is somewhat different. They are not so central in the overall network – actually there are four other actors that are more central (Table 2.6) – yet they remained the wealthiest family in Renaissance Florence. Why is this? I believe the interaction effects we observe in Model 4 (Table 2.5b) partly provide the answer. We find a positive and significant interaction effect ($p<.10$) on family wealth from information centrality and belonging to Niche 3. Table 2.4 and Figure 2.8 demonstrate that within this subset there is a high density among the families (in addition to being loosely connected to Niches 1 and 4), and it seems that access to information and resources from disparate parts of the systems is particularly beneficial in such a context. Altogether, belonging to a densely connected niche does not seem to provide benefits per se, but is rather contingent upon each actor's position in the field. I will not elaborate this issue in length now, but I will return to the topic in the following chapters.

Finally, we observe a significant negative effect from information centrality on wealth for the families belonging to Niche 4, but if we go back to Table 2.3, we observe that there are only two nodes in this niche. Accordingly, I will not pay too much attention to this finding. Table 2.6 shows that the relatively wealthy Lamberteschi family is not so central in the marital network whereas the position is the opposite for the relatively poor Guadagni family.

To sum up, the analyses show that by including interaction terms between the identified niches and actors' individual network positions, explained variance was greatly increased and we also observed a number of significant parameters. This indicates that both cross-level and mixed-determinant mechanisms were at work, and furthermore highlights the importance of conducting empirical analyses that simultaneously examine both the focal actor's external ties and relational characteristics for collectives. Thus, rather than serving as exhaustive proof of the interplay between different levels of analyses, the above illustration teaches us that there might be "something more" to the concept of social capital than empirical research has so far uncovered. Furthermore, this is in line with Gabbay and Leenders (1999: 5) who argued that the very nature of social capital runs through various levels of analysis and a *"full study of social capital should thus incorporate structure... at multiple levels of analysis."*

I fully acknowledge that the Florentine case does not account for alternative explanations of causality between dependent and independent variables, but nevertheless I argue that the illustration discloses an avenue for further research that I believe will provide fuller and richer insights to our understanding of concept of social capital.

Conclusion and Research Question

Conceptual Clarifications and Limitations of the Scope of the Study

So far in this chapter, I have emphasized that the focal actor's external relations and relational characteristics for collectives represent different levels of analyses in the study of social capital. I have also intended to demonstrate that by using a cross-level and mixed determinant study, researchers may gain a fuller insight of the concept than by merely focusing at one single level. Before ending this chapter, however, I find it legitimate to clarify further a few conceptual issues regarding these different approaches to social capital. First I focus on the focal actor's external relations, and next I emphasize relational characteristics for collectives. Accordingly, the aim with this section is to give these concepts a more explicit description and clarify those limitations I have chosen to conduct in the remaining chapters of the dissertation.

Focal Actor's External Relations. As previously described, the focal actor's external relations can be conceptually interpreted as his configuration of direct or indirect ties. An actor is central locally if he has a large number of connections with other nodes in the immediate environment; i.e. if he has a neighborhood of many direct contacts (Freeman 1979). Thus, local centrality is concerned with the relative prominence of a focal point in the neighborhood

(Scott 2000). Freeman (1979) conceptualized it as a measure of activity and involvement in the network. Brass and Burkhardt (1992) argued moreover that local centrality represents the number of alternatives available to an actor, in addition to the avoidance of relying on mediating positions for direct to access to vital information.

A different approach in the study of the focal actor's external relations is to focus on indirect ties or his overall strategic significance in the relevant network structure. For instance, if he has established external relationships to other actors that in turn are connected to many others, he will possess many indirect ties. The easiest way to operationalize this measure is to simply count the number of indirect ties (Ahuja 2000a). Many indirect ties can indicate that the focal actor has established external relations to other central actors, which in turn may enable him to access more resources and better information than just being connected to alters possessing few ties.

A similar (though not identical) concept is the focal actor whose configuration of external ties enables him to reach each node in the network structure in relatively few steps. This network approach has been denominated *closeness centrality*. Freeman (1979) argued that actor closeness should be measured as a function of geodesic distance, i.e. the shortest number of steps between a given actor to all other actors in the network. As geodesic distance increases in length, the actor's closeness centrality decreases along with his strategic significance in the overall network structure (Scott 2000).

External relations providing focal actor access to non-redundant resources and information can be defined as a positive function of the level of nonadjacent relational ties (Freeman 1979). This statement grows out of the idea that actors in a network are somehow central to the degree they stand between others on the paths of interaction (Anthonisse 1971; Bavelas 1948; Cohn and Marriott 1958; Freeman 1977; Friedkin 1991; Shaw 1954; Shimbel 1953). Among other things, such actors have access to parts of the network that are not strongly connected to each other, allowing richer and more differentiated information to reach them (Krackhardt 1990). Freeman (1977; 1979) has operationalized the concept of actor betweenness centrality as the number of geodesics (i.e. shortest paths) between each pair of nodes in a network that passes through the given actor. In a later contribution, Freeman and colleagues (Freeman, Borgatti and White 1991) further developed the measure to include not only the geodesic paths, but all independent paths between pairs of points in the network.

They argued, *"the flow [of information and other resources] between two points is a global phenomenon; it depends, not just on the capacity of the channel linking the points directly, but on the capacities of all the channels on all paths – both direct and indirect – that connect the two"* (Freeman, Borgatti and White 1991: 146). The refined measure is called *actor flow betweenness*. The idea behind the notion is somewhat similar to Burt's (1992a) structural hole theory. However, whereas Freeman and colleagues emphasized the entire graph, Burt focused on the egocentric network structure in measuring the spanning of structural holes, i.e. to what degree the focal actor's external relations are connected or disconnected to each other.

There are, however, a number of other approaches to study the focal actor's external relations that go beyond the scope of this dissertation. For instance, an actor may report many advice ties to other players, but few others report seeking advice from him. This shows a high level of out-degree centrality, but a low level of in-degree centrality. This may furthermore affect how we model and interpret the other centrality measures that I have described above. Yet since this contribution focuses on symmetric network ties, i.e. we do not emphasize eventual directionality of contacts between nodes, I do not elaborate on this issue (for details, see for instance Freeman, Borgatti and White 1991; Freeman 1979; Scott 2000; Wasserman and Faust 1994).

Studying a focal actor's external relations can also imply a careful investigation of different kinds of network ties. A node can, for instance, have a number of advice ties to other nodes with whom he also shares friendship ties. However, these relations do not necessarily overlap, and for the same actors it is possible to uncover layers of different network structures, dependent upon characteristics of the ties. Krackhardt (1992) claimed that in a study from a high-tech company, friendship ties could better explain how the firm was prevented from being unionized, than advice ties (and formal organizational structure).

I have mentioned Granovetter's (1973) weak tie theory; this is somewhat similar to the argument behind the advantage of accessing non-redundant information, however the causal agent is different. The previous review has also indicated how strong ties may be beneficial in a number of occasions, indicating that the benefits from tie strength are context dependent (Hansen 1999; Krackhardt 1992; Krackhardt and Stern 1988). Research has also undertaken the task of investigating characteristics of the focal actor's partners as opposed to merely studying tie characteristics. For instance, ego may draw benefits from a resourceful alter by means of status, or through the information the alter may offer (e.g. De Graaf and Flap 1988; Lin, Ensel and Vaughn 1981a; Lin, Ensel and Vaughn 1981b; Marsden and Hulbert 1988). In a study of venture-capital-backed biotechnology firms, Stuart, Hoang et. al (1999) found that privately held biotech firms with prominent strategic alliance partners and organizational equity investors went to IPO faster and earned greater valuations at IPO than firms lacking such connections. Another study showed that biotech organizations with large and innovative alliance partners performed better than otherwise comparable firms that lacked such partnerships (Stuart 2000).

All the above illustrations show how a focus on the focal actor's external relations can be undertaken. The research question and purpose of the study must, of course, serve as primary guidelines when deciding which concepts to include or exclude. The three concepts, local centrality, strategic significance in the overall network structure, and the level of nonadjacent relational ties – all described above – constitute the focal actor's external relations that are included as variables in this study. Whereas the two latter parameters play the role as independent variables, local centrality is merely included as a control variable in a number of models. Moreover, the study focuses on symmetric network ties, rather than (eventually) directional ties. Finally, the study emphasizes the very structure of network ties, rather then elaborating on the content of these relationships. As described, this is in accord with Hinde (1976: 8), who referred to the term structure *"as a patterning of relationships that is independent of the particular individuals concerned."* He further stated that *"[i]n moving to this more abstract level we focus on aspects of the content... that show regularities across individuals and across societies..."*

Relational Characteristics for Collectives. The dissertation has so far illustrated that a researcher has a number of options at hand when choosing how to identify groups of actors in a field, varying from partition based upon the naturalistic approach, classification of attributes, structural cohesion, and structural equivalence (DiMaggio 1986). I have finally argued why partition based on structural equivalence is perceived to constitute a better decision (Arabie, Boorman and Levitt 1978; Burt 1982; Carley 1986; DiMaggio 1986; Galaskiewicz and Burt 1991; Greve and Salaff 2001; Meyer 1979; White 1983). If a researcher wants to examine relational characteristics for collectives – e.g. niches of structurally equivalent corporate actors (Burt and Talmud 1993) – he has a number of alternatives at hand. However, as emphasized, research question and purpose of the study must always serve as primary guidelines in how to undertake such a task, yet for niches (or other types of identified collectives) examining the density of contacts is at least one such viable option.

Regarding the density approach, the Florentine case, presented in this chapter, can illustrate how such a task can be conducted. We remember that the density table (Table 2.4) shows the density of marital ties for niches of structurally equivalent families. Earlier in this chapter, I have stated that Coleman (1988; 1990) developed a general wide-scale theory of social capital in relation to the study of actors who are pursuing interest-driven goals by describing how "closed" and dense networks may create normative sanctioning mechanisms, fine grained information sharing, higher levels of trust, and consequently decreased fear of opportunism. If we again turn to Table 2.4, we observe a high density of marital ties within Niche 3 (block alpha = .833).[13] This implies that "almost" all the four families in this niche are connected to each other through marriage. Everything else being equal, the higher the density of relational ties in collectives, the more closed the network is as well. According to Coleman's theory, this should thus create an atmosphere of fine-grained information sharing, trust and low fear of opportunistic behavior for the involved nodes.

However, this line of thinking has not been without criticism. A counterargument to the above argument could be that densely embedded niches, despite fine-grained information sharing and low risks of opportunistic behavior, face the risk of encountering a "redundancy trap" as a result of looking inward and ignoring novel and perhaps better solutions that are being developed in different parts of the system. This is in accordance with both Burt's (1992a) structural hole theory and Granovetter's (1973) weak tie argument, emphasizing the importance of avoiding connections to other, similar nodes. Nonetheless, in the next chapter I argue that these seemingly opposite arguments are complementary rather than contradictive, and convey different levels of analysis.

It is also worth noting that densities of contacts can be studied *across* different niches of structurally equivalent actors. Thus, such an approach not only gives us a clue of what is

[13] Table 2.4 shows that Niche 4 has a density of 1, but this niche only consists of one pair of nodes. The very presence of a martial tie between these two families will consequently produce maximum density, and absence of a tie, minimum density.

going on within niches, but also between niches in the field. Among other things, we can discern patron-client patterns, and elucidate agency structures (White 1983). Density patterns between niches can also investigate the directionality of network ties (e.g. niches of firms that control other niches of firms through ownership). Furthermore, we could study structural equivalence for all kinds of relations, single or multiple relations, dichotomous or valued relations. It is, however, beyond the scope of the dissertation to debate this issue, but for an excellent discussion of different patterns of network ties within and between collectives, and how they can be interpreted, see Wasserman and Faust (1994).

Moreover, regarding the study of characteristics within (and between) niches, a whole variety of variables developed at the group level could be applied, and practically only fantasy limits the researcher. The level of pressure to group conformity, described earlier in this chapter, is one such example.

Brief Summary and Limitations of the Scope of the Study. Summed up, with regard to the focal actor's external relations, this dissertation emphasizes three concepts: local network centrality, strategic significance in the whole network structure, and level of nonadjacent ties. Relational characteristics for collectives imply densities of reported contacts within the respective niches of structurally equivalent actors. The network structure that I have analyzed is non-directional, non-valued, and excludes possible multilayer characteristics. Further details of how I have modeled and measured network variables are described in Chapter 4.

Research Question

In this chapter, I first elaborated the concept of organizational fields (DiMaggio 1991) within the social network perspective. I argued that perhaps the best way to study subsets of organizational actors in a field is to conduct block-modeling techniques in order to distinguish structurally equivalent actors, defined as ecological niches (Burt and Talmud 1993). Next, I presented a brief overview of the very concept of social capital and described how a focus on the focal actor's external relations and relational characteristics for collectives, entails different forms of the term. In the third section, I illustrated how cross-level and mixed-determinant models, possessing these forms of the concept, represent metaphors of the focal actor's network position in the field and niche characteristics. For illustrative purposes, the chapter also addressed level issues by analyzing two different networks – one artificial and the second adapted from Padgett's (1987) study on marital ties between 15 prominent Florentine families. This latter section was intended to clarify a few conceptual issues and limits the scope of the network variables that will be applied in the following chapters.

To sum up, I argue that both theoretical issues as well as empirical illustrations presented throughout the chapter indicate that level issues seem to play an important role in the study of social capital. In particular, it seems that cross-level and mixed-determinant models may enhance a researcher's understanding of both the focal actor's external relations and relational characteristics for collectives, as well as portray effects on focal actor outcome from the interplay between these forms. This motivates the following research question, which is also illustrated in Figure 2.9:

Research Question: Do we observe unique effects or interaction effects on focal actor outcome from his external relations in the field and niche characteristics? Thus, to what extent do we observe cross-level or mixed-determinant network predictors of social capital?

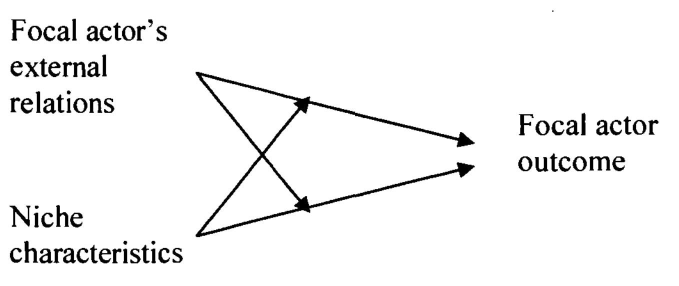

Figure 2.9 A cross-level and mixed-determinant model of social capital.

In the following chapters of the dissertation, I describe in detail how the focal actor's network position in the field and niche densities may affect the outcome in terms of venture success. The next chapter develops a number of hypotheses that entail both these approaches to social capital, and in addition suggests possible interaction effects between the forms. The hypotheses are in turn empirically tested in Chapter 5. The data presented in this study has been gathered from start-ups in the emerging hydroelectric micro-power field in Western Norway.

3. Hypotheses

The major issue in this chapter is to discuss how different network configurations in the emerging micro-power field may enable an entrepreneur to overcome his "liability of newness" (Stinchcombe 1965). Hannan and Carroll (1992) maintained that a great challenge for actors in emerging industries is to establish ties with an environment that neither understands nor acknowledges their existence; yet once these are in place, I argue that network connections can play an extremely critical role for the start-ups in the development of social capital. I elaborate some hypotheses where I apply the focal actor's external relations in the field and niche characteristics (i.e. relational characteristics for collectives). This implies both a cross-level and a mixed-determinant approach to the concept.

The final section of the chapter shifts the focus outward from network predictors of social capital and addresses issues from population ecology theory and institutional theory. Here, I question whether start-up success/failure of being an early or late adopter in the emerging field is a possible outcome of population density (Hannan 1986) or mimetic behavior (DiMaggio and Powell 1991).

Network Configurations and Venture Success

Focal Actor's External Relations in the Field and Venture Success

I believe it can be fruitful to distinguish between the stage of investment and the stage of operation when discussing how network positions in the field may enable small hydro-electrical plants to overcome their "liability of newness". The first stage focuses on how to spend the money as wisely as possible during the investment phase, whereas the latter emphasizes – after invested capital has been "sunk" – how to get the best out of the plant. Below I discuss the first issue, and start with elaborating a hypothesis where I propose a curvilinear relationship with the shape of a negative 2^{nd} degree polynomial between the focal actor's network distance to the center of the field at start-up and electricity production per capital invested (in real terms). I define the center of the field as a position of strategic significance in the overall network (Scott 2000). Thus, I emphasize the focal actor's external relations in the field.

Most ventures are faced with several problems and challenges, and this is especially the case for start-ups in emerging fields. In his seminal paper Stinchcombe (1965: 148) described these constraints as the "liability of newness" stating that *"[a]s a general rule a higher proportion of new organizations fail than old. This is particularly true of new organizational forms, so that if an alternative requires new organization, it has to be much more beneficial then the old before the flow of benefits compensates from the relative weakness of the newer social structure."* Thus, entrepreneurs in young fields have to learn new roles without the benefit of role models in discovering and creating effective routines and competencies (Aldrich 1999; Barron 1998). In spite of that, I review a number of contributions below showing that it is possible to outdo the "liability of newness" by accessing tangible and intangible resources from inter-firm links.

In an ecological study of daycare centers and nurseries in Toronto, Baum and Oliver (1991) discovered that environmental linkages reduced the mortality rate to a higher degree for young establishments compared to older ones. In their interpretation of these findings, they stated *"young organizations that confronted a liability of newness were shown to benefit to a significantly greater extent from institutional linkages than older organizations... Young organizations may be capable of obtaining early legitimacy and access to resources through the formation of institutional attachments, and these stable relations with important constituents may succeed in sheltering young organizations from the risks of youth and inexperience"* (Baum and Oliver 1991: 214). A similar study has shown that young biotech firms benefited more from strategic alliances in terms of growth than did old organizations (Stuart 2000).

Shan, Walker et al.'s (1994) examination of the association between inter-firm cooperation and innovative output is another example from the young biotech industry. Arguing that these organizations lacked financial, marketing and distribution resources on their own, they hypothesized and showed empirically that an entrepreneurial firm's number of cooperative relationships had a positive effect on the number of patents issued. More recently, Stuart and colleagues (Stuart 2000; Stuart, Hoang and Hybels 1999) found that technology start-ups with prominent alliance or exchange partners performed better than comparable ventures without endorsements. Endorsement by well-regarded affiliates increased sales growth rates among U.S. semiconductor start-ups, and resulted in faster initial public offerings (IPO) – at higher valuations – among U.S. biotechnology start-ups. Baum, Calabrese et al. (2000) discovered that the more partnerships the Canadian biotech firms had from founding with pharmaceutical companies, universities and marketing companies, the higher the revenues were in following years. Alliances with pharmaceutical companies, universities and government labs predicted a significant relationship with the number of patents issued. Moreover, the higher the biotech partners' relative scope and innovativeness, the higher the number of patents issued. The interaction effect from partners' relative scope and innovativeness was also positive for both revenues and number of patents issued. Finally, Choonwoo, Lee et al. (2001) have shown that linkages to venture capital companies positively predicted performance for South Korean technological start-ups.

All these findings accordingly indicate certain relationships between ventures' possession of inter-firm links and outcome. It is therefore reasonable to assume that critical resources may span the firm's boundaries within inter-organizational processes and activities (Dyer and Singh 1998). Nevertheless, the studies reviewed above do not explicitly emphasize the focal actor's inter-firm position in the field. Hannan and Carroll (1992: 32) maintained that even if a venture succeeds at creating structures and routines for adapting successfully to the inferior regions of the "resource space", in the course of doing so it may commit itself to persisting at the margins. The specialized learning, the collective experience, and connections with the environment all become specialized to exploiting the areas of lower value. Attempting to shift toward the richer center, on the other hand, entails a high risk of failure during periods of protracted reorganization. If the organization should succeed, it would bring itself into competition with others more experienced in exploiting the center, and in either case, the firm will have a higher than average risk of failure.

In my opinion, the description of the "resource space" above is analogous with what DiMaggio and Powell (1991: 64-65) conceptualized as an organizational field; *"those organizations [or corporate actors] that, in the aggregate, constitute a recognized area of institutional life..."* Drawing upon Hannan and Carroll's (1992) arguments it is thus likely to expect that nascent entrepreneurs – positioning themselves at the margins of the field, or striving towards the center during the investment period – will reap an inferior return from their investments. At the margins, both vendors and advisors, in addition to other already established hydroelectric plants, most likely have inferior abilities in how to achieve optimal output from investments in micro-power systems. They probably possess some knowledge, but only the less experienced reach these inferior sections of the field. Thus, if an entrepreneur places himself at these margins of the "resource space", this will result in inferior and sub-optimal investment solutions.

On the other hand, the candidate who – intentionally or unintentionally – strives towards the center of the "resource space" during the investment stage will most likely encounter vendors and providers with better-developed skills and knowledge than he has. In turn, a high degree of asymmetric knowledge will place the entrepreneur in a disadvantageous bargaining position regarding investments. I argue that this is analogous to a state of asymmetric power relations. According to Emerson (1962: 32), one's power resides implicitly in another's dependency. The dependence of actor A on B is therefore *"directly proportional to A's motivational investment in goals mediated by B, and inversely proportional to the availability of those goals to A outside of the A-B relation"*. The dependence of A on B thus provides the basis for B's power over A, as B is in control of, or otherwise has influence over goods and services that A desires.

Hence, let us now assume that A (e.g. a start-up plant) desires to choose B (e.g. a vendor or consultant of hydroelectric micro-power systems) as his major provider due to his assumption that B is an expert with maximum knowledge in the emerging field. A might have gained such information by communication with other start-ups that have approached B (or other central actors in the field) out of similar motives. He is moreover convinced that he has to choose this provider (or other central actors in the field) rather than marginal actors, believing that central actors will support him with the best and latest technology developed in the field. This, in turn, places A in a disadvantageous bargaining position due to the asymmetric knowledge and power.

It is unlikely to expect any competition for the electricity that will be produced from the start-ups once in place, due to the marginal contribution at each plant and the homogeneity of product. Even though experienced professional providers and consultants should have interests in the electricity market, they would have no incentives in preventing the highest possible production for their clients. Nevertheless, they do desire to reap the highest possible returns for the products and services they provide, and hence have incentives towards encouraging their clients to overinvest, either by selling a plant that is more expensive than the optimal model, or by charging a premium price.

It is also likely to expect that the tendency for overinvestment for start-ups approaching the center of the field would be dampened by cooperation with other micro-power plants that neither sell equipment nor charge anything for sharing experiences and advice with newcomers. Yet, if these plants are also close to the center of the field, they might possibly be unaware of more economical options at hand. Consequently, information and advice will be in accordance with what has been shared from established professional vendors and consultants in the field.

Altogether the review above, illustrating the possibility to overcome the "liability of newness" through access to tangible and intangible resources from inter-actor links, definitely indicates that there are benefits from cooperating with other actors. Yet, my discussion emphasizes that it is important to examine who you choose to collaborate with in the field, or where you place yourself in the "resource space". If the plant establishes itself too distant or close to the center of the field, low performance is the most likely outcome. Actors who place themselves in intermediate positions, on the other hand, escape from the disadvantages described. They are likely to achieve certain knowledge in how to build the plant since they have not placed themselves at the margins with low competence, nor have they been squeezed at the center due to an inferior bargaining position or disadvantaged by asymmetric information.

I have found no study that directly investigates the issues I have described above, yet it is worth noting – as previously briefly stated – that Greve, Golombek et al. (2001) discovered a curvilinear relationship between pollution levels and network centrality in the Norwegian pulp and paper industry. Actors in central and marginal positions had high pollution levels, whereas actors in intermediate positions polluted less. They described the findings as a cry for help from actors with high pollution levels (and also financial problems), but an alternative or complementary explanation could be that actors who strive towards the center in hope of optimal solutions place themselves in an inferior position due to asymmetric information and lack of bargaining power. They therefore become vulnerable to either overinvest or choose suboptimal solutions, so I hypothesize:

Hypothesis 1: There is a curvilinear relationship with the shape of a negative 2nd degree polynomial between the focal actor's network distance to the center of the field at start-up and electricity production per financial capital invested. Production is low for plants at the margins and in the center of the field, whereas it is high for plants in intermediate positions.

Niche Characteristics and Venture Success

So far, I have only emphasized the focal actor's external relations in the field, but in this section, I additionally highlight how niche characteristics may enable start-ups to overcome their "liability of newness". This means that I have expanded the focus to involve relational characteristics for collectives implying both cross-level and mixed-determinant approaches to the concept of social capital. I begin with developing a hypothesis that argues that start-ups embedded in densely connected niches are likely to outperform their colleagues in sparsely connected niches. Next, I propose that access to non-redundant information is more beneficial in densely connected niches than in sparsely connected niches.

Although network ties are essentially dyadic exchanges, the key precursors, processes, and outcomes associated with them can be influenced by the characteristics of the niche into which actors are embedded. Niche characteristics of the Florentine families in Table 2.4 and Figure 2.8 illustrate density levels of contacts (marital ties) between and within the identified subsets, and I emphasize the latter issue below. Previously I have defined niche density as the number of relations *(l)* among *(n)* actors that exist compared to the maximum possible number of relations, $l/[n(n-1)/2]$, within the subset.

Ahuja (2000a) argued that resource-sharing benefits of collaboration arise from actors combining their skills and imparting their knowledge and experience. This is in accordance with a number of other scholars who argued that dense and extensive relations between nodes may foster the development of shared norms of behavior and explicit inter-firm knowledge-sharing routines (e.g. Dyer and Noboeka 2000; Uzzi 1997; Walker, Kogut and Shan 1997). The social constraints associated with dense, embedded networks can facilitate large relationship-specific investments that can help maximize the benefits from collaboration where common partners can serve as referral agents to encourage cooperation and sharing (Gulati 1995; Shan, Walker and Kogut 1994; Uzzi 1997). Deeply embedded networks can also foster fine-grained information transfer and joint problem solving, two essential components of successful resource-sharing (Ahuja 2000a; Uzzi 1997).

Dense ties are furthermore likely to help curb tendencies of opportunistic and genuinely self-seeking behavior (Coleman 1988; 1990; Walker, Kogut and Shan 1997). This is the case when, for instance, consultants and providers are inclined to encourage start-ups to overinvest. Due to close contact between alters, information diffuses rapidly to relevant actors, imposing sanctions on deviant behavior as well as preventing its occurrences.

As described, Ahuja (2000a) discovered that closed egocentric networks of strategic alliances among firms in the chemical industry resulted in higher innovative outputs in terms of patents issued. Similar results have moreover been reported by Hansen (1999), and these findings are in accordance with Coleman (1988; 1990) arguing for the benefits of possessing dense and closed network ties.

Structural-equation approaches can indicate roles distributed among actors according to similarity in communication structures (Greve and Salaff 2001), and in addition identify groups of actors with shared cognitions (Carley 1986; Galaskiewicz and Burt 1991). Accordingly, I find it likely to expect hydroelectric start-ups to perform better in densely connected niches compared to their colleagues in sparsely connected subsets. Considerable sharing of experiences and skills will most likely take place here as a result of the high degree of contacts between actors. This is particularly important in a field where well-developed templates or schemata are to be established from a less extended and more fragmented knowledge base (Aldrich 1999; Spender 1989). Fine-grained information transfer and joint problem solving will accordingly place actors in highly connected niches in a superior position with regard to getting as much as possible out of their investments in micro-power systems. Finally, transparency within the niche – as a result of rich flows of communication and resource-sharing – will curb tendencies of opportunistic- and genuinely self-seeking behavior among professional consultants and vendors. Altogether, this suggests following hypothesis:

Hypothesis 2: Actors in densely connected niches have higher electricity production per financial capital invested than actors in sparsely connected niches.

A counterargument to my above statements is that densely embedded niches, despite fine-grained information sharing and low risks of opportunistic behavior, face the risk of encountering a "redundancy trap" as a result of looking inward and perhaps ignoring novel and better solutions developed in different parts of the system. This is in accordance with both Burt's (1992a) structural hole theory and Granovetter's (1973) weak tie argument, which both emphasize the importance of accessing non-redundant information. As stated before, the hydroelectric micro-power field is still in its infancy and the established knowledge base is therefore fragmented. An alternative hypothesis could therefore be that start-ups in sparsely connected niches are expected to outperform their colleagues in densely connected niches.

I argue, however, that there is not necessarily a contradiction between being established in a highly embedded or dense niche and at the same time accessing non-redundant information from disparate parts of the system. Embeddedness has both a relational and a structural aspect, and Granovetter (1992: 33) emphasized that ignoring the social structure only gives a partial picture, warning that one can easily slip into "dyadic atomization", a type of reductionism. Drawing upon the embeddedness perspective (Granovetter 1985; 1992) I thus examine if the intensity of contacts within niches moderates the value of accessing information from disparate sources. Accordingly, what I emphasize is how the structure of relationships in these subsets is expected to influence outcomes from the focal actor's relational ties with nodes that to some extent are considered to provide non-redundant information.

The above discussion highlights the importance of examining the density structure within niches, and Figure 3.1 portrays a two-dimensional matrix where start-ups belong either to a densely or sparsely connected niche, and either have access to non-redundant information or not. I define non-redundant information to be a positive function of the level of nonadjacent relational ties (Freeman 1979).

		Niche density	
		Low	High
Access to non-redundant information	High	Medium outcome	High outcome
	Low	Low outcome	Medium outcome

Figure 3.1 A two-dimensional matrix of network predictors of social capital.

I have already argued that highly embedded subsets of actors provide transparency, curb tendencies of opportunistic behavior, and make available fine-grained information transfer and joint problem solving. Yet I believe that such a condition furthermore establishes a potential of what Cohen and Levinthal (1990: 128) described as "absorptive capacity", conferring an ability to evaluate and utilize outside knowledge as a function of the level of prior related knowledge, basic skills, and shared language. Thus, I find it reasonable to assume that the benefits achieved in densely connected niches additionally grant the focal actor a "capacity" – but not necessarily an advantage per se – to further develop his skills in building an efficient power plant. I elaborate this argument below.

An entrepreneur accessing information about a novel solution from one or more nodes might succeed in exploiting this opportunity as a result of being part of an embedded structure where he can share and discuss innovative ideas with others. If he opts for the novel solution, a high degree of mutual interaction could furthermore grant him complementary skills and experience, assisting him to gain maximum outcome from his decision. A high level of internal discussion and communication could also provide him with advantages if he accesses information about two (or more) alternative investment opportunities. He could now discuss and share his thoughts and questions and receive feedback from a collective where the stream of ideas and suggestions flow relatively extensively. From this exchange of information – where both the knowledge level is relatively developed and where mutual trust exists – he would now be in a fairly good position to make the right decision. I therefore expect a positive interaction effect on electricity production from access to non-redundant information and being part of a niche where the network structure is dense. This is illustrated as "high outcome" in the upper right quadrant in Figure 3.1.

On the other hand, if the entrepreneur accesses the same kind of novel information, but belongs to a niche with low density, he would not gain the same advantages. The same set of opportunities to discuss novel ideas within his own subset would not be established, and he could accordingly decide upon solutions that are better known to him. As a result of being unfamiliar with the high level of fine-grained information sharing where actors constantly exchange innovative ideas, this condition could even influence his attitude toward novelty. In turn, this could constrain him from considering seemingly better options as beneficial at all. It would also be likely to expect that the start-up would have a lesser ability to exploit novel ideas to their full potential since there would not be as much mutual exchange of "how to do things" within his niche. Altogether, this implies that despite access to novel and innovative ideas, there would not have been established any platform of mutual interaction where this increased knowledge could reach its full potential. To paraphrase Cohen and Levinthal (1990) we can say that there is low capacity within the niche to absorb and apply to commercial ends the new information that has been made available. On the other hand, in accordance with Burt's (1992a) structural hole theory and Granovetter's (1973) weak tie argument, I expect that non-redundant information possesses some genuine advantage. As illustrated in the upper left quadrant in Figure 3.1, I therefore propose that start-ups in weakly connected niches, but with access to non-redundant information, will be "medium" in performance.

If we now turn to the lower right quadrant of Figure 3.1, I hypothesize that actors in highly embedded niches who lack access to non-redundant information, will also gain "medium outcome". Previous discussion has explained that niche density per se is expected to be positive for the focal actor, and the absorptive capacity of exploiting novel ideas should also be in place. However, by lacking access to non-redundant information, the start-up misses the opportunity to further improve his plant through innovative and novel ideas, despite that mutual trust and fine grained-information sharing are already in place in his niche.

An implication of the above discussion is that start-ups in the lower left quadrant in Figure 3.1 become low performers. They gain neither benefits from non-redundant information, nor do they possess advantages from fine-grained information sharing and mutual trust, which is the case in densely connected niches.

I have found no contributions that explicitly investigate the issues that I have described above, but as previously mentioned, investigations of Burt's (1992a) structural hole argument have been inconclusive. Thus, while a number of studies supported the theory (for a review, see Burt 2000), others showed opposite results (Ahuja 2000a; Hansen 1999). Apparently – both for arguments and empirical evidence – there still seems to be certain tensions between the camp that favors Burt's theory and the one that favors Coleman's (1988; 1990) closure argument. I believe, however, that my illustration above may provide a meeting point for the diverging positions. Burt (2000) also addressed a similar solution to the controversy by arguing that the spanning of structural holes does not necessarily benefit actors per se, but is contingent upon whether there is some kind of internal constraint within a group. Only when both conditions are present, he argued, would the players achieve their maximum potential.

Reagan's and Zuckerman's (1999) study of performance in corporate R&D units, adds another bit of empirical support to my line of thinking. They reported high performance in units in which scientists where drawn from diverse employee cohorts (implying that their networks reached diverse perspectives, skills and resources outside the team), and where it at the same time were dense communication networks within the section. Greif (1989) moreover argued that network closure was critical to the success of the medieval Maghribi traders in North Africa. Each trader ran a local business in his own city that depended on sales to distant cities. Network closure among the traders allowed them to coordinate so as to trust one another, and profitably trade the products of their disparate business activities. The traders individually had networks rich in brokerage opportunities, but they needed closure with one another to take advantage of the opportunities (Greif 1989).

Controversies regarding outcomes from spanning structural holes or closures (Ahuja 2000a; Burt 1992a; Coleman 1988; Hansen 1999), along with findings from Reagan's, Zuckerman's (1999) and Greif's (1989) studies on corporate R&D units and medieval traders in North Africa, grant pieces of empirical indications that there might exist interaction effects between niche density and access to non-redundant information. Previous discussion also maintains that non-redundant information per se is expected to be positive for the focal actor, and these issues are summarized in the following two hypotheses:

Hypothesis 3: There is a positive relationship between the focal actor's access to non-redundant information at start-up and electricity production per financial capital invested.

Hypothesis 4: There is an interaction effect between niche density and focal actor's access to non-redundant information at start-up on electricity production per financial capital invested:

a) Production is high at plants in densely connected niches where focal actor has high degree of access to non-redundant information.
b) Production is medium at plants in sparsely connected niches where focal actor has high degree of access to non-redundant information.
c) Production is medium at plants in densely connected niches where focal actor has low degree of access to non-redundant information.
d) Production is low at plants in sparsely connected niches where focal actor has low access to non-redundant information.

Population Density and Mimetic Behavior

In this section, I turn the focus outward from possible network predictors of social capital and question whether being an early or late adopter in the emerging field influences the ability of the focal plant to overcome its liability of newness. This implies that I address issues from population ecology theory and institutional theory, and question whether start-up success/failure of being an early or late adopter in an emerging field is a possible outcome of population density (Hannan 1986) or mimetic behavior (DiMaggio and Powell 1991). Drawing upon these different frameworks, I develop two alternative hypotheses. One suggests that it is negative to be an early adopter (compared to being a late adopter), whereas the other proposes the opposite outcome.

Population Density and Venture Success

A central aspect of the ecology approach is that the density of an organizational form – i.e. the number of organizations of a given type sharing a *"common fate with respect to environmental variation"* (Hannan and Freeman 1977: 929) – can be interpreted as a measure of the legitimacy of that particular population (Hannan and Carroll 1992).[14] Carroll and Hannan (1989: 525) argued that organizational density serves as an indicator of the status of the form, the extent to which it is taken for granted, and the extent to which *"relevant actors regard it as the 'natural' way to organize for some purpose."* An implication of this argument is that increased density – i.e. increased legitimacy – will increase the founding rate[15] by facilitating the establishment of similar organizations. Hannan (1986) developed a density dependence model which states that the size of a population of similar organizations reflects two underlying processes: legitimacy and competition. Increasing organizational density at the beginning of a new organizational form increases legitimacy, facilitating an increase in start-ups. Later, at high levels of density, factors inhibiting start-ups become dominant, such as heightened competition for resources. Considered jointly, increased density predicts a start-up rate with the shape of a negative 2nd degree polynomial.

According to Hannan (1986), increased density has the opposite effect on the disbanding rate[16]. At low-density level, the level of competition with other organizations is modest.

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[14] Note that the definition of population differs from the definition of field. Whereas the latter emphasizes an aggregate of institutional life, including key suppliers and regulatory agencies (DiMaggio and Powell 1991: 61), the population approach only emphasizes organizations that are similar in their dependence on the environment.

[15] Defined as the number of organizations added to a population during a specified unit of time, relative to the number already in the population (Aldrich 1999: 266).

[16] The number of organizations that disband in a population during a specified unit of time, relative to the number already in the population (Aldrich 1999: 266).

Disbandings are, however, high due to low level of legitimacy. An increase in density in this case predicts a decrease in the disbanding rate, shaped as a positive 2nd degree polynomial. The reason why the disbanding rate is not linearly negative is that increased density is also expected to spur competition of limited resources throughout the population. A number of empirical studies give support to Hannan's (1986) density dependence model (for a review, see Baum 1996).

For now, I will not so much emphasize what triggers the start-up rate, but rather draw upon Hannan's (1986) argument of a decreased disbanding rate in the early life of a population as a result of increased density, spurring legitimacy of the new form. The concept of organizational legitimacy is rather broad, but here I focus on cognitive legitimacy and learning.

Cognitive legitimacy refers to the acceptance of a new kind of a venture as a taken-for-granted feature of the environment (Jeppersen 1991). The highest form of this kind of legitimacy is when a new product, process, or service is accepted as a part of the sociocultural and organizational landscape. From a producer's point of view, cognitive legitimacy means that new entrants to an industry are likely to copy an existing form, rather than experiment with a new one. From a consumer's point of view, cognitive legitimacy means that people are committed users of the product or the service (Aldrich 1999).

As described, learning means that entrepreneurs develop their own organized knowledge structures through experience, and use those structures as templates (schemata) to give information form and meaning (Walsh 1995). Entrepreneurs in established populations can benefit from templates that already exist and adopt the most preferable (Spender 1989). However, in young populations, well-developed templates are scarce, and pioneering entrepreneurs must learn new schemata from a fragmented knowledge base.

If we apply these arguments to the emerging hydroelectric industry in Western Norway, the likely expectation is that late adopters will be better prepared to face the challenges of the "liability of newness" (Stinchcombe 1965) than the first pioneers in the field. Rather than experimenting with solutions where both the level of investments and outcomes are unknown, late adopters can draw upon skills and experiences that have already been developed in the field. They can accordingly draw upon a better developed and less fragmented knowledge base than their precursors. From an ecological perspective, this implies that late adopters have a lower possibility of failure than early adopters in the field.

Personally, I believe that the disbanding rate in the field under most circumstances will be extremely low, independent of density and legitimacy level. The reason is that most of the costs in the micro-power sector are attached to the investment phase, whereas variable maintenance costs approach zero. Conventional financial theory teaches us that if invested capital is "sunk" – i.e. has low or no alternative value – and the variables costs are low, the plants will continue to operate even if they are totally unprofitable regarding their total investments. However, I believe that density and legitimacy issues are likely to predict venture success in terms of electricity production per capital invested. According to this argument, early adopters will be inferior performers (but unlikely to disband due to "sunk" investments and low variable costs), whereas increased density and legitimacy will provide competence to late adopters, enabling them to become successful entrepreneurs.[17]

Altogether, I hold that there is a positive linear relationship between being an early or late adopter and electricity production per invested capital, due to accumulation of learning and competence throughout the field. Thus I hypothesize:

Hypothesis 5: Early adopters in the hydroelectric micro-power field have low electricity production per financial capital invested, whereas late adopters have high production.

Mimetic Behavior and Venture Success

The term mimetic behavior is based upon central elements from institutional theory, and this typology emphasizes "isomorphism" as an important causal mechanism to understand certain organizational phenomena. According to this theory, organizations change over time to

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[17] The second issue in Hannan's (1986) density dependence model regarding disbanding rates is that the curve will become positive at a certain level, due to increased competition of limited resources. Regarding the emerging hydroelectric micro-power industry, however, I do not find it reasonable that this will induce a non-linear pattern in outcome between early and late adopters. The reason for this is that the production from the micro-power industry is marginal compared to total electricity production in Norway, so their appearance will have practically no effect at all on competition and price settings in the markets. Even if it should affect the electricity price, this would depress the founding rate rather than the disbanding rate due to low variable costs.

become more similar to other organizations in their environment (DiMaggio and Powell 1991). When faced with uncertainty, organizations economize on search costs and imitate the actions of other seemingly successful organizations, substituting institutional rules for technical rules (Cyert and March 1963; Meyer, Scott and Deal 1983). Mimetic behavior can thus be portrayed as a consequence from the actors' efficient responses to uncertainty (DiMaggio and Powell 1991). Yet the process can also be driven by a kind of social-constructionist role inducing what has been described as "obligatory action" (March 1981). According to this model, once enough social actors do things in a certain way, then that particular course of action becomes taken for granted or institutionalized, and thereafter other social actors will undertake that course of action without thinking. If enough of one type of social actors adopts a certain course of action, then other similar social actors will imitate them. Thus, *"bureaucratization and forms of organizational change occur as the result of processes that make organizations more similar without necessarily making them more efficient"* (DiMaggio and Powell 1991: 64).

Early adopters of organizational innovations are commonly driven by a desire to improve performance (DiMaggio and Powell 1991). However, new practices can become *"infused with value beyond the technical requirements of the task at hand"* (Selznick 1957: 17). As an innovation spreads for instance, a threshold is reached beyond which adoption provides legitimacy rather than improves performance (Meyer, Scott and Deal 1983). Strategies that are rational for individual organizations may not be rational if adopted by large numbers. Yet the very fact that they are normatively sanctioned increases the likelihood of their adoption (DiMaggio and Powell 1991).

A number of studies have shown evidence of mimetic behavior (e.g. Greve 1995; Gulati 1995; Knoke 1982; Starr 1982; Venkatraman, Koh and Loh 1994), and a contribution that nicely illustrates the above arguments is Tolbert's and Zucker's (1983) work on the adoption of civil service reform in the United States. Early adoption was related to internal governmental needs and strongly predicted by city characteristics such as the size of immigrant population, political reform movements, socioeconomic composition and city size. Later adoption, on the other hand, was not predicted by city characteristics, but related to institutional definitions of the legitimate structural form of municipal administration.

The arguments so far, however, emphasize adoption of new practices among already existing organizations as a result of mimetic isomorphism. Yet I find it reasonable to also apply this line of thinking to the decision to establishing a new venture (or not). In the early life of the emerging field, candidates are most likely driven by a desire to reap potential economic benefits from access to a natural resource (e.g. waterfall) when deciding to build a micro-power plant. These actors are probably highly motivated and would strive accordingly to gain the technical necessary skills to accomplish the task at hand.

Later, however, word of mouth might inspire other potential candidates but who lack the same motivational skills. Furthermore, since they might not have considered all the economic and labor effort that it takes to complete the project, these late adopters are prone to catch the wave of this "new thing" without possessing the necessary capabilities. They might also feel certain pressure from vendors, consultants and even family- or local community members who (possibly) encourage them to develop a natural resource in an environmental friendly manner that will benefit "everybody".

Summed up, early adopters will manage to build efficient plants out of genuine interest as well as careful considerations of what it takes to establish a plant. On the other hand, late adopters will establish to a larger extent plants as a result of "moments of inspiration" or some kind of pressure from the environment. At the same time, they will also probably lack the same motivation to learn the new technology, and finally fail to sincerely calculate costs and benefits. Thus, the alternative hypothesis suggests:

Hypothesis 5 alt: Early adopters in the hydroelectric micro-power field have high electricity production per financial capital invested, whereas late adopters have low production.

Conclusion

In this chapter, I first elaborated a number of hypotheses where I applied the focal actor's external relations and niche characteristics (i.e. characteristics for collectives) as independent variables. This implies both a cross-level and mixed-determinant approach to the concept of social capital.

Next, I turned the focus outward from network predictors of social capital and addressed issues from population ecology theory and institutional theory, questioning whether start-up success or failure from being an early or late adopter is a possible outcome of population density (Hannan 1986) or mimetic behavior (DiMaggio and Powell 1991). The hypotheses are summed up in Table 3.1.

In Chapter 5, I test the hypotheses. Data for the empirical analyses were gathered from actors in the emerging hydroelectric micro-power field in Western Norway, and in the next chapter, I describe how I modeled the variables for this study.

Form(s) of social capital	**Hypo-thesis**	**Simplified text**	**Predicted outcome**
Focal actor's external relations	1	Production is low for plants at the margins and in the center of the field at start-up, whereas it is high for plants in intermediate positions.	∩
Characteristics for collectives	2	Actors in densely connected niches have higher production than actors in sparsely connected niches	+
Focal actor's external relations	3	There is a positive relationship between actor's access to non-redundant information at start-up and production.	+
Both	4a	Production is high at plants in densely connected niches where actor has high degree of access to non-redundant information at start-up.	High
Both	4b	Production is medium at plants in sparsely connected niches where actor has high degree of access to non-redundant information at start-up.	Medium
Both	4c	Production is medium at plants in densely connected niches where actor has low degree of access to non-redundant information at start-up.	Medium
Both	4d	Production is low at plants in sparsely connected niches where actor has low access to non-redundant information at start-up.	Low
	5	Early adopters have low production whereas late adopters have high production.	+
	5alt	Early adopters have high production whereas late adopters have low production.	-

Table 3.1 Summary of the hypotheses.

4. Research Methodology

A scientific method can be defined as *"a system of explicit rules and procedures upon which research is based and against which claims for knowledge are evaluated"* (Frankfort-Nachmias and Nachmias 1996: 13). As the definition maintains, a scientific method has to be explicit enabling the reader to evaluate the validity of the study and eventually conduct similar research in other empirical settings to assess the generality of the findings from a research project.

This chapter expounds the applied methodology in this dissertation. First, I introduce sampling strategies in network research with a description of how the relevant respondents for this study were identified. Next I explain the research instrument for this project; how data was gathered, and subsequently a description of in what way the independent variables and the dependent variable were modeled. Finally, I portray a number control variables and how they were operationalized.

Sampling

Sampling- and Data Collection Strategies in Network Research

Network variables can be measured on one, two, or more modes of data where the term "mode" refers to a distinct set of entities on which the structural variables are measured (Arabie, Carroll and DeSarbo 1987; Kroonenberg 1983; Tucker 1963; Tucker 1964; Tucker 1966). Structural variables measured on a single set of actors portray one-mode networks and this is the most common approach within this framework. However, structural variables can also be measured on two (or more) sets of entities. For instance, in an affiliation network, we first have a set of actors (first mode) and second a set of events or activities (second mode) to which the actors in the first set attend or belong. The events are often defined on the basis of memberships in clubs or voluntary organizations (McPherson 1982), social events attendance (Davis, Gardner and Gardner 1941), sitting on a board of directors, or socializing in a small group (Bernard and Killworth 1982; Bernard, Killworth and Sailer 1980; Wilson 1982).

In this study, I have applied one-mode network data, and will not elaborate any further on two-mode perspectives. Examples of one-mode network ties can be individual evaluations such as friendship, liking and respect, transactions of material resources, strategic alliances between otherwise independent firms, and exchange of information and advice, to mention a few.

I have previously described the phrase "social network" as a set of actors and the ties among them (Wasserman and Faust 1994). Yet there is no universally agreed upon approach for how to delimit a network sample and how to develop a data collection strategy that is applicable in every empirical setting. Scholars in the field have also struggled over these issues for more than three decades (e.g. Burt and Ronchi 1994; Carley and Palmquist 1992; Frank 1971; Freeman, Romney and Freeman 1987; Granovetter 1976; Killworth and Bernard 1976; Killworth and Bernard 1979; Krackhardt 1987; Kumbasser, Romney and Batchelder 1994; Laumann, Marsden and Prensky 1983; Marsden 1990; McPherson 1982; Scott 2000).

A convenient sampling strategy in social science research is to identify a population of relevant units (e.g. firms operating in a particular industry) and from this collection randomly draw a sample. In network research, however, this approach is not applicable since analyses focus explicitly on interdependencies among the units studied.[18] The omission of pertinent elements or arbitrary delineation of boundaries can lead to misleading or artificial results (Barnes 1979). For instance, let us assume that the theoretical size of the population being studied is 1,000 and that the researchers randomly select and gather data on 100 entities from this population. As long as the researchers collect information on autonomous attributes (for instance firm size, age, revenues, profits, etc.) and there is no bias in the sample – i.e. it is representative for the whole population – convenient methodological criteria in social science research should be met. In network research, on the other hand, this is not the case. If we again assume that the population size is 1,000 and the researchers only gather data from 10% of the relevant actors, the loss of information about (possible) network ties is dramatic. The maximum number of directional ties among *(n)* actors in a given one-mode network is $n(n-1)$. Thus, by merely gathering data on "our" sample, we are theoretically in danger of losing information about more than 99% of the possible relational ties, and this will most likely strongly disturb any applied network measure. It is therefore essential for the researcher to be very conscious about sampling strategy and boundary specification in network research as compared to other areas in social science studies.

[18] An exception is research on egocentric networks. For details, see, for instance, Wasserman and Faust (1994: 41-43) or Burt (1992a).

Laumann, Marsden et al. (1989) described two lines of attack in regard to boundary specification in social network studies. The first they referred to as the realist approach and it focuses on actor set boundaries and membership as perceived by the actors themselves. For instance, a street-corner gang is acknowledged as a social entity by its members and the membership of the gang is the collection of people the members acknowledge as belonging to the gang. The second is what the authors denominated as the nominalist approach, and is based on the theoretical concern of the researcher. Wasserman and Faust (1994: 32) describe the following example: *"[A] researcher might be interested in studying the flow of computer messages among researchers in a scientific specialty. In such a study, the list of actors might be the collection of people who published papers on the topic in the previous five years. This list is constructed for the analytical purposes of the researcher, even though the scientists themselves might not perceive the list of people as constituting a distinctive social entity."*

The composition of relevant actors to include in a network study thus depends on both theoretical and practical considerations. Of course, the case is most straightforward when we have an a priori and a clearly defined set of actors with specified boundaries, such as pupils in a classroom, employees in firm, inhabitants in a village, or manipulated laboratory groups. However, in many real world studies the task is not always that simple (admittedly, most students in classrooms, employees in a firm and inhabitants of a village also have network ties that go beyond the described boundaries). A recommended technique when we do not have an a priori identified set of actors is to conduct a procedure referred to as "snowball sampling" (Erickson 1978; Goodman 1949; Goodman 1961). This could include elements from both the realist and nominalist approach. By means of archive data (e.g. newspapers, web-searches, public databases, journals, etc.), a researcher would be able to identify a number of relevant candidates for a network study (a nominalist approach). He could also contact a core of assumed "key" actors and ask them who they believe are the relevant actors within the given sector (a realist approach). As a second step, he could ask these actors to inform him about network ties to other nodes that he has not been able to discover. These additional actors constitute the "second-order" zone, and the technique can proceed through several such steps. To decide when to stop snowball sampling depends on both theoretical and practical considerations, but the most convenient strategy is to end it when most of the new contacts have already been cited by the respondents at previous levels (Wasserman and Faust 1994).

With this procedure, sampling goes on until a certain saturation point is reached (Marsden 1990).

Applied Sampling Strategy in this Study

In Chapter 1, I argued that the growth of hydroelectric micro-power plants in Norway has predominately taken place in the Western region of the country, and this is the major reason why I have constrained the empirical setting in this study to the counties (in Norwegian: fylker) Rogaland, Hordaland, Sogn og Fjordane, Møre og Romsdal. This area additionally represents a relatively homogenous zone for both climatic and geological conditions.

In order to access data from these plants I applied a nominalist, realist, and partly a snowball sampling strategy. First, I accessed data (an Excel file) from The Norwegian Water Resources and Energy Directorate (NVE) (2000) which represented an overview of the start-ups in the country. However, this list only mapped hydroelectric micro-power start-ups that were established before 2000, and communication with actors in the field taught me that the list had flaws and was incomplete. I therefore undertook the task to make phone calls to all the local municipalities (in Norwegian: kommuner) in Western Norway where the NVE (2000) Excel file stated that one or more micro-power stations had been built. Through this strategy, I was able to identify 27 hydroelectric micro-power plants.[19] This list excludes two actors where one – after showing him a list of relevant actors in the field – claimed that he had not cooperated with any of other listed actors, and the other asserted that he had even built the generator on his own. In order to study novel entrepreneurs, the list also excludes two plants that were built by a company that is also professional vendor and consultant of micro-power systems. In mapping network ties, however, the candidates approached were asked if they were having or had had relationships to this firm (and these plants) implying that they were included in the network. In order to map unrecognized micro-power entrepreneurs, I eventually asked every respondent to name other newly established plants in Western Norway, and this strategy identified two more respondents.

[19] One of these plants was built as common project between two neighbors as a chain of two generators at different altitude levels. I approached one of these actors, but he was one of those who failed to return the questionnaire.

Altogether, I discovered a number of 29 possible candidates for data-collection. Despite a number of attempts, I was unable to get in touch with one of them, but the other 28 that were contacted by telephone were first given brief information about the research project and were next asked if they wanted to participate in the study. Three of them informed me that their plant was built before 1994 and were accordingly deleted from the study.[20] All the 25 remaining candidates responded that they were willing to participate in the study. The oldest plant in my study was established in 1994 and youngest were established in 2001. I did not discover any micro-power plants that started electricity production in 2002.

Data Instrument and -Collection

Data Collection Instrument

Before developing an instrument for data collection, I spent considerable time searching the publicly available information in order to get an overview of the particular sector. I also conducted an open-ended interview with an actor who was considered an authority in the field. Additionally, I conducted an open-ended interview with a micro-power start-up to whom I also presented a draft of the questionnaire. Finally, to gain more insight on the particular sector and to get further feedback on the draft of the questionnaire, I communicated with an engineer and expert in small-scale hydroelectricity.

The language that I applied in the questionnaire is "nynorsk" which is the written idiom that is most commonly used in the rural areas in Norway (compared to "bokmål", which predominates in urban areas). Linguistically, it is also closest to most of the different dialects spoken in the region. The instrument consists of five parts. The first section explains the content of the questionnaire and how to complete it. In the part following, a number of vendors and consultants of micro-power systems are listed, in addition to Sintef, a Norwegian technology research institute. These candidates were identified by conducting a web-search in addition to information provided by a micro-power entrepreneur. I argue that mapping network ties between start-ups and suppliers – in addition to merely gathering network ties between the plants – represents a strength in this study. This approach expands the strategy of only studying the focal population of start-ups to include an aggregate of what constitutes a

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[20] The participants, however, were asked if they had ties to these actors.

recognized area of institutional life. It is furthermore consistent with the organizational field paradigm (DiMaggio and Powell 1991).

In the first column, I presented the suppliers and consultants in alphabetic order. In following columns the respondents were asked to give information about the content of regular contacts they have/had with the different providers. Actors may have different kinds of relations with each other, and some contacts overlap. This is referred to as multiplexity in relationships (Greve and Salaff 2001). In order not to miss the richness in the network structure, I divided the contents of the relations or contacts into four classes. I discussed and developed the questions in cooperation with a hydroelectric entrepreneur and an electrical engineer, and the content of the questions was phrased as follow (translated from Norwegian [nynorsk]):

1. contact regarding legal issues and environmentalism
2. contact regarding choice of product, technological solutions, and hydroelectric conditions
3. contact regarding installation/building and upstart
4. contact regarding operation and maintenance

The candidates were asked to note whether they have/had one or more of these contacts with different vendors, consultants, or Sintef. Freeman, Romney et al. (1987) have shown that people are good at recalling regularly occurring relations as opposed to ad hoc contacts, so in two other columns, I asked the respondents to identify the year the contacts were established and eventually terminated. Since this dissertation studies the development of a structural graph where network constellations at the time of start-up are modeled as independent variables, it was particularly important to identify the year different contacts were established. This procedure is also in accordance with scholars' recommendations for gathering longitudinal and dynamic network relationships (Burt 1992a; Podolny and Baron 1997).

Below the listed actors there was an empty space in which the respondents could add other vendors and consultants with whom they have/had network ties in the process of building the plant.

In the third part of the questionnaire, I listed all the hydroelectric micro-power plants and miniature power plants that I was able to identify in the Western region of Norway. The reason for also including miniature plants was that there is no substantial difference in technical terms between the two classes of hydro turbines, except for the size.[21] By this strategy, I was able to identify possible network ties to plants that also went beyond what is strictly defined as hydroelectric micro-power.

In the first column, I placed the name of the plant (in a number of cases the name of the owner of the plant also). With the aim of making it easier for the respondents to discern the different plants, in the second column, I placed in alphabetic order the name of the local municipality (in Norwegian: kommune) where the different actors were located. In following columns, the respondents were asked exactly the same questions about possible network relationships as in the previous part of the questionnaire. Again, I left an open space where the respondents could add network ties to unrecognized candidates. Interestingly, only one respondent mentioned a network tie to a plant that was not already on the list, and this plant was located in Western Norway. This indicates that the described region represents a natural boundary regarding network ties between micro-power plants in the emerging field.

In the fourth part of the questionnaire, I first asked the respondents about autonomous characteristics of the plant. I requested the month and year electricity production was started, and since my intention was to model monthly production as the time-window for the dependent variable, I next asked them about total monthly electricity production in kWh since start-up. The strategy of gaining information about monthly production partly failed, however. Due to the smallness of these plants, a number of them have not been particularly strict about recording production within a monthly time frame, so I decided instead to register yearly production (description below). I also asked about the size of the plant in terms of maximum production in kWh, and other technical terms such as maximum throughput (operating flow), total head difference, the size of headrace dam, and whether they were having dam in the catchment area or not. I also asked them to name the closest station for meteorological observations, how large their total investment had been, and what percentage of total investment had been spent on connecting the plant to the electricity grid.

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[21] As I described in the introductory chapter, an important difference that goes beyond the difference in size is that micro-power plants are exempted from paying 6 øre (almost one cent) in taxes (in Norwegian: forbruksavgift) for every kWh they sell.

In the latter part of the questionnaire, I asked the respondents about personal characteristics such as year of birth, education level, and if building of the plant was a one-man project or not. To discern whether the entrepreneurs were novices in the area of building small-scale hydroelectricity, I asked them if they had previously been involved in a similar project. Only two respondents reported any such experience. Finally, I asked, as described earlier, if they knew about other micro-power start-ups in the region that were not among those already listed in the questionnaire.

Data Collection

The data collection instrument was mailed to the respondents in the beginning of September 2002 (except for a few that were mailed later). Together with the questionnaire, I attached a cover letter where there was a reference to previous telephone conversation(s) and thanked them for participating in the study again. I briefly, and in general terms, described the purpose of the project, guaranteed the respondents full anonymity, and finally promised those who returned the questionnaire participation in a lottery where the prize was a gift certificate for NOK 10,000 with a tour operator. The respondents also received a letter of confirmation from one of my supervisors and an addressed and prepaid envelope in which they could return the questionnaire. Finally, all the candidates for the study received a lottery ticket (in Norwegian: flax-lodd) in the state lottery with a value of NOK 20.

After about a month, I phoned the candidates who had not yet returned the questionnaire, and after waiting another period of time, I called again. I also sent new questionnaires to those who had not yet responded. Out of 25 candidates, I received 23 usable questionnaires for modeling network data, representing a response-rate of 92% (88.5% if we consider the micro-power start-up that I was unable to reach). I described above that I was unable to gain monthly total electricity production from a large number of the respondents, and consequently decided to register yearly production instead. This change in strategy was an easy task for those who had already provided me with reliable monthly data. Here I just summed reported production for each month. Some of the respondents, who were unable to report monthly production, reported also yearly production of their own accord.

With the aim of gaining reliable data from as many respondents as possible, I mailed them a letter in December 2002 informing them that I would make another phone call in early

January 2003. In this telephone roundup I intended to access more data on electricity production and gain other information that had not been reported in some of the returned questionnaires. The strategy turned out rather successfully, resulting in data on yearly production from 20 respondents. I also received reliable data on other issues enabling me to model both the dependent variable and the control variables. Altogether, this represented data on autonomous characteristics from 80% of the respondents; but note, regarding network data – from which I modeled the independent variables and a control variable – the response rate was 92%.

In addition to gathering data from micro-power start-ups on network ties and autonomous characteristics, I also accessed data from Statistics Norway (SSB) on the consumer price index. Moreover, the Norwegian Institute of Meteorology (MET) provided me with data on yearly precipitation from a number of weather stations in the Western region of Norway. The following describes how I applied data from these external sources in modeling the dependent variable and a control variable.

Modeling Network Ties and Variables

Modeling Network Ties

Wasserman and Faust (1994) argued that substantive concerns and theories motivating a specific network study usually determine which variables to measure, and which techniques are most appropriate for their measurement. Figure 4.1 portrays two different dimensions to consider when modeling a one-mode network. A relation can be considered symmetrical or asymmetrical, valued or non-valued (dichotomized). An example of an asymmetric network tie is that A gives money to B, but the contribution is not reciprocated. Examples of valued network ties can be frequency of contact, duration of contact, level of intimacy, level of multiplexity in the relation, size of transaction between organizational actors, etc. It is, of course, up to the researcher to decide how to measure different values of network ties. We end up with four different alternatives of how to model a one-mode network: Symmetric and valued (a), asymmetric and valued (b), symmetric and dichotomized (c), asymmetric and dichotomized (d).

		Symmetric tie	
		Yes	No
Valued	Yes	a	b
	No	c	d

Figure 4.1 Different alternatives of how to model one-mode network data.

In the introduction, I stressed that this study focuses on the formal structure of the ties that make up the social network in the emerging hydroelectric micro-power field, rather than focusing on the content of these ties. Hinde (1976: 8) referred to the term structure *"as a patterning of relationships that is independent of the particular individuals concerned... "*. He further stated that *"[i]n moving to this more abstract level we focus on aspects of the content that show regularities across individuals and across societies... "* I accordingly modeled the network data as symmetric and dichotomized (c), and this implies that I intended to uncover among which pair of actors contacts have been reported.

Reported relations in this study, however, were not inherently symmetrical. For instance, if A contacts B for advice in building a micro-power plant, this does not necessarily mean that B contacts A for advice. According to Krackhardt (1990: 352), there are two ways to treat these asymmetries when modeling network properties such as actor-centrality measures:

> "On the one hand, one could assume that information only travels in the one direction specified by the asymmetric relation. For example, if A goes to B for advice, then one could assume that relevant information flow is from B to A and not vice versa. On the other hand, it may be more reasonable to assume that information flows in both directions as a result of an exchange, independent of who initiates the exchange. That is, just because A defers to B (by going to B for advice) does not mean that no information is passed from A to B in the exchange. In fact, by the very act of asking for advice, A is providing B with information about what A is doing or what is going on around A. For this reason, I assume... that the presence of a relationship from A to B indicates an opportunity for an exchange of information in both directions, from A to B and from B to A."

As stated above, this study models symmetric relationships. Therefore, I have applied Krackhardt's (1990: 352) operational definition of actor-centrality in the network based on following equation of R^*:

$$R^*s_{i,j} = \begin{cases} 1 \;\; if \;\; R^*_{i,j} = 1 \;\; or \;\; R^*_{j,i} = 1 \\ \quad 0 \;\; otherwise \end{cases} \tag{4}$$

According to Equation 4, this implies that a network tie exists between A and B if one or both report that a relationship exists. This approach enabled me to model network data between micro-power start-ups and actors outside the identified sample, which in practical terms implies that I also identified relationships that included vendors, consultants, and miniature power plants. This approach expands the strategy of only studying the focal population of start-ups to also include an aggregate of what constitutes a recognized area of institutional life, consistent with the organizational field paradigm (DiMaggio and Powell 1991). Note that the relations are also dichotomized.

Since this study intended to uncover the development of a network structure in an emerging field, rather than merely focusing on static network properties measured at one point of time, I had to develop a strategy of how to capture such an unfolding dynamic process. This led me to focus on the initiation and duration of the reported network ties. For almost every identified contact, the respondents reported the year it had been established, except in very few cases. In those few cases where year of initiation was lacking, the relationships were modeled as ties established in the very early phase of the emerging field. The argument behind such an approach is that it is easier to – everything else being equal – correctly identify the time dimension of more recent events compared to events that took place (or were initiated) in the distant past. I therefore interpreted the few ties that were lacking year of initiation as enduring events that were established such a long time ago that the actor was unable to record the exact year.

With regard to handling network ties that are reported as terminated, perhaps the most intuitive way of handling this issue is to model the year of termination. This, however, underestimates important aspects of the enduring influences a network tie is expected to have on the involved actors. For instance, let us assume that an established contact between A and B was reported as terminated in 1997. Does this imply that there was no influence of this tie after this year? I argue that this is not so. If we assume that two years later B establishes a contact with C, it is most likely that the experiences and skills B gained through cooperation with A will be passed on and developed further to a certain extent in working with C. To account for the expected enduring influence of terminated network ties, I added 5 years duration from the year of termination to those relations. In order to assess the validity of this strategy, I also modeled network data where I added 3 years and 7 years, respectively, but unreported analyses indicated by and large no substantial differences in the results. Interestingly, for a number of models explained variance was considerably larger when I added 5 (and also 7) years as compared to only adding 3 years.

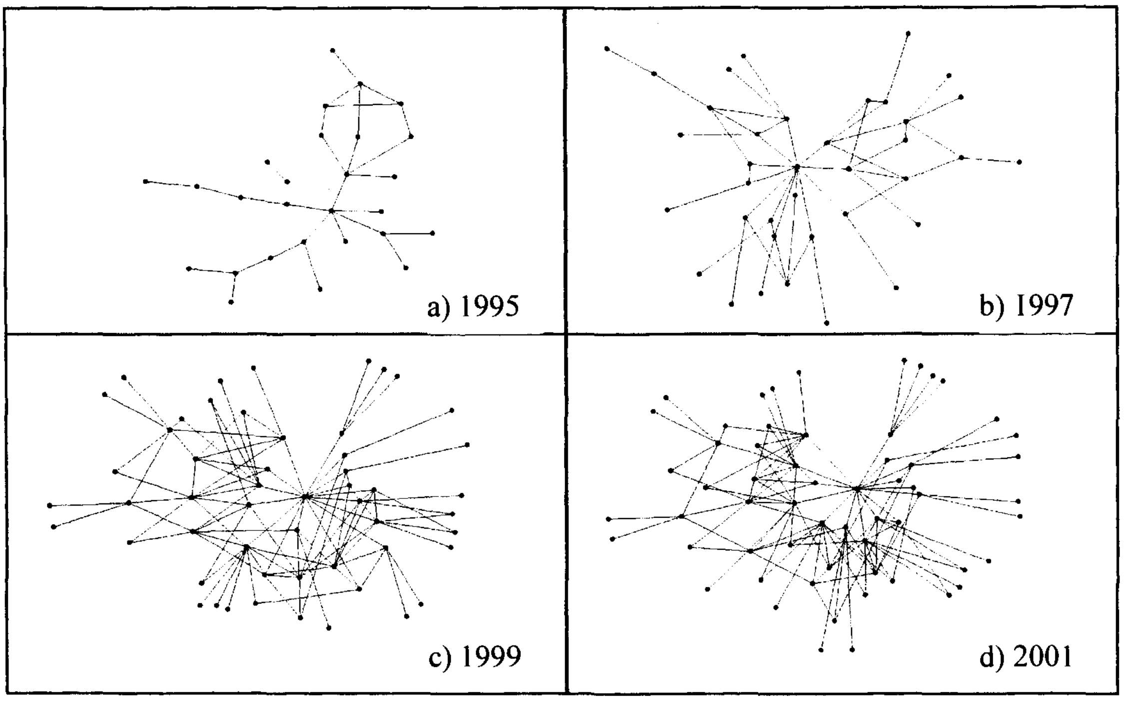

Figure 4.2 A graphic display of the network structure in the emerging field.

By following the strategies that I have described above, I identified 115 network ties between 59 actors that were established before 2002. Figure 4.2 shows the network structure from the years 1995, 1997, 1999, and 2001, respectively, illustrating the dynamic of the developing network structure in the emerging field. We can observe – with the exception of one dyad that was unconnected to the rest of the structure in 1995 (which is also the case for 1996) – a coherent and connected network. We can also notice a steady increase in both the number of actors entering the network, and the increased density in contacts.

Independent Variables

Network Distance to the Center of the Field. Hypothesis 1 suggests a curvilinear relationship with the shape of a negative 2nd degree polynomial between network distance to the center of the field at start-up and electricity production per financial capital invested. I have defined the center of the field as a position of strategic significance in the overall network (Scott 2000). Closeness centrality is a centrality measure of how close an actor is to all other actors in the network in terms of the number of steps the focal actor has to pass through to reach each other node. By drawing upon the works of a number of scholars (Bavelas 1950; Beauchamp 1965; Harary 1959; Moxley and Moxley 1974; Rogers 1974; Sabidussi 1966), Freeman (1979) proposed that actor closeness should be measured as a function of geodesic distance, i.e. the shortest number of steps between a given actor to all other actors in the network. As geodesic distance increases in length, the closeness centrality of the actor decreases. Thus, this centrality measure depends not only on direct ties, but also on indirect ties in the network.

I argue that closeness centrality captures essential aspects of whether the focal actor has a position of strategic significance in the overall network. Everything else being equal, an actor at the center of the field will have to go through fewer steps than marginal actors do to reach each other node due to average shorter geodesic distance. Graph theorists have also simplified this concept of centrality and talked about the center of a graph (i.e. the network), using the graph-theoretic notion of distance (Jordan 1869). To determine the actors' distance to the center of the field, I applied Freeman's (1979) closeness centrality measure, where closeness is the inverse sum of the distances so that infinite distances contribute a value of zero. High values denote proximity to the center, whereas low values denote distance to the center.

As we see in Figure 4.2, the number of actors entering the network increases throughout the life of the emerging field. I therefore applied the normalized closeness centrality score, achieved by multiplying the initial measure with the maximum possible closeness value for each given year. A maximum possible closeness centrality value is the case when the actor is adjacent to all other actors (Beauchamp 1965). An unconnected graph produces infinite geodesic distances, and as I have described, this is the case for 1995 and 1996. However, these disconnected nodes were not among the start-ups for these two years, so I decided to delete them from centrality calculations for 1995 and 1996. From 1997 and beyond, the graph is connected.

Niche Density. Hypothesis 2 proposes that actors in densely connected niches have higher electricity production per financial capital invested than actors in sparsely connected niches. Burt and Talmud (1993) defined an ecological niche as a subset of structurally equivalent actors, and block model techniques can be applied to identify such partitions (White, Breiger and Boorman 1976). A block-model splits actors in the network into discrete ecological niches, and each such pair states the presence or absence of ties within them or between them (Wasserman and Faust 1994).

In this dissertation, I applied what is called the Concor (convergence of iterated correlations) technique to identify structurally equivalent niches. This is one of the earliest approaches to partitioning actors into structurally equivalent subsets, and was developed by White and colleagues (White, Boorman and Breiger 1976; White, Breiger and Boorman 1976). The method has been extensively used by network researchers in many fields (Wasserman and Faust 1994), and is based on the observation that repeated calculations of correlations between rows or columns of a matrix will eventually result in a correlation matrix consisting of only +1's and -1's. The procedure starts with a matrix (or a collection of matrices) and first computes the correlations among rows and columns. Then it uses this new matrix and again calculates the correlations on rows or columns and continues until all correlations in the matrix equal 1 or -1. Concor can be repeated on the sub-matrices defined by an earlier partition. Thus, this technique may be thought of as a divisive hierarchical clustering method. It is, however, rare that a given set of actors are perfectly structurally equivalent in a set (or sets) of network data, so Concor is intended to uncover actors that are approximately structurally equivalent.

As described, an important decision when using Concor is to decide how fine the partition should be. Wasserman and Faust (1994: 378) held that *"[t]heory and interpretability of the solution are the primary considerations in deciding how many... [partitions] to produce."* They furthermore argued that making too many splits can lead to unstable correlations, due to the small number of elements. I used the Concor method to divide the field into 4 niches, i.e. I conducted two splits. This measure is open to interpretation, and – as we shall see – clearly indicates that a certain degree of clustering took place within a number of the niches, yet with varying density levels. Moreover, in unreported analyses, I increased the number of splits, but the change in R-square indicated no specific saturation point.

To my knowledge there are no explicit recommendations for the application of Concor (or other structural equivalence measures) on network data that possess a dynamic structure, for both the number of actors entering (or leaving) the network and the relational structure between them. Wasserman and Faust (1994: 366) warned that the use of static models for the representation of dynamic systems may lead to measurement errors, and in order to face this challenge, I undertook two different tasks. First, I modeled the entire static network structure as it was reported before 2002. Next, I modeled a matrix of the network structure for each respective year from 1995 through 2001. Altogether, this provided me with 8 data matrices, which I treated as multirelational networks in the software program Ucinet 6.12 (Borgatti, Everett and Freeman 2002). This gave me the advantage of inspecting the overall structure within and between different niches, as well as portraying the dynamic in this pattern over time.

By applying the above strategy, the accumulated network and the networks for different time periods were transformed into different block-models, as illustrated in Tables 4.1- 4.8. Table 4.1 shows the reduced block matrix with densities within blocks (diagonal) and between blocks for the accumulated network structure in the emerging field. Density is the number of relations *(l)* among *(n)* actors that exist compared to the maximum possible number of relations, $l/[n(n-1)/2]$, and the overall density level (block alpha) is .067. The total number of actors within each niche – including micro-power start-ups, vendors and consultants – is 23 in Niche 1, 15 in Niche 2, 9 in Niche 3 and finally, 12 in Niche 4. The table reveals a number of interesting issues. First, for Niches 1, 2, and 3, we observe density levels well above the overall density level – reported in bold letters – indicating that a certain degree of clustering has taken place within these niches. However, while the density level in block 1 is about 40% higher than overall network density, the levels are roughly 245% and 190% higher in Niches 2 and 3, respectively. This static picture indicates substantially higher niche densities in Niches 2 and 3 as compared to Niche 1.

	Niche 1	Niche 2	Niche 3	Niche 4
Niche 1	**.092**			
Niche 2	.052	**.228**		
Niche 3	.000	.027	**.192**	
Niche 4	.005	.021	**.189**	.000

Table 4.1 Density matrix for the years 1995 to 2001. Block alpha = .067

It is somewhat surprising to note that the density level in Niche 4 is zero, but by inspecting the actors in this subset, we learned that they were vendors and consultants of micro-power systems, and were not a part of the micro-power start-ups from which I gathered data. In addition, Table 4.1 teaches us that actors in Niche 3 were not only densely connected to each other, but also seem to have had extensive contacts with the vendors and consultants in Niche 4.

If we now take a closer look at the dynamics in the block structure between 1995 and 2001, the picture from Table 4.1 is generally confirmed. In Tables 4.2 - 4.8 we observe that some clustering was already taking place in Niches 2 and 3 in 1995, and throughout the whole period, the same niches were substantially more densely connected than Niche 1. Note, however, that both overall density level (alpha) and density levels within and between the niches are underreported in these tables due to the fact that in the early life of the field a number of nodes would not yet have made their appearance into the network. This would particularly depress the numbers reported in the early years, but since this is the case for overall density (alpha) and densities within and between blocks, the general tendencies we observe will not be substantially affected.

	Niche 1	Niche 2	Niche 3	Niche 4
Niche 1	.013			
Niche 2	**.020**	**.051**		
Niche 3	.000	.005	**.090**	
Niche 4	.000	.000	**.035**	.000

Table 4.2 Density matrix for 1995. Block alpha = .016

	Niche 1	Niche 2	Niche 3	Niche 4
Niche 1	**.026**			
Niche 2	**.029**	**.059**		
Niche 3	.000	.009	**.103**	
Niche 4	.000	.000	**.042**	.000

Table 4.3 Density matrix for 1996. Block alpha = .022

	Niche 1	Niche 2	Niche 3	Niche 4
Niche 1	**.039**			
Niche 2	**.039**	**.081**		
Niche 3	.000	.014	**.115**	
Niche 4	.000	.000	**.070**	.000

Table 4.4 Density matrix for 1997. Block alpha = .030

	Niche 1	Niche 2	Niche 3	Niche 4
Niche 1	**.046**			
Niche 2	**.049**	**.154**		
Niche 3	.000	.023	**.141**	
Niche 4	.000	.011	**.105**	.000

Table 4.5 Density matrix for 1998. Block alpha = .044

	Niche 1	Niche 2	Niche 3	Niche 4
Niche 1	**.072**			
Niche 2	.052	**.206**		
Niche 3	.000	.023	**.154**	
Niche 4	.005	.021	**.147**	.000

Table 4.6 Density matrix for 1999. Block alpha = .057

	Niche 1	Niche 2	Niche 3	Niche 4
Niche 1	**.078**			
Niche 2	.049	**.213**		
Niche 3	.000	.023	**.167**	
Niche 4	.005	.021	**.182**	.000

Table 4.7 Density matrix for 2000. Block alpha = .061

	Niche 1	Niche 2	Niche 3	Niche 4
Niche 1	**.092**			
Niche 2	.046	**.221**		
Niche 3	.000	.027	**.167**	
Niche 4	.005	.021	**.175**	.000

Table 4.8 Density matrix for 2001. Block alpha = .063

Altogether, Tables 4.1- 4.8 teach us that a certain clustering has taken place within Niches 1, 2, and 3, but with a substantially lower density level in Niche 1 compared to the other niches with micro-power start-ups. I therefore concluded that Niches 2 and 3 had high-density levels, whereas Niche 1 had a low level of density.

Access to Non-Redundant Information. Hypotheses 3 and 4 contain the concept of access to non-redundant information, which I defined to be a positive function of the level of nonadjacent relational ties (Freeman 1979). This intuition grew out of the idea that actors in a network are somehow central to the degree they stand between others on the paths of interaction (Anthonisse 1971; Bavelas 1948; Cohn and Marriott 1958; Freeman 1977; Friedkin 1991; Shaw 1954; Shimbel 1953). Among other things, such actors have access to parts of the network that are not strongly connected to each other, allowing richer and more differentiated information to reach them (Krackhardt 1990). Freeman (1977; 1979) operationalized the concept of actor betweenness centrality as the number of geodesics (i.e. shortest paths) between each pair of nodes in a network that passes through the given actor. In a later contribution Freeman, Borgatti et al. (1991) further developed the measure to include, not only the geodesic paths, but all independent paths between pairs of points in the network. They stated, *"the flow [of information and other resources] between two points is a global phenomenon; it depends, not just on the capacity of the channel linking the points directly, but on the capacities of all the channels on all paths – both direct and indirect – that connect the two"* (Freeman, Borgatti and White 1991: 146). This refined measure they called actor flow betweenness. As with actor closeness centrality, it is possible to measure a normalized score of flow betweenness, allowing comparisons between different graphs and graphs of different sizes (for details, see Freeman, Borgatti and White 1991). Accordingly, in this dissertation I have adopted the normalized score of flow betweenness to measure the focal actor's access to non-redundant information.

Being an Early or Late Adopter. The last independent variable I have applied in this dissertation is reflected in Hypotheses 5 and 5alt. Here I have argued that there is either a positive or a negative relationship between being an early or late adopter on electricity production per financial capital invested. The way I operationalized this variable was simply to model the year of start-up. As we shall see later, in one model I applied the start-up year as a nominal variable and in others as a continuous variable.

Dependent Variable

I have mentioned a number of times that the dependent variable I applied in this study is electricity production per financial capital invested, discounted in real terms. For the 20 actors from whom data was accessed on yearly electricity production, I also accessed data on their total investment in building the plant. Moreover, I gained information about how much of the total investment eventually was incurred in connecting the plant to the electricity grid. Since these costs could vary as a result of proximity to already established infrastructure, I decided to subtract this amount from their total investment. Data on investment is a nominal measure and does not take into account inflation throughout the period. I therefore divided these values on the deflator of consumer price index – accessed from Statistics Norway (SSB) – at the year of start-up for each plant.

Concerning modeling the year of start-up there are two exceptions. One is the actor who reported to have started the plant in 1994. Between 1994 and 1999, he claimed that he was merely experimenting with two small turbines, before upgrading the plant to its present form in 1999. I therefore divided his total investments on the consumer price index for this year, which I also modeled as start-up year. The other exception is the actor who informed me that he started electricity production in the very beginning of 2001. Since practically all his investments had taken place prior to this, I modeled 2000 as the start-up year.

Among the 20 start-ups from which I had data on electricity production – along with other autonomous characteristics – 3 were started in 1995, 1 in 1996, 4 in 1997, 2 in 1998, 4 in 1999 (including the one who was merely experimenting from 1994), 4 in 2000 (including the one who claimed that he started electricity production at the very beginning of 2001), and 2 in 2001. I divided their yearly electricity production in kWh by their real investments, as described above. For the entrepreneurs from whom I accessed more than one yearly observation, I applied the average production from their total reported years of operation.

Control Variables

So far, I have only focused on variables that are reflected in the hypotheses from Chapter 3. However, it was likely that a number of other factors could affect the dependent variable. I therefore found it reasonable to include a number of control variables, which will be discussed below.

The Size of the Plant. First, I have included the size of the plant's maximum capacity in kWh. The largest plant in this study had a size of 99 kWh, the smallest 7 kWh. There were a number of reasons for including this control variable. First, discussions with both an engineer and micro-power start-ups taught me that – everything else being equal – the larger the size of the plant, the more efficient it is. It was therefore reasonable to expect that this would be reflected in larger production per financial capital invested. Clients that invested in larger plants could also perhaps gain certain rebates, due to their relatively larger investments.

On the other hand, a large plant would require a higher flow-through to be more efficient than a small plant, and would accordingly be more vulnerable to variations in precipitation. Thus, as long as there is plenty of water in the river this would have no impact, but in seasons with little water, the efficiency of a small plant would likely be superior, compared to a large plant.

Total Head Difference. It is intuitive to think that the effect from the plant would increase with increased total head difference, due to higher pressure on the turbines. On the other hand, total head difference would also increase total investment, due to longer pipelines. I accordingly controlled for this variable and the parameter is measured in meters.

Human Capital. I have included three control variables that capture possible effects from human capital on the dependent variable. First, I included a dummy variable, which indicated whether building the micro-power plant has been a one-man project or not. Cooper and Bruno (1977) found team size to be associated with growth in the high-tech industry, and in an ecological study, Singh, House et al. (1986) found that the board size at birth depressed the death rate for Canadian voluntary social service organizations. Eisenhardt, Bird et al.(1990) furthermore showed that the size of the founding top-management team influenced the growth of new semiconductor firms.

In this particular study, I found it reasonable that the number of people involved in building a micro-power plant could produce two possible effects. Perhaps the most intuitive interpretation from the above review is that the presence of more than one person in the project adds knowledge, experience, and participates in adding a variety of perspectives about how to solve the task at hand. This would enable the entrepreneurs to pick the better solution from a variety of available alternatives, and would likely be reflected in high production per capital invested. On the other hand, since practically all the entrepreneurs in this study had no previous experience with micro-power, the presence of a number of people in the project could constrain the process due to the lack of an established platform of competence from which these individuals could benefit in exchanging ideas. So, if a number of persons are directly involved in the project, this could constrain the flow of knowledge and competence that is being established throughout the field. A lone entrepreneur, on the other hand, would probably pay greater attention to his external network ties, due to lack of input and ideas from other sources.

Secondly, I have included a variable on the level of formal education. In the questionnaire, the respondents were asked to indicate on a scale whether they had completed secondary school (in Norwegian: grunnskole), high school (in Norwegian: videregående skole), 1-3 years in college/university, or 4 years or more in college/university. If more than one person were involved in the project, I included the length of education for the person with the most years of schooling. I modeled this scale as a continuous variable, and in accordance with other studies that include measures of human capital (e.g. Greve, Golombek and Harris 2001), I found it likely to expect that level of formal education would positively predict the dependent variable.

In a study of German business founders, Bruderl, Preisendorfer et al. (1992) found that years of work experience reduced the failure rate for venture firms in Upper Bavaria, and other studies have also shown a positive relationship between work experience and performance (Eisenhardt, Bird and Schoonhoven 1990; Greve, Benassi and Harkola 2001; Roure and Maidique 1986). To apply a control variable for work experience I modeled the entrepreneurs' age in years at start-up. If more than one person was involved in the project, I included the age of the eldest person. I decided to include this variable instead of "professional" work experience as a consequence of these actors' predominant background in non-academic work. A large number of them were farmers who had been involved in practical and mechanical farm work – often since childhood. Work experience per se became a slippery concept due to ambiguity about when a large number of these people actually started working. Moreover, studies have shown that on a number of occasions older workers seem to outperform their younger colleagues in solving novel and complex tasks such as strategic decision-making and negotiations (Haukedal 1990; Røvang 2003).

Deviations in Precipitation. I have also included a variable where I have controlled for average deviations in yearly precipitation. Intuitively we understand that dry periods negatively affect the production of hydroelectricity, whereas abundant rainfall enables stable and high production. The Norwegian Institute of Meteorology (MET) provided me with data on yearly precipitation from a number of weather stations in the Western region of Norway. I modeled the percentage deviation in yearly precipitation from the most geographically approximate weather station in the region that I was able to discover, from which I also gained sufficient data. Next, I applied average deviation for the plants from which I accessed data for more than one year of electricity production. MET calculates deviations in yearly precipitation by dividing total rainfall for each respective year on average yearly precipitation from 1961 to1990.

Local Network Centrality. In a number of models, I also included a network measure of local centrality. As described, an actor is locally central if he has a large number of connections with other nodes in the immediate environment, i.e. if he has a neighborhood of many direct contacts (Freeman 1979). Whereas network distance to the center of the field concerns prominence in the whole network, local centrality is concerned with the relative prominence of a focal point in the neighborhood (Scott 2000). Freeman (1979) conceptualized it as a measure of activity and involvement in the network. Brass and Burkhardt (1992) argued that local centrality represents the number of alternatives available to an actor, in addition to avoidance of relying on mediating positions for direct access to vital information. A great number of studies have shown positive relationships between local network centrality and performance (e.g. Ahuja 2000a; Baum, Calabrese and Silverman 2000; Choonwoo, Lee and Pennings 2001; Shan, Walker and Kogut 1994; Smith-Doerr, Owen-Smith and Powell 1999; Stuart 2000; Stuart, Hoang and Hybels 1999).

The major reason for having included this measure is that it would most likely correlate with closeness centrality and flow betweenness. For instance, an actor that has many contacts will – everything else being equal – be closer to each node in the network. If he is connected to every actor, he will of course gain a maximum score of closeness centrality for the given graph. In Chapter three, I suggested a curvilinear relationship with the shape of a negative 2nd degree polynomial between network distance to the center of the field and electricity production. Despite the fact that most studies show a linear relationship between local centrality and performance, it would not be unlikely to expect that local network centrality could also produce a similar curvilinear relationship. Whereas possessing some network contacts can be positive, it is not unlikely that the effect could become negative beyond a certain maturation point as a result of a possibly negative, marginal effect from each new tie. Finally, being active in the network beyond a certain point can indicate “a cry for help”; entrepreneurs that are really struggling in their project may have a tendency to search for more help, and therefore would establish more contacts than more fortunate start-ups.

Flow betweenness will probably also correlate with local centrality. Everything else being equal, the more contacts an actor has means he will also stand between other pairs of nodes in the network to a larger extent.

I operationalized the parameter by applying Freeman's (1979) normalized degree centrality measure, which counts all the contacts a given node has, divided by the size of the graph minus one.

Conclusion

This chapter has presented the methodology that I have applied in this dissertation. I have described in detail the strategies that I undertook in order to gather data as well as how I modeled independent variables, the dependent variable and a number of control variables. The hypotheses are empirically tested in the next chapter.

5. Results

The major focus in this chapter is to empirically test the hypotheses that I developed in Chapter 3. First, I present the results from a number of statistical analyses. All statistical calculations have been conducted in the software program JMP5 (2003), whereas network variables have been calculated in Ucinet 6.12 (Borgatti, Everett and Freeman 2002). Next, I present a lengthy discussion of my interpretations and the implications from the findings in the study. The chapter also emphasizes other potentially interesting findings that are not necessarily reflected in the hypotheses.

The Hypotheses

Normal Distributions and Correlation Matrix

Table 5.1 shows calculations of skewness and kurtosis from the continuous variables in the data set, and we observe that the absolute value for kurtosis and skewness for normalized flow betweenness along with kurtosis for the dependent variable (Mean Production), are larger than ±1.96. This indicates that for these two parameters we can reject the assumption about normal distributions at a probability level larger than .05. However, by modeling the natural logarithm (nFlow BetweennessLn and Mean ProductionLn) we observe a marked decrease in the absolute value of kurtosis (and skewness), so now these variables, along with the other variables, fulfill the requirements for normal distribution. This enabled me to conduct ordinary least square regressions (OLS) or standard least square which it is also called (JMP Version 5.0.1.2 2003).[22]

[22] Two actors had normalized flow betweenness centrality scores of zero, so calculating the natural logarithm for this variable was not straightforward. In order not to lose data from these actors, I added 1 to each respondent's score and calculated the natural logarithm from the new values.

Continuous Variables	Skewness	Kurtosis
Mean Production	1.718	5.235
Mean ProductionLn	-.474	.9543
nCloseness	-.743	-.441
nFlow Betweenness	2.874	9.830
nFlow BetweennessLn	-.070	-.490
Start-up year	-.280	-1.040
Size of the Plant	.568	-1.093
Total head difference	.378	-1.198
Formal Education	.537	.820
Age of the Actors	-.458	1.125
nDegree	.435	-.286

Table 5.1 Calculations of skewness and kurtosis for continuous variables. n=20

Moreover, I have to emphasize that later in this chapter the variable "Start-up year" has been modeled as a nominal variable. Yet since this implies a relatively great loss in degrees of freedom, and the data set is relatively small, I also conducted calculations where "Start-up year" was modeled as a continuous variable.

Table 5.2 shows a correlation matrix for all the continuous variables that have been included in this study. The relatively high and significant correlation between formal education and the size of the plant indicates that the more educated the entrepreneur is, the higher the propensity to build large plants. This can give us a clue that other factors than merely hydrological and climatic conditions are at play when deciding upon the size of micro-power turbines. It is likely to expect that novel entrepreneurs perceive a certain level of risk when deciding to build a micro-power plant. On the average, the larger the plant the more expensive it is, and reported investments in this study vary between NOK 50,000 and 1,100,000. Thus for a number of entrepreneurs this can definitely be considered to be more than a hobby, so the higher the level of formal education (particularly in natural science), the better ability the candidate has to reduce the risk by conducting calculations on hydrologic and climatic conditions. In turn, these reduced risks possibly induce (novel) entrepreneurs to go for a larger investment than they otherwise would have spent.

Min	Max	Mean	St. Dev.		Size pl	Ed	Age act	H diff	Start-up Y	MDevP	nDeg	nCl	nFBLn
7	99	41.525	30.635	Size of the plant									
1	4	2.25	.716	Education	.514*								
25	71	53.1	10.896	Age of actors	-.203	.057							
23	200	99.9	55.615	Head difference	.138	.118	.283						
1995	2001	1998.15	1.954	Start-up Year	.428§	.047	-.149	.157					
76.9	107	92.392	10.11	MeanDevPre%	-.389§	.114	.148	-.123	-.787****				
2.174	21.154	10.745	5.446	nDegree	.480*	.175	-.100	-.029	.066	-.390§			
25.275	44.444	36.133	5.606	nCloseness	.388§	.358	-.344	-.043	.414§	-.492*	.654**		
0	3.96	1.736	1.091	nFlowBetwLn	.290	.299	.016	.134	-.171	-.138	.719***	.526*	
-1.867	.437	-.692	.534	MeanProdLn	.368	.298	-.147	-.090	-.186	-.176	.705***	.447*	.571**

n = 20; § p<.10; * p<.05; ** p<.01; *** p<.001; **** p<.0001 (two tailed tests)

Table 5.2 Correlation matrix for continuous variables.

There was, moreover, a significant correlation between the size of the plant and local network centrality (nDegree), which I find reasonable. It is not surprising that entrepreneurs who aim for large and accordingly more expensive plants are more active in the network in order to reduce the risk involved and to ensure that they are doing the "right" thing. An alternative or complementary explanation could be that entrepreneurs who are active in the local network for some reason tend to build larger plants, because they seek information or receive network ties from others. For instance, such an amount of activity could create a certain involvement and enthusiasm for micro-power, which in turn leads to a desire attempt something that is beyond what was initially planned. The significant correlation between nCloseness and size of the plant could imply that entrepreneurs building large plants also seek an overall more central position in the field, or it could merely be a reflection from local network centrality (which correlates strongly and significantly with closeness centrality). The lower and less significant correlation coefficient between size of the plant and closeness centrality (as compared to the correlation between size of the plant and degree centrality) gives support to the latter argument.

The significant correlation between size of the plant and start-up year indicates a tendency to build larger plants over the years. This could imply that the established knowledge among the involved actors has matured, and that the emerging field has moved beyond merely the experimental stage over the time span. Later in this chapter, I conduct multivariate analyses where the size of the plant is the dependent variable and formal education, start-up year and the three centrality measures constitute the independent variables. I do this in order to better uncover the factors that might genuinely influence the size of the plant.

In addition, the correlation matrix indicates a positive relationship between closeness centrality and start-up year, indicating that late adopters have a larger propensity to approach the center of the field than do the early adopters. I return to this issue later in the chapter.

Unsurprisingly, we observe high correlations between the three centrality measures nDegree, nCloseness, and nFlowBetwLn. As described, the more direct ties a focal actor has, the fewer steps he has to pass in order to reach each other node in the network. It is therefore logical that the network distance to the center of the field correlates strongly with the local centrality measure. We also observe that degree centrality correlates with flow betweenness which is in accord with the previous statement; the more contacts an actor has, the higher degree he also stands between other pairs of nodes in the network.

Between the applied network centrality measures and the dependent variable (MeanProdLn) there are also strong and significant correlations, indicating that network predictors of social capital are present. In the following sections I discuss these issues in detail.

We furthermore observe a strong and negative correlation between mean deviation in precipitation (MeanDevPrec%) and start-up year. This can be explained as a result of a number of overall dry years in the Western Region of Norway at the end of the 1990s and the beginning of this decade; late adopters have accordingly spent a relatively larger time of their existence under conditions of less rainfall than older plants. We also see that deviation in precipitation correlates significantly with a number of other variables. First, the negative correlation with both degree centrality and closeness centrality is not logical to assume. However, I believe that this relationship has been reflected from the late adopters' relatively higher closeness centrality scores that I have explained earlier, and the strong and significant relationship between the two centrality scores. I furthermore believe that the significantly negative relationship between deviation in precipitation and the size of the plant was produced as a result of late adopters' propensity to build larger plants.

The remaining correlation coefficients are insignificant, but for a number of pairs of variables we observe relatively high coefficients, and it is not unlikely that some of them would have been significant with a larger sample size. I therefore briefly describe some of them here. The positive correlation between size of the plant and the dependent variable could indicate that entrepreneurs who attempt relatively large systems get more out of the money they have invested in terms of average yearly electricity production. The positive relationship between closeness centrality and education teaches us that entrepreneurs with many years of formal schooling have a tendency to approach the center of the field. On the other hand, older actors seem to prefer to operate at the margin of the field. Finally, it is interesting to note that there appears to be a positive relationship between formal education and venture success.

Regression Analyses

Table 5.3 (pages 109 and 110) portrays a number of regression analyses with t-values in parentheses. In the following, I present the results from the different models.

Table 5.3 Regression analyses.

See pages 109 and 110. Dependent variable: MeanProdLn. n=20; §p<.10; *p<.05; ** p<.01; (two-tailed tests).

Models 1-3 include the reported control variables that have been applied in this study, except local network centrality (degree centrality), which will be added later. The nominal variable "Built alone" I have modeled the following way: 1=built alone, 2=not built alone. The reason for measuring the control variables as illustrated in the first three models is that the relationship between size of the plant and the dependent variables produced a significant lack of fit estimate in JMP5 (2003) (F-Ratio = 14.59; p<.001).[23] In order to account for this problem I first decided to control for this possibly "inappropriate" variable alone. Next, I included the other control variables (but excluded the size of the plant), and finally I included all control variables. We observed, however, no significant parameter in any of the three first models, and the explained variance was low and insignificant. Since the data set has only 20 observations and accordingly is sensitive to losses in degrees of freedom, I accordingly decided to exclude these control variables from further analyses in Table 5.3.

Hypothesis 1. Hypothesis 1 suggests a curvilinear relationship with the shape of a negative 2^{nd} degree polynomial between network distance to the center of the field and venture success. In Model 4, I tested this hypothesis by including a 2^{nd} degree polynomial of closeness centrality. Compliant with Cronbach's (1987) recommendations about how to avoid severe multicollinearity problems, throughout the analyses I have mean-centered all polynomials and interaction effects that include continuous variables. A significantly negative 2^{nd} degree polynomial from closeness centrality would have gained empirical support for the hypothesis, but in Model 4, no such result was observed. For the time being, we can therefore conclude that Hypothesis 1 is rejected.

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[23] For detailed description of the lack of fit function in JMP5 (2003) and its interpretation, see the user manual, pages 188-189.

In Model 5, I tested if there is a linear relationship between closeness centrality and venture success, and now we observe a statistically significant positive regression coefficient. It is therefore reasonable to assume a positive linear relationship between network distance to the center of the field and the dependent variable, rather than a negative 2nd degree polynomial, as suggested. Nevertheless, I argue that such a conclusion can be premature and misleading. From the correlation matrix (Table 5.2), we remember that closeness centrality and degree centrality were strongly correlated. Since degree centrality was also strongly correlated with the dependent variable, the significant estimate we observe in Model 5 can therefore be a reflection from a genuine linear relationship between degree centrality and venture success.

The high correlation between degree centrality and closeness centrality might have caused problems in the statistical analyses if both of them had been included in the same model. In particular, this can be the case if the number of observations is low, as it was in our case. I therefore conducted a lack of fit test between these parameters, but the estimate appeared insignificant (F-Ratio=.342; p=.894). By regressing closeness centrality on degree centrality I furthermore discovered only 43% explained variance, and altogether this indicated that it was defendable to include both parameters in the same model. Model 6 accordingly includes the control variable for degree centrality along with the 2nd degree polynomial effect of closeness centrality. In accordance with the correlation matrix (Table 5.2), we observed a significant and genuine linear effect from degree centrality on the dependent variable, but now we also observe that the polynomial estimate for closeness centrality is significantly negative. This has gained empirical support for Hypothesis 1.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-.959 (-4.907)	.264 (.210)	.023 (.015)	-1.614 (-1.657)	-2.232 (-3.043)	-.372 (-.456)	-.382 (-.457)	-0.666 -5.406
Size of the plant	.006 (1.678)		.002 (.300)					
Built alone		.183 (1.316)	.171 (1.148)					
Education		.280 (1.598)	.234 (.991)					
Age of actors		-.001 (-.057)	.000 (.003)					
Head difference		-.001 (-.600)	-.001 (-.604)					
MeanDevPre%		-.016 (-1.227)	-.013 (-.838)					
nDegree (nD)						.077** (3.658)	.070* (2.781)	
nD*nD							.002 (.513)	
nCloseness (nCl)				.029 (1.154)	.043* (2.123)	-.027 (-1.123)	-.026 (-1.019)	
nCl*nCl				-.004 (-.967)		-.006§ (-1.859)	-.007§ (-1.810)	
nFlowBetwLn (nFB)								
Niche 1 (N1)								-.153 (-.896)
Niche 2 (N2)								.227 (1.222)
Niche 3 (N3)								-.075 (-.451)
N1*nFB								
N2*nFB								
N3*nFB								
Start-up 1995								
Start-up 1996								
Start-up 1997								
Start-up 1998								
Start-up 1999								
Start-up 2000								
Start-up 2001								
Start-up year (SY)								
SY*SY								
RSquare	.135	.258	.263	.242§	.200*	.587**	.594**	.084
RSquare Adj	.087	.007	.077	.153§	.156*	.510**	.486**	.024

	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 17
Intercept	-1.132 (-1.084)	-1.177 (-6.105)	-1.267 (-6.846)	-0.948 (-3.666)	-0.650 (-4.750)	37.737 (.307)	290.116 (2.327)	306.871 (2.813)	240.329 (2.180)
Size of the plant									
Built alone									
Education									
Age of actors									
Head difference									
MeanDevPre%									
nDegree (nD)									
nD*nD									
nCloseness (nCl)	.020 (.750)						0.034 (1.374)	0.031 (1.399)	
nCl*nCl	-.009* (-2.144)						-.008 (-1.607)	-.009* (-2.366)	
nFlowBetwLn (nFB)		.279** (2.948)	.344** (3.750)	.203 (1.665)					.129 (1.133)
Niche 1 (N1)	-.380* (-2.193)		-.325* (-2.386)	-.199 (-1.270)			-.413* (-2.288)	-.444** (-3.064)	-.186 (-1.335)
Niche 2 (N2)	.120 (.663)		.264§ (1.885)	.180 (1.238)			.305 (1.581)	.333§ (1.984)	.348* (2.321)
Niche 3 (N3)	.260 (1.457)		.060 (.467)	.019 (.145)			.107 (.659)	.112 (.714)	-.163 (-1.130)
N1*nFB				-.250 (-1.247)					-.384§ (-2.040)
N2*nFB				.026 (.148)					.127 (.784)
N3*nFB				.225 (1.649)					.257§ (2.114)
Start-up 1995					.365 (1.221)				
Start-up 1996					.353 (.734)				
Start-up 1997					-.141 (-.525)				
Start-up 1998					-.559 (-1.581)				
Start-up 1999					-.079 (-.296)				
Start-up 2000					-.214 (-.798)				
Start-up 2001					.274 (.775)				
Start-up year (SY)						-.019 (-.315)	-.146* (-2.343)	-.154* (-2.823)	-.121* (-2.188)
SY*SY						.064§ (1.901)	.011 (.316)		
RSquare	.433§	.326**	.512**	.597*	.286	.204	.641*	.638**	.705**
RSquare Adj	.281§	.288**	.421**	.453*	.043	.110	.476*	.509**	.569**

In Model 7, I added local centrality as a 2nd degree polynomial, but this effect was insignificant. This accordingly rejects the previous statement where I – due the possible negative, marginal effects from each new tie – suggested a curvilinear relationship on venture success.[24] The non-linear effect for closeness centrality – on the contrary – remained significant.[25] Furthermore, visual inspection of the data-plots in Models 6 and 7 did not indicate collinearity problems, and we did not have significant lack of fit estimates in any of these models. So far, the conclusion is that after controlling for local network centrality, Hypothesis 1 has gained overall empirical support.

Hypothesis 2. Hypothesis 2 suggests that entrepreneurs in densely connected niches will be better performers than entrepreneurs in sparsely connected niches, and in the previous chapter I showed that Niches 2 and 3 were relatively densely connected whereas Niche 1 was sparsely connected. Model 8 tested Hypothesis 2 by including a dummy variable for each of the three niches. Nominal factors are accordingly expanded to all levels where the regression estimate for Niche 3 represents the negative sum of the other niches.

JMP5 (2003) is programmed in a way that estimates to what extent each nominal factor deviates from the sum of the remaining observations in the regression analyses, and the estimates for Model 8 indicated no significant effects. However, in order to dig deeper into the deviations between each respective niche and to uncover if and eventually how the three niches deviated from each other, I conducted what are called "contrast effects" in JMP5 (2003). For the parameters in Model 8, the contrast effect between niche 1 and 2 produced a t-value of -1.202 where p=0.246. The contrast effect between Niche 1 and 3 produced a t-value of -.28 where p=.783. The contrast effect between Niche 1 and the totality of observations for Niches 2 and 3 produced a t-value of -.896 (which we can also observe in Model 8) where p=.383. So far, all analyses have gained no empirical support at all for Hypothesis 2. Explained variance for the model was furthermore low and insignificant.

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[24] In unreported models where I have deleted closeness centrality – first the polynomial effect and next also the linear effect – the polynomial effect from degree centrality on venture success remained insignificant.

[25] In an unreported model, I also tested closeness centrality as a linear variable together with degree centrality as a linear variable. However, closeness centrality was insignificant here.

Model 9 included the polynomial effect for nCloseness, and we now observe significant effects from the nominal niche variable on venture success; start-ups in Niche 1 were significantly less productive than their colleagues in Niches 2 and 3 were. This is in accordance with what Hypothesis 2 predicted and the least square means (adjusted means) reported in Table 5.4 also confirmed the pattern observed from Model 9.

Niche	Mean	Least Square Mean	Std. Error
1	-.819	-.795	.175
2	-.439	-.295	.279
3	-.741	-.156	.263

Table 5.4 Means, least square means (adjusted means) and standard deviations for the three niches. Least square means and standard deviations are adapted from Model 9, Table 5.3. n=20.

To get a more detailed picture of the deviations between the different niches I again conducted contrast effects on the nominal factors. The genuine contrast effect between Niches 1 and 2 was insignificant (t-value=-1.632; p=.124), but we must nevertheless keep in mind that the number of observations was low. In Niche 1, there were 7 start-ups while Niche 2 had only 5 (Niche 3 had 8 start-ups). The insignificant difference between Niches 1 and 2 was most likely a result of too few observations. The contrast effect between Niches 1 and 3, on the other hand, was significant (t-value = -2.123; p<0.10 [p=.051]). Finally, I conducted the contrast effect between Niches 2 and 3, but as expected, the effect was far from significant here (t-value = -.443; p = .664). The overall significant difference in venture success between actors in the sparsely connected Niche 1 compared to their superior colleagues in the densely connected Niches 2 and 3, gained empirical support for Hypothesis 2.

In addition, Model 9 showed that the negative polynomial effect from closeness centrality remained significant. Moreover, whereas the adjusted R-square was practically zero in Model 8, it became higher than 28% in model 9. This is well above Model 5, which only included the polynomial effect from closeness centrality (an increase of almost 13%). The findings altogether illustrate the importance of including different levels of analysis when researchers approach the concept of social capital (and other concepts in the field of social sciences, for that matter). If for some reason we had overlooked the focal actor's external relations (in this case the extent to which his external relations connected him to the center of the field), we would probably (wrongly) have concluded that relational characteristics for collectives (in this case the density of contacts within niches) had no predictive power at all on the dependent variable. So far, however, social capital has appeared to be a mixed determinant phenomenon where both the focal actor's network distance to the center of the field (nCloseness) and the niche to which he belongs significantly predict venture success.

Niche	Means nCloseness	Standard Error
1	37.073	1.827
2	40.468	2.162
3	32.601	1.709

Table 5.5 Means and standard deviations in nCloseness for actors within the different niches. n=20

Table 5.5 shows mean scores (and standard deviations) in nCloseness for actors within the respective niches. On the average, actors in Niche 3 seemed to have positioned themselves at the margins of the field, whereas entrepreneurs in Niche 2, overall, are the most central players. Analyses also revealed that the deviations were statistically significant (I present these results in a later section). These large differences in overall closeness centrality between Niches 2 and 3 were perhaps the explanatory factors that have masked the genuine difference in output for the subsets. We have so far learned from theoretical arguments, supported by regression analyses, that being too close or too distant to the center of the field is negative. By controlling for this factor in Model 9, we discovered that belonging to Niche 2 or 3 was positive. Thus, if an entrepreneur manages to position himself in Niche 2 or 3, but at the same time avoids the margins or the center of the field, he should be in a fairly good position to become a successful micro-power start-up.

Nevertheless, it is reasonable to warn that drawing conclusions that are too firm from the reported effects in Model 9 could be misleading. In an unreported analysis, I found that actors in Niche 2, on the average, had an approximately 50% higher degree centrality score than their colleagues in Niches 1 and 3, and the difference was also significant (t-value = 2.073; $p<.10$).[26] The niche effects observed in Model 9 could accordingly be a reflection of local

[26] I return to the details of this analysis in a later section.

network centrality, which we know from previous models has a strong predictive effect on the dependent variable. In another unreported model, I also included degree centrality in addition to the parameters from Model 9. What I observed here was that degree centrality – as before – had a positive and significant effect on the dependent variable, closeness centrality still appeared as a significant negative 2^{nd} degree polynomial, yet the niche effect now became insignificant. In a third unreported model, I only included the niche variable and degree centrality, but also here local network centrality was positive and significant whereas the niche effect again appeared insignificant. My conclusion is that the significant niche effect observed in Model 9 is possibly a reflection of an overall high level of degree centrality within Niche 2. Altogether, these discoveries have rejected Hypothesis 2 whereas Hypothesis 1 still has empirical support.

Hypothesis 3. Hypothesis 3 suggests a positive relationship between access to non-redundant information and venture success, and in Model 10 this hypothesis was tested by including Freeman et al.'s (1991) normalized centrality measure of flow betweenness. We observed strong significant effects for both the parameter and explained variance, so our conclusion is that Hypothesis 3 has been empirically supported. Nevertheless, this might also be a preliminary and misleading conclusion. Table 5.2 reveals that degree centrality and flow betweenness were strongly correlated, therefore what we observed in Model 10 could be a reflection of the strong relationship between these centrality measures. The ideal situation would be to test these centrality measures against each other in the very same model (as we did between degree centrality and closeness centrality), but a significant lack of fit estimate between these two variables constrained us from doing so (F-Ratio=87.673; $p<.10$). Later I will come back to how I dealt with these two centrality measures.

Hypothesis 4. From Chapter three we remember that Hypothesis 4 proposed a strong positive effect on venture success if the entrepreneur is positioned in a densely connected niche and at the same time accesses high level of non-redundant information, a medium effect if he is positioned in a densely connected niche but accesses low level of non-redundant information, a medium effect if he is positioned in a sparsely connected niche accessing high level of non-redundant information, and finally a low effect on venture success if he is positioned in a sparsely connected niche with low access to non-redundant information. It is now time to empirically test this hypothesis, and I have done this by conducting interaction effects between the niche variable and normalized flow betweenness. Before this, I present in Model 11 the additive effect from these two variables.

Since flow betweenness appears significantly positive here as well, we have again gained strong and significant support for Hypothesis 3. As before, Niche 1 was significantly less productive than the actors in Niches 2 and 3 were, indicating support for Hypothesis 2. We now also observe that Niche 2 was significantly more productive that the sum of Niches 1 and 3, but the contrast effect between Niches 2 and 3 was still insignificant (t-value=.875; p=.394). The contrast effect between Niches 1 and 2 was significant (t-value=-2.412; p<.05), and the contrast effect between Niches 1 and 3 was "almost" significant (t-value=-1.708; p=.107). We accordingly conclude that we have gained overall empirical support for Hypothesis 2 again. The empirical analyses also teach us that with regard to simultaneously measuring the focal actor's access to non-redundant information (i.e. lower level aggregate) and niche effects (higher level aggregate), we still observe that we are dealing with an empirical phenomenon that is mixed-determinant in nature.

In Model 12, I tested Hypothesis 4 by including interaction terms between the niche factor and flow betweenness. Surprisingly, we observe that no parameter appeared significant, nor did any contrast effect between each respective niche.[27] However, the adjusted R-square actually increased as compared to the previous model (though the significance level was slightly decreased), and this might indicate that the loss of degrees of freedom by adding the interaction term explains the insignificant parameters.[28]

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[27] Contrast effect between Niches 1 and 2 produced a t-value of -1.395 where p=.185. Contrast effect between Niches 1 and 3 produced a t-value of -.868 where p=.400.

[28] The lack of fit function in JMP5 (2003) was nevertheless insignificant for Model 12 (F-ratio=1.341; p=.597).

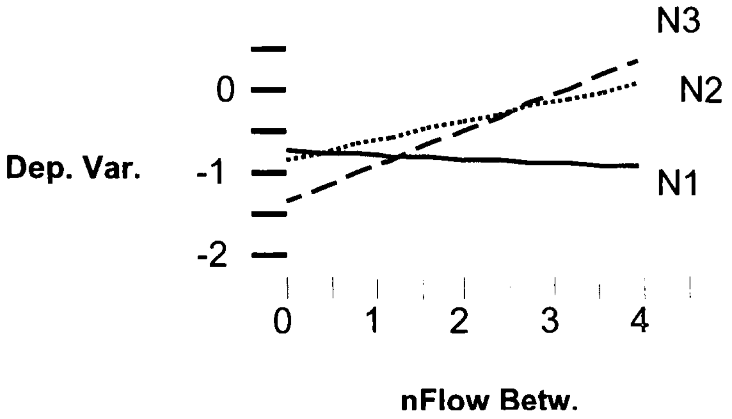

Figure 5.1 Interaction effects between niche (N) and flow betweenness. Adapted from Model 12, Table 5.3.

The interaction terms between the niche effect and flow betweenness in Model 12 are illustrated in Figure 5.1. We observe that in the densely connected Niches 2 and 3 it was positive to access non-redundant information whereas it had no effect at all in Niche 1. Thus, the dotted lines for Niches 2 and 3 granted directional support for Hypothesis 4a, which stated that production will be high at plants in densely connected niches if the focal actor accesses non-redundant information. On the other hand, entrepreneurs in Niche 1 accessing non-redundant information (i.e. high flow betweenness) were expected to have medium outcome according to Hypothesis 4b. In Figure 5.1, however, we observe that these were low performing start-ups. The same can be said about entrepreneurs in Niches 2 and 3 with low access to non-random information. Yet according to Hypothesis 4c, these actors were also expected to be medium performers. Finally, we observe that players in Niche 1 with low access to non-redundant information were also low in outcome, which is in accordance with Hypothesis 4d.

Altogether, Model 12 gave somewhat mixed directional support to Hypothesis 4. It seems to be most beneficial to belong to a densely connected niche and at the same time have access to non-redundant information. On the other hand, if the start-up lacks non-redundant information, it appears it does not matter at all in which niche he is positioned. Finally, access to non-redundant information in the sparsely connected Niche 1 apparently had no effect on venture success at all. Nevertheless, due to insignificant parameters in the statistical analyses, we must be extremely careful to draw conclusions that are too firm from these discoveries. I find it reasonable to believe, however, that a larger sample size most likely would have produced significant results.

Hypothesis 5 and 5alt. We remember from Chapter three that Hypotheses 5 suggested that late adopters would outperform early adopters as a result of increased density (Hannan 1986) of micro-power start-ups (reflected in increased competence and learning throughout the emerging field). Hypothesis 5alt, on the other hand, suggested that the relationship might be the opposite as a result of mimetic behavior among late adopters (DiMaggio 1991). In Model 13, I tested these competing hypotheses by including a nominal variable for the start-up year. Network variables will be included in later models.

Start-up year	Means	Standard Error
1995	-.284	.315
1996	-.297	.545
1997	-.790	.273
1998	-1.208	.386
1999	-.729	.273
2000	-.864	.273
2001	-.376	.386

Table 5.6 Means and standard deviations for start-up year.

Standard deviations adapted from Model 13, Table 5.3.

The results from the regression analysis indicated no significant effects, but if we take a closer look at the means in output for start-ups within each yearly cohort in Table 5.6, we observe that entrepreneurs who started in 1995 seem to be the superior performers. From this year on, we see a steady decrease in venture success that continues until 1998. Contrast effects in JMP5 (2003) actually revealed that the entrepreneurs who started production in 1998 were significantly less productive than their colleagues who started in 1995 (t-value = 1.856; $p<.10$). However, beyond 1998 the curve becomes positive and we observe the contours of a non-linear relationship with the shape of a positive 2nd degree polynomial between start-up year and venture success, where 1998 is the turning point.[29] The described effect is perhaps best illustrated in Figure 5.2

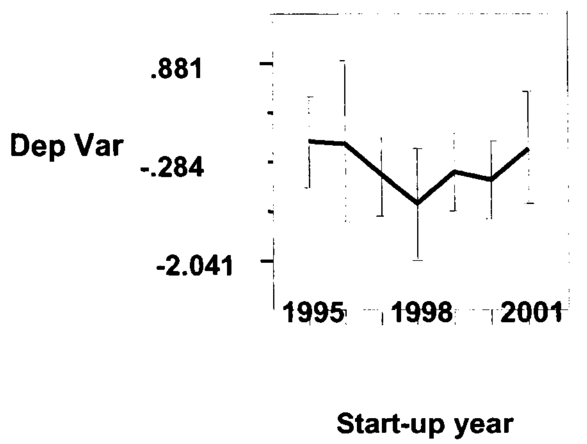

Figure 5.2 Means for start-up year. Adapted from Model 13, Table 5.3.

The results so far give partly a directional support for both of the competing hypotheses. Between 1995 and 1998, the trend was negative which according to Hypothesis 5alt supports the argument behind mimetic behavior (DiMaggio 1991). From this year on, however, the curve becomes positive, indicating support for the density argument (Hannan 1986). It thus seems that these latter entrepreneurs have benefited from an overall increase in learning and competence that has been established throughout the emerging hydroelectric micro-power field.

Model 13 taught us that there is probably a non-linear relationship with a shape of a positive 2nd degree polynomial between start-up year and venture success. Therefore, in Model 14 I modeled the start-up year as a continuous variable and included it in the regression analyses as a polynomial effect. The major reason for doing this was the loss in degrees of freedom that the nominal start-up year variable represented, constraining me from simultaneously testing this parameter against network predictors of social capital in later models. First, we observe an increase in adjusted R-square from practically zero to about 11%. The explained variance, however, was still insignificant, but I again found it reasonable to explain this as a

[29] The small decrease from 1999 to 2000 was far from being statistically significant (t-value=-.349; p=.733).

result of too few observations (F-Ratio = 2.176; p=.144). Next, we observe a significantly positive polynomial effect that confirmed the findings from the previous model. Thus, again we have gained partly empirical support for both Hypothesis 5 and 5alt. After decreasing the number of parameters, the non-linear effect is now also significant. Altogether, this indicates that in the first phase of the emerging hydroelectric micro-power field there was a negative trend in output for adopters, which supports the argument behind mimetic behavior. Beyond 1998, however, we observe a general increase in venture success for subsequent adopters, which most likely was a result of a general increase in knowledge and legitimacy that had been spreading throughout the emerging field.

Since average deviation in precipitation (MeanDevPre%) correlated strongly with the start-up year variable (Table 5.2), I decided to test this effect in isolation in two separate models. These are reported in Table 5.7 (t-values in parentheses), in the first as a linear effect, and in the second as a polynomial effect. We observe, however, no significant effects at all, neither from the parameters nor in explained variance.[30]

	Model 1	Model 2
Intercept	.167	.427
	(.147)	(.316)
MeanDevPre% (MDP)	-.009	-.012
	(-.760)	(-.833)
MDP*MDP		-.001
		(-.381)
RSquare	.031	.039
RSquare Adj	.023	.074

Dependent variable: MeanProdLn. n=20; § p<.10 (two tailed tests).

Table 5.7 The effects from deviations in precipitation.

In Model 15, I conducted the somewhat bold task of simultaneously including start-up year as a 2nd degree polynomial along with the closeness centrality variable as a 2nd degree polynomial and the niche factor. In other words, I included the parameters from both Models 9 and 14, and I did this to uncover possible genuine effects on venture success when we

[30] In unreported models I also replicated Models 15 through 17, but replaced start-up year with deviations in precipitations. In all models, however, the parameter was far from being statistically significant, as both a linear and a polynomial effect.

simultaneously model network predictors along with a parameter capturing elements from institutional theory and population ecology. The results were – at least in my opinion – interesting. If we look at the parameters for the start-up variable, we observe that the linear regressor has now become significantly negative, whereas the polynomial effect is practically zero and far from significant. Thus after controlling for network predictors of social capital, we have learned that there seems to be a genuine negative relationship between late versus early adopters and venture success.

Next, we observe that explained variance for the model was both high and significant. Then we see that the 2nd degree polynomial effect from closeness centrality is still negative (but the effect is now insignificant). Thirdly, we observe that entrepreneurs in Niche 1 – in line with Model 9 – were significantly inferior in performance compared with their colleagues in Niches 2 and 3. The contrast effect between Niches 1 and 2 was significant (t-value = -2.133; $p<.10$ [p=.0523]) which was also the case between Niches 1 and 3 (t-value=-1.833; $p<.10$). Finally, the contrast effect between Niches 2 and 3 was insignificant (t-value=-.644; p=.531). Altogether, this gave directional support for Hypothesis 1 and significant support to Hypothesis 2. Overall, the results are in accord with the previous analyses.

Since the polynomial effect for start-up year now appeared unnecessary, I decided to delete this effect in Model 16. First, we observe that the adjusted R-square has steadily increased and was more significant. The start-up year variable here also appears to be significantly negative. We furthermore see that the polynomial effect from closeness centrality now appears to be significantly negative, which is in accordance with Hypothesis 1. As before, actors in Niche 1 were significantly less productive than the sum of actors in Niches 2 and 3. The contrast effect between Niches 1 and 2 was significant (t-value = -2.86; $p<.05$), as was the contrast effect between Niches 1 and 3 (t-value = -2.22; $p<.05$). Again, the contrast effect between Niches 2 and 3 was insignificant (t-value = .762; p = .459). Visual inspections of the data-plots in JMP5 (2003) indicated no collinearity problems, and there were no warnings of significant lack of fit estimates.

In an unreported model, I included degree centrality – in addition to the parameters in Model 16 – yet all the variables remained stable and significant, and there was no substantial change from the reported effects in Model 16. This is also interesting, I argue. We remember from previous discussion that when degree centrality was included, in addition the parameters from Model 9 (niche effect and closeness centrality as a 2^{nd} degree polynomial), the genuine niche effect became insignificant. After controlling for start-up year, however, the niche effect remained stable and significant even when the parameter for local network centrality was included in the model. This gained empirical support for Hypothesis 2 and indicated that the start-up year parameter was an important parameter, which definitely "belonged" to the model. For degree centrality, there was also a positive and significant effect on the dependent variable, which is in accord with previous analyses. Finally, the adjusted R-square has increased to 60.1% ($p<.01$). Visual inspections of the data plots in JMP5 (2003) indicated no multi-collinearity problems for this unreported model, nor did the lack of fit function give us any warning regarding losses in degrees of freedom.

Perhaps the most interesting and novel finding from Models 15 and 16 was that the positive polynomial effect on venture success seemed to become genuinely negative when I controlled for network predictors of social capital. Later, I will give a lengthy discussion of the implications of both this (and other) findings, but my preliminary interpretation is that to gain from the increased level of organizational learning that has taken place in the emerging field over the last years (i.e. after 1998), it is essential to acquire this competence through access to social capital. In other words, despite the fact that an overall increase in knowledge has been established over the latter years, this asset does not benefit late adopters per se, but has to be gained through the specific network constellations that this dissertation has discovered.

Model 17 includes the parameter for start-up year in addition to the interaction effects between the niche variable and flow betweenness from Model 13. As in the previous model, we observe that there was a significantly linear negative relationship between start-up year and venture success, and in an unreported model that included a 2^{nd} polynomial effect for start-up year, the nonlinear effect was also far from being significant (t-value = .62; p = .548). We furthermore observe that the adjusted R-square has increased by almost 12% from Model 12 and more significant now.[31]

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[31] Despite relatively many parameters, the lack of fit function in JMP (2003) gave no warning of loss of degrees of freedom. Visual inspection of the data plots in the statistical program indicated no multicollinearity problem.

Compared with Model 12, the effects from the network predictors were very much the same, but a number of parameters appeared significant in this model, which also controlled for start-up year. The nominal parameters show us that Niche 2 was significantly more productive as compared with the actors in Niches 1 and 3. Contrast effects furthermore show that Niche 2 was significantly more productive than Niche 3 (t-value = 1.801; p<.10), but the contrast effect was insignificant between Niches 1 and 2 (t-value = -1.656; p = .124). Altogether, this indicated mixed support for Hypothesis 2; actors in Niche 2 now seem to have outperformed their colleagues in the two other niches, in particular Niche 3. I do not know why it seems that entrepreneurs in Niche 2 have outperformed their colleagues in Niche 3, which was also densely connected. However, a plausible explanation could be that Niche 2 had a slightly higher density level than Niche 3; at least this was the case in the latter years of the emerging field.

To get a more comprehensive picture of how entrepreneurs within each respective niche performed, I decided to graphically illustrate the interaction terms with flow betweenness in Figure 5.3. Here we can see – as described above – that start-ups in Niche 2 outperformed their colleagues in Niche 3, but access to non-redundant information was positive in both niches. Actors in Niche 3 outperformed their colleagues in Niche 1, given that they had access to non-redundant information. If not, they were actually outperformed by Niche 1. Comparing the interaction effects by applying a what is called a custom test in JMP5 (2003), we actually find that there was a significant difference between Niches 1 and 3 (t-value = -2.35; p<.05).

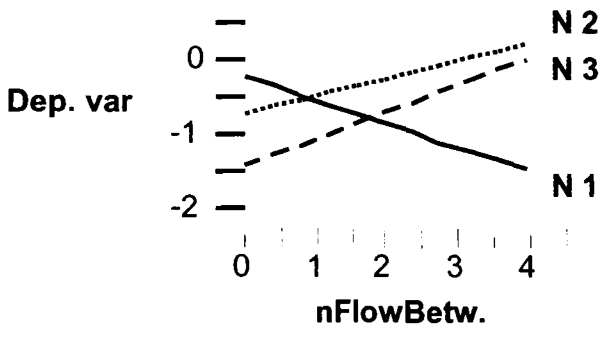

Figure 5.3 Interaction effects between niche (N) and flow betweenness. Adapted from Model 17, Table 5.3.

If we compare actors in Niches 1 and 2, we observe that their performance was more or less equal if they had low access to non-redundant information. However, when access to non-redundant information increased, so did venture success in the densely connected Niche 2, whereas it actually decreased in Niche 1. The custom test effect, however, was insignificant, which is most likely explained by too few observations, particularly in Niche 2 (t-value = -1.55; p = .145).

Altogether, the interaction effects described above are generally similar to what we have previously discovered, indicating partial support for Hypothesis 4. Now, however, we observe a number of significant effects. Figure 5.3 reveals that we are dealing with network predictors of social capital that are both cross-level and mixed-determinant in nature; mixed-determinant since Niche 2 seems to have outperformed Niche 3 and cross-level since access to non-redundant information was negative in Niche 1, but positive in Niches 2 and 3. Finally, it is interesting to observe that access to non-redundant information did not seem to have a genuine effect on venture success, but seemed to be contingent upon niche characteristics. This rejects Hypothesis 3, and the findings again illustrate that a researcher can lose important insight in his study of social phenomena by ignoring that different levels of aggregates could possibly be at play.

Previous models have taught us that local network centrality – degree centrality – seems to appear as an important control variable, and seems to have strong genuine effect on the dependent variable. We have furthermore observed in Table 5.2 that flow betweenness and degree centrality were highly correlated. What we observe in Model 17 could accordingly be a reflection between possible genuine interaction effects between niche characteristics and local network centrality. In order to find out more about this issue, I decided to replicate Model 17, with the important difference that I included degree centrality instead of flow betweenness. The results are shown in Table 5.8 with t-values in parentheses.

Intercept	163.789	(1.407)
nDegree (nD)	.0406	(1.569)
Niche 1 (N1)	-.188	(-1.254)
Niche 2 (N2)	.256	(1.280)
Niche 3 (N3)	-.068	(-.457)
N1*nD	-.025	(-.576)
N2*nD	-.019	(-.548)
N3*nD	.044	(1.555)
Start-up year	-.083	(-1.417)
RSquare	.642*	
RSquareAdj.	.477*	

Dependent variable: MeanProdLn. n=20. § p<.10; * p<.05; (two tailed tests).

Table 5.8 Interaction effects with degree centrality.

Without going into detail about the parameters, contrast effects and custom tests, the overall picture from Table 5.8 is that none of the variables appeared significant, not even start-up year. The explained variance was still high, but the adjusted R-square was actually reduced by more than 9% from Model 17 (Table 5.3). I accordingly concluded that access to non-redundant information most likely had a genuine effect on the dependent variable through its interaction with the niche variable.

In two unreported models, I conducted the interaction effect between closeness centrality – in the first model as a 2nd degree polynomial and in the second as a linear variable – and the niche parameter. As in Model 17, the start-up year was also included in the analyses. The new interaction terms, however, produced an even worse explained variance than what we observed in Table 5.8. In the first, the adjusted R-square was 43.8% (p<.05) and in the second 42.4% (p<.05). Moreover, there were no significant interaction terms to observe. It accordingly seems that access to non-redundant information is the only lower level network predictor that interacts significantly with the niche parameter.

Further Analyses

So far, the regression analyses have revealed to what extent different predictors might induce venture success for micro-power start-ups. We have thus tested the hypotheses that I developed in Chapter 3, in addition to the effects of a number of control variables. In this section, I intend to go somewhat beyond the strictly hypothesized relationships and conduct an exploratory approach on other variables in the dataset.

Regression Analyses II

We remember from the correlation matrix in Table 5.2 that the size of the micro-power plant correlated significantly with education level, start-up year, closeness centrality, and degree centrality. This indicates that perhaps the dimension of the hydro turbines was not only decided exogenously as a result of river conditions or other hydroelectric and meteorological considerations; endogenous characteristics as described above could also be at play. Therefore, I decided to conduct a number of statistical analyses that included the following independent variables as candidates: whether the plant had been built as a one man project or not, start-up year, formal education, degree centrality, closeness centrality, flow betweenness, age of actors at start-up, and head difference. The size of the plant was modeled as the dependent variable. Lack of fit tests in JMP5 (2003) had indicated that flow betweenness and closeness centrality produced significant estimates when tested against the size of the plant; therefore I decided to treat them separately in the analyses.[32]

In Model 1 (Table 5.9) we observe no significant effect from flow betweenness on the dependent variable (t-values in parentheses). The explained variance was also practically zero and insignificant. Accordingly, I concluded that access to non-redundant information had no effect at all upon the decision to build a large or small plant. In Model 2, on the other hand, we observe that closeness centrality significantly predicted the dependent variable. It thus seems that the entrepreneurs who were approaching the center of the field had a tendency to build large plants. However, due to a significant lack of fit estimate, we must be cautious about drawing conclusions that are too firm; this finding could also be a reflection of the strong and significant relationship between degree centrality and closeness centrality. Therefore, in Model 3, I tested the effect from degree centrality on the dependent variable, and here we observe both better model fit and more significant parameter estimate than in Model 2.

[32] For flow betweenness F-Ratio = 76.789 ($p<.10$) and for closeness centrality F-Ratio = 445.62 ($p<.05$).

In order to reduce the risk and to ensure that they are doing the "right" thing, it is not surprising that entrepreneurs who build larger and accordingly more expensive plants would be more active in their local network. Yet an alternative explanation could be that entrepreneurs who are active in the local network, either by seeking information or receiving network ties from others, for some reason tend to build larger plants. For instance, such an amount of activity could create a certain involvement and enthusiasm for micro-power, which in turn could lead to a desire to attempt something that was beyond what was initially planned.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	27.386 (2.125)	-35.008 (-.807)	12.500 (.897)	-12687 (-2.206)	-11951 (-1.832)	-12017 (-2.327)
nFlowBetwLn	8.146 (1.287)					
nCloseness		2.120§ (1.784)			.327 (.268)	
nDegree			2.701* (2.323)			2.138* (2.272)
Start-up year				6.347* (2.204)	5.973§ (1.825)	6.003* (2.322)
Education				21.173* (2.696)	20.304* (2.333)	18.382* (2.572)
RSquare	.084	.150§	.231*	.428**	.430*	.567**
RSquare Adj	.033	.103§	.188*	.361**	.324*	.486**

Dep. var: Size of the plant: n=20; § $p<.10$; * $p<.05$; ** $p<.01$ (two tailed tests)

Table 5.9 Regression Analyses II.

In order to produce Model 4, I first conducted what is called forward stepwise regression in JMP5 (2003) where the candidates for independent variables were: whether the plant was built as a one-man project or not, start-up year, formal education, age of actors at start-up, and head difference. The significance probability to enter was set to .25, whereas the probability to leave is .10. The model produced (Model 4) shows that the tendency to build larger plants throughout the lifespan of the emerging field was significant, and every year the size increased by about 6 kWh maximum capacity. This could imply that established knowledge among the involved actors was maturing, and that the emerging field over the time span moved beyond the merely experimental stage. Perhaps late adopters perceived lower risk as a result of the competence that had been established throughout the field and consequently felt comfortable to attempt overall larger (and more expensive) solutions than early adopters.

If we now look anew at Figure 1.1 in the very beginning of this dissertation, the results we see in Model 4 can explain why we observed a marked increase in the building of miniature plants at the end of the nineties, whereas the number of micro-power start-ups peaked. This can actually imply that new entrants, to an increasing extent, were moving beyond what can strictly be defined as micro-power.

We furthermore observe that the more educated the entrepreneur was, the larger the plant he tended to build. As described earlier, this is logical. Everything else being equal, the better educated the entrepreneur is, the better scientific skills he will possess. In turn, these would enable him to better calculate and predict the outcome from different sizes of the hydro turbines, and to altogether reduce the risk of attempting relatively large investments. On the other hand, entrepreneurs with a low formal education face higher risk and uncertainty of the outcome due to lack of formal competence. They would consequently feel inclined towards smaller (and less expensive) solutions.

To test the robustness of the parameters presented in Model 4, first I tested closeness centrality together with size of the plant and education (Model 5), and next I replaced closeness centrality with degree centrality (Model 6). We observe in Model 5 that the parameters for education and year of start-up remained stable and significant, whereas the effect from closeness centrality has now become insignificant. In Model 6, however, we notice that local network centrality, along with start-up year and education level, remained significant and had similar parameter values as before. High explained variance furthermore indicated good model fit.

Finally, in an unreported model I tested if there was tendency within some of the niches to build either small or large plants, but no contrast effects between any of the three niches produced significant effects.

Regression Analyses III

My conclusion so far is that there most likely are a few endogenous factors that seem to predict the size of the micro-power turbines. Therefore, it is not unlikely to expect that similar factors might also influence the head difference. Consequently, in unreported models I first tested separately the centrality measures, degree centrality, closeness centrality and flow betweenness on this parameter, but none of these variables had any effect on head difference. Next, I undertook the task of conducting stepwise regression as described above with head difference as the dependent variable. Variables that were candidates for the model were: whether the plant had been built as a one-man project or not, start-up year, formal education, size of the plant, and age of the actors. I found, however, that none of these variables was close to significantly predicting the dependent variable. Finally, I included the niche factor as an independent variable, but again I found no significant contrast effect between any of the three identified niches. Altogether, it seems that the question about head difference was totally exogenously decided (i.e. by climatic and hydrological conditions).

When modeling degree centrality as the dependent variable and conducting forward stepwise regression on the parameters "built alone", start-up year, education, age of actors, and head difference, I found that none of these variables seemed to predict the focal actor's local network centrality. In Table 5.10 (Model 1), however, we observe that the size of the plant seemed to predict local network centrality, but this is actually what we already knew from previous analyses; there was a positive relationship between these variables, but we did not necessarily know the causal direction. As previously mentioned, the entrepreneurs that were active in the local network, either by seeking information or receiving network ties from others, tended to build larger plants. For instance, such an amount of activity could create certain involvement and enthusiasm for micro-power, which in turn could lead to a desire to attempt something that is beyond what was initially planned. Alternatively, entrepreneurs building larger, and accordingly more expensive plants, were possibly more active in the local network with the aim of reducing the risk involved in the project.

	Model 1	Model 2
Intercept	7.200 (3.830)	11.202 (9.552)
Size of the plant	.085* (2.323)	
Niche 1		-1.875 (-1.155)
Niche 2		3.673§ (2.073)
Niche 3		-1.799 (-1.143)
RSquare	.231*	.202
RSquare Adj	.188*	.108

Dependent variable: nDegree. n=20; § p<.10; * p<.05 (two tailed tests). T-values in parentheses.

Table 5.10 Regression analyses III.

Next, I included the Niche effect in Model 2, and as I have previously described, we observe that actors within Niche 2 were more active overall in their local network then their colleagues in Niches 1 and 3. Moreover, contrast effects showed that actors in Niche 2 had a significantly higher degree centrality score than entrepreneurs in Niche 1 (t-value = 1.842; p<.10) and Niche 3 (t-value = 1.866; p<.10), respectively. The contrast effect between Niches 1 and 3 was insignificant (t-value = .029; p = .977).

Regression Analyses IV

Again, I undertook similar explorative procedures as described above, but this time with closeness centrality as the dependent variable. The initial variables for stepwise regression analysis were: "built alone", start-up year, education, age of actors, size of the plant, and head difference. The result from the stepwise procedure is presented in Model 1, Table 5.11 (t-values in parentheses).

	Model 1	Model 2
Intercept	-1969	36.714
	(-1.725)	(33.316)
Start-up year	1.005§	
	(1.759)	
Education	2.813§	
	(1.823)	
Age of actors	-.161	
	(-1.569)	
Niche 1		.359
		(.235)
Niche 2		3.754*
		(2.255)
Niche 3		-4.113*
		(-2.781)
RSquare	.381*	.335*
RSquare Adj	.265*	.257*

Dep. var: nCloseness; n=20; § p<.10; * p<.05 (two tailed tests)

Table 5.11 Regression analyses IV.

We learn from Model 1 that late adopters had a larger tendency to search the center of the field than early adopters did. I have no obvious explanation for this observed pattern, but a plausible reason might be that a few vendors, consultants and perhaps also previously established micro-power plants appeared to be the most visible operators within the emerging field. Such a kind of implicit branding has in turn been a motivational factor for new entrants to approach these central actors.

We moreover observe that relatively highly educated entrepreneurs had a tendency to search the center of the field. I have no good rationalization for why there was a significant relationship between these parameters either, but a tentative explanation could be that years of schooling inspired the entrepreneurs to behave in a more "professional" manner, which in turn induced them to approach the more established, well-known, and "reputable" vendors and other micro-power plants.

The relationship between age of the actors and closeness centrality was negative but insignificant. However, the insignificant relationship was possibly a result of low sample size.

Earlier in this chapter, I briefly mentioned that there was a significant relationship between closeness centrality and which niche the actors belonged to, and in Model 2 (Table 5.11), I have formally presented these results. As previously described, we observe that micro-power plants in Niche 2 were generally closer to the center of the field than the other actors were, whereas the case was the opposite for start-ups in Niche 3. Niche1 fell somewhat between the other niches. Moreover, the contrast effects between each respective niche revealed that Niche 2 was significantly more central than Niche 3 (t-value = 2.855; p<.05), and that Niche 1 was significantly more central than Niche 3 (t-value = 1.788; p<.10). The contrast effect between Niches 1 and 2, on the other hand, was insignificant (t-value = -1.200; p=.247). Note, however, that the results I presented in Model 2 (Table 5.11) did not necessarily reveal causal direction between these parameters, but rather indicated a relationship between to which niche the actors belonged to and the focal actor's overall centrality within the emerging field.

If we now compare the analyses from Model 2 in Table 5.10 with Model 2 in Table 5.11, the overall pattern is that actors in Niche 2 were the more central actors overall, both with regard to degree centrality and closeness centrality.

I furthermore conducted step-wise regression where flow-betweenness was modeled as the dependent variable. Candidates for independent variables were: "built alone", start-up year, education, age of actors, size of the plant, and head difference. However, none of these parameters significantly predicted the focal actor's access to non-redundant information.[33] There was furthermore no significant effect from the niche predictor on flow betweenness as the dependent variable.

Discussion

Figure 5.4 sums up what the statistical analyses have revealed in this chapter. The dotted arrows represent relationships that were either weak or unstable throughout the analyses. Double-headed arrows indicate relationships where there was not necessarily a clear causal direction. Since the major focus in this dissertation has been to uncover possible network predictors of social capital, I will pay the most attention to these issues throughout the

[33] As previously described, the relationship between flow betweenness and size of the plant produced a significant lack of fit estimate (F-Ratio 6.111; p<.05), so in the unreported models I first decided to include this parameter separately. Next, I included the remaining parameters separately in the stepwise procedure, and finally I included all parameters in the stepwise procedure. I found, however, no significant estimates at all.

discussion. Next, I will debate to what extent being an early or late adopter in the emerging field seemed to influence venture success, and finally, I will include a discussion of the results from the exploratory approach that I undertook in the previous section. Note however, as the model in Figure 5.4 reveals, there seemed to be a number of indirect effects where certain parameters appeared as intermediate variables. This will most likely be reflected throughout the discussion where some issues might be repeated, but hopefully in different and informative contexts.

Some readers will perhaps raise objections that the model presented in Figure 5.4 is both complex and not easily interpretable, and I can fully understand such demurs. Yet what I actually intend to do here is to discuss the information uncovered by a number of analyses throughout this dissertation. In Chapter 3, I developed a few hypotheses that narrowly focused on a number of network predictors on venture success and questioned to what extent being an early or late adopter might influence the same effect variable. Below, I discuss the empirical findings in light of these hypotheses, in addition to – in my opinion – other interesting results. However, in the concluding chapter, I again constrain the focus to the research question that I presented in Chapter 2, as well as how I have interpreted the interplay between institutional issues and the concept of social capital. In other words, the next chapter focuses on what I believe is the very core contribution from this research project.

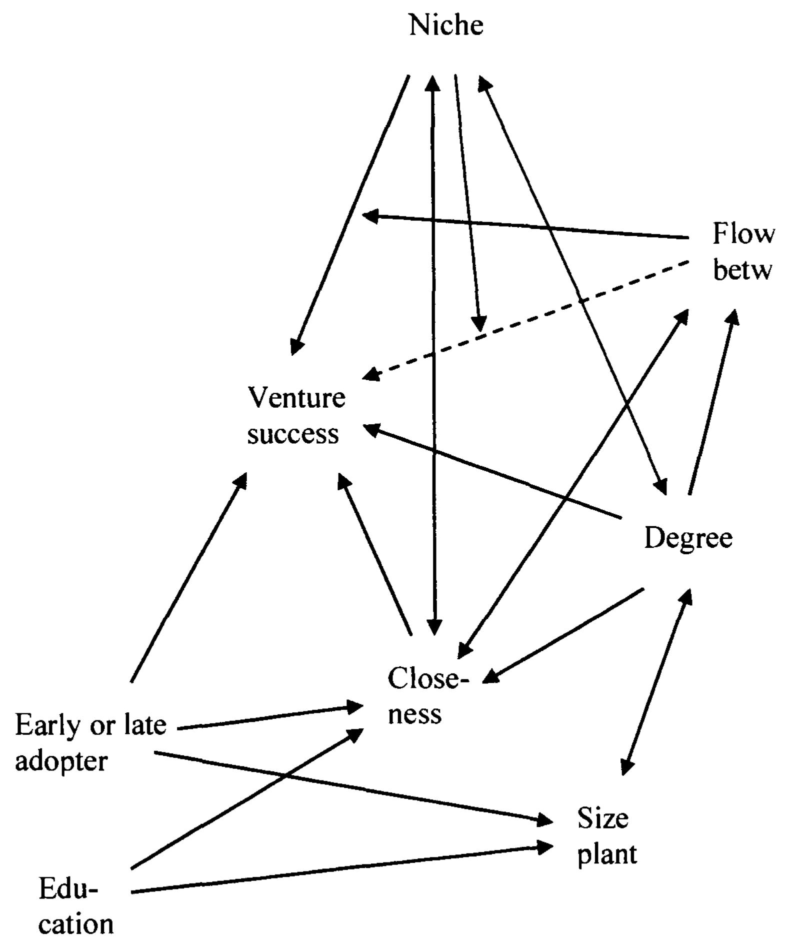

Figure 5.4 Model of the empirical analyses.

The Hypothesized Effects

Hypothesis 1. Hypothesis 1 suggested a curvilinear relationship with the shape of a negative 2^{nd} degree polynomial between network distance to the center of the field and venture success. In Table 5.3, we observe that this hypothesis gained empirical support when I controlled for local network centrality (Models 6 and 7) and the niche effect (Models 9 and 16). I accordingly maintain that this hypothesis has gained overall empirical support. Thus, it seems that start-ups operating either at the margins or at the center of the field were inferior in performance, as compared to entrepreneurs who were placed in intermediate positions.

To my knowledge, this is the first contribution that explicitly argues that there is a non-linear relationship between the extent to which an actor possesses a position of strategic significance in the overall network and outcome. Yet as described, other contributions have revealed similar empirical findings. Greve, Golombek et al. (2001) discovered a curvilinear relationship with the shape of a positive 2^{nd} degree polynomial between pollution levels and network centrality in the Norwegian pulp and paper industry. The centrality measure they applied in their contribution was information centrality (Stephenson and Zelen 1989), and is identical with the measure that I applied in the Florentine case from Chapter 2. Despite deviating slightly from closeness centrality in conceptual interpretation, the pattern was nevertheless similar to the empirical findings that this dissertation has uncovered. Actors in central and marginal positions had high pollution levels (i.e. they were inferior performers) whereas actors in intermediate positions polluted less (i.e. they were superior performers). The authors described these findings as a cry for help from actors with high pollution levels (and also financial problems), which of course might be the case. Nevertheless, this dissertation partly takes into account this issue since each entrepreneur's network configuration has been modeled at the year of start-up, and the dependent variable has been calculated from the average yearly electricity production in subsequent years. In other words, since the independent variable was measured prior to the effect variable, this revealed with relative certainty that the causal direction went from the focal actor's strategic significance in the overall network to venture success, and not the opposite.

Altogether, I argue that a probable (though not possibly the only) causal agent between the non-linear effects revealed in both these contributions is that actors who strive towards the center place themselves in an inferior position due to asymmetric information and lack of bargaining power. They accordingly become vulnerable to over investment or suboptimal solutions.

Table 5.5 and 5.11 (Model 2) reveal that entrepreneurs in Niche 2 were the most central actors overall in terms of network distance to the center of the field, start-ups in Niche 3 were the most distant, whereas actors in Niche 1 fell somewhat between the two other niches. We are not dealing with a clear causal direction here, and this is reflected in the double-headed arrow between the parameters in Figure 5.4. It is perhaps not particularly surprising to learn that start-ups within the 3 identified niches were encountered in different locations throughout the resource space, yet what I believe is most interesting to note is that we observe a significant negative polynomial effect from the closeness variable on venture success, even after controlling for this higher level aggregate.

Hypothesis 2. Hypothesis 2 suggested that entrepreneurs embedded in densely connected niches will outperform entrepreneurs in sparsely connected niches. In this empirical study, we did not have the possibility to model the niche factor as a continuous variable, so the three niches identified have been included as nominal variables. The density matrices in Chapter 4 categorized Niche 1 as a sparsely connected niche, whereas Niches 2 and 3 were described as densely connected. Regarding the statistical analyses, it is interesting to note that when we only included the niche factor in Model 8 (Table 5.3), we observed practically no effect on venture success. However, when we also included closeness centrality (as a polynomial effect) in the following model, the niche factor became significant.

This finding illustrates the importance of considering level issues when conducting research in the social sciences. If a researcher had stopped his analyses in Model 8 and had not simultaneously considered the different level aggregates – in this example the focal actor's network distance to the center of the field and to which niche each actor belonged – he could have (wrongly) concluded that niche characteristics had no effect at all on venture success. The overall pattern throughout the subsequent models, on the other hand, showed that the niche factor does matter. In Models 9, 11, 15 and 16 (Table 5.3) we learn that start-ups in Niche 1 were significantly inferior to their colleagues in Niches 2 and 3. Previously reported contrast effects largely indicated significant differences between Niches 1 and 2 and 1 and 3, respectively, whereas the difference between Niches 2 and 3 was insignificant. Altogether, these findings have given support to Hypothesis 2.

I have described that when degree centrality was included in addition to the parameters from Model 9 (Table 5.3), the genuine niche effect became insignificant. This model, however, did not control for start-up year. Thus, after also controlling for this parameter, the niche effect remained stable and significant (along with the 2nd degree polynomial for closeness centrality), even when degree centrality was included. Altogether, this has gained support for Hypothesis 2 and furthermore indicates that the start-up year parameter was an important control variable and definitely "belonged" to the model.

Nevertheless, in Models 12 and 17 (Table 5.3), which included the interaction effect between niche and flow betweenness, the genuine distinction in venture success between the sparsely connected Niche 1 and the densely connected Niches 2 and 3 became somewhat masked and less clear respectively. Yet in Figure 5.3 we observe that it was positive to belong to the densely connected Niches 2 and 3 – in particular to Niche 2 – when it was a given that the focal actor accessed non-redundant information. We do not know why it seems that entrepreneurs in Niche 2 outperformed their colleagues in Niche 3, which was also densely connected. Previously, I have suggested that the slightly higher density level in Niche 2, at least in the latter years of the emerging field, could explain this pattern. Yet other plausible causal mechanisms were also possibly at play, such as the very size of the niche or relational characteristics within these collectives, that went beyond the simplified density approach that I have applied in this study. In the next chapter, I discuss these issues in length.

Hypothesis 3. Hypothesis 3 suggested that access to non-redundant information will predict venture success, and the dissertation operationalized this independent variable by applying Freeman, Borgatti et al.'s (1991) centrality measure of flow betweenness. In Models 10 and 11 (Table 5.3) we observe significant support for this hypothesis, but in Models 12 and 17 (Table 5.3), which included interaction effects between the niche factor and flow betweenness, the genuine positive effect became insignificant. Accordingly, Hypothesis 3 has only gained partial support and it seems that access to non-redundant information did not have genuine explanatory power on venture success, but was contingent upon niche characteristics. I also return to this issue later.

Hypothesis 4. We remember that Hypothesis 4 proposed a strong positive effect on venture success if the entrepreneur is placed in a densely connected niche and at the same time accesses high level of non-redundant information, medium effect if he is placed in a densely connected niche but lacks non-redundant information, medium effect if he is placed in a weakly connected niche accessing high degree of non-redundant information, and finally low effect on venture success if he is placed in a weakly connected niche and at the same time lacks non-redundant information. Models 12 and 17 (Table 5.3) tested this hypothesis by including the interaction effect between the nominal niche variable and flow betweenness. What is perhaps most noteworthy here is that there definitely seemed to be cross-level effects between the parameters, and after controlling for start-up year (Model 17, Table 5.3) the effects were also significant. Figure 5.5 below (adapted from Model 17, Table 5.3 and identical with Figure 5.3) perhaps best illustrates the interaction effects uncovered. Between Niches 1 and 3, we actually observe a purely cross-level effect, similar with what was illustrated in Figures 2.3c and 2.4c, and this effect was also significant. On the other hand, the cross-level effect between Niches 1 and 2 was insignificant, but we have clear directional support for a cross-level effect. The significant contrast effect between these two respective niches furthermore indicated that we were dealing with an empirical phenomenon that was also mixed-determinant in nature.

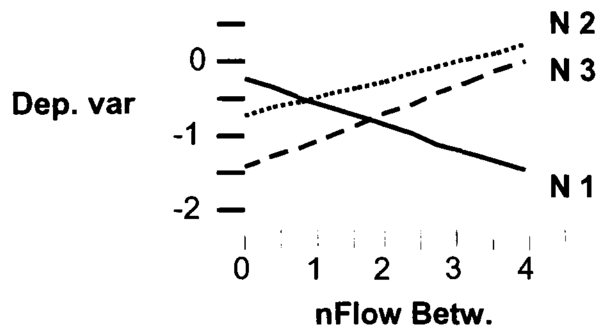

Figure 5.5 Interaction effects between niche (N) and flow betweenness. Adapted from Model 17, Table 5.3. Dependent variable: MeanProdLn.

The findings presented in Model 17 (Table 5.3) and Figure 5.5 reveal that it is positive to be placed in a densely connected niche (Niches 2 and 3) and at the same time access non-redundant information. This supported Hypothesis 4a. We observe, however, that actors in densely connected niches who lacked access to non-redundant information were actually low in performance. Hypothesis 4b, on the other hand, suggested that they would be medium in performance. In Hypothesis 4c, I predicted that start-ups in a sparsely connected niche that accessed a high degree of non-redundant information would be medium in performance. Yet, according to Figure 5.5, they were also low in performance. Finally, in Hypothesis 4d, I predicted that actors in a sparsely connected niche with little access to non-redundant information would be low in performance, whereas we observe that they were actually medium to high in performance (Niche 1, Figure 5.5).

Altogether, this indicates that there was somewhat mixed support for Hypothesis 4. However, we again definitely seem to be dealing with an empirical phenomenon that is both cross-level and mixed-determinant in nature. Furthermore, if we keep in mind that the lower level aggregate variable, network distance to the center of the field, appeared as a negative second degree polynomial, the totality of the findings demonstrated the importance of carefully considering level issues in network research.

Finally, it is interesting to note in Table 5.8 – where the flow betweenness parameter from Model 17 (Table 5.3) was replaced with degree centrality – that the adjusted R-square was reduced by more than 9%. Moreover, the parameters in Table 5.8 were insignificant indicating – at least regarding interaction effects between the niche parameter and centrality measures – that access to non-redundant information seemed to have genuine predictive power on the dependent variable. The reported results also illustrate that different centrality measures not only varied in their conceptual content (Freeman, Borgatti and White 1991; Freeman 1979; Scott 2000; Wasserman and Faust 1994), but also revealed substantial differences throughout the statistical analyses.

Hypothesis 5 and 5alt. The two final hypotheses suggest that late adopters will outperform early adopters due to increased density and competence in the emerging field (Hannan 1986). Alternatively, the relationship is the opposite as a result of mimetic behavior among late adopters (DiMaggio 1991). In Models 13 and 14 (Table 5.3) partial support has been gained for both arguments. Adopters in the early life of the emerging field seemed to be prone to mimetic behavior and were accordingly inferior in performance. Yet, the pattern changed in 1998 and in the following years we observe an increasing trend in venture success. Therefore, the most likely interpretation of these findings is that the opposing causal forces predicted in both Hypotheses 5 and 5alt were at play. In the early years, it seems that the negative effect of mimetic behavior was superior in predictive power, whereas the increased competence and learning that was developed throughout the field more than outweighed this negative trend beyond 1998.

In Model 15, I included start-up year as a 2^{nd} degree polynomial simultaneously along with a selection of network variables. Whereas the previous two models had revealed a non-linear effect with a shape of a positive 2^{nd} degree polynomial (illustrated in Table 5.6 and Figure 5.2), the non-linear effect from the start-up year has now faded away and we observe a linear negative trend. This pattern furthermore remained robust in Models 16 and 17 (Table 5.3) where the polynomial regressor of start-up year has been deleted.

The way I interpret the totality of these findings is that throughout the life of the emerging field there seemed to be a negative trend on the dependent variable, venture success, as a result of mimetic behavior. Nevertheless, Table 5.6 and Figure 5.2 give us a clear indication that some learning has taken place. It is accordingly reasonable to state that competence developed throughout the field could reach the entrepreneurs, but only to the extent that they possessed certain network constellations, which have been uncovered throughout this dissertation. I think that Figure 5.6 is a good illustration of the observed pattern. The dotted line is similar with what we learned from Table 5.6 and Figure 5.2 and illustrates how difference in venture success between early and late adopters took the form of a positive 2^{nd} degree polynomial. In the early years, we observe a negative trend as a result of mimetic behavior and low level of competence. For late adopters, however, the increased competence level throughout the field more than outweighed this negative trend.

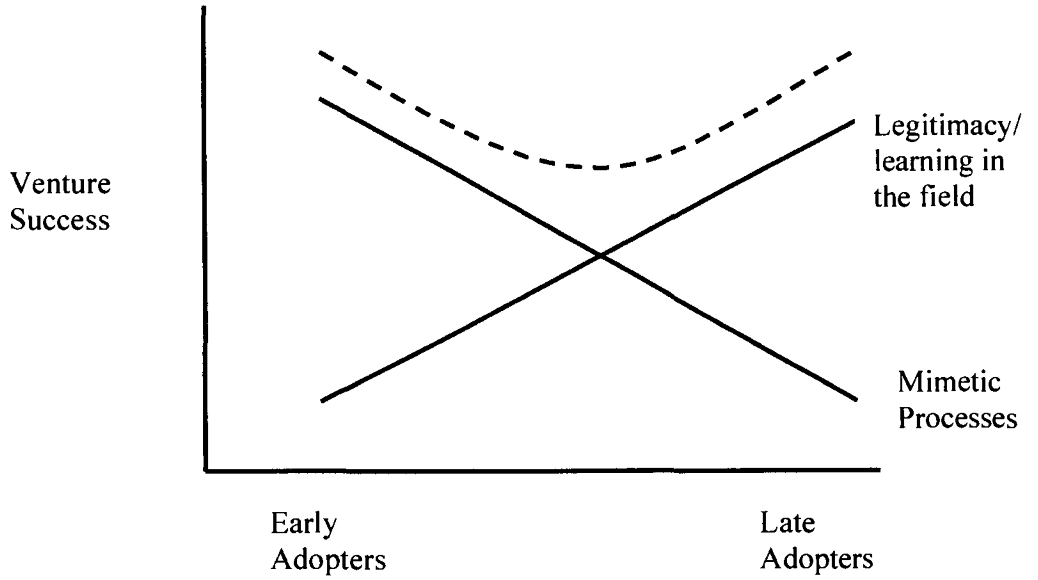

Figure 5.6 Legitimacy and mimetic process in the emerging field.

The negative line in Figure 5.6 crystallized the genuine effect from mimetic behavior on venture success when we controlled for learning and legitimacy effects, and was also analogous with the linear and negative effect from year of start-up, which we observed in Models 15-17 (Table 5.3). In other words, this reveals what happens when we controlled for the focal actor's access to social capital through his network constellations. To my knowledge, this is the first attempt where two such divergent approaches in the area of organization studies have been simultaneously tested against each other; so despite the application of a simple empirical approach to network density and mimetic behavior (i.e. modeling start-up year as the independent variable), I believe that the findings discussed above can spur an avenue of further research in a dual context that is ripe to provide increased insight in the area of organization studies.

The Exploratory Approach

Local Network Centrality. The control variable I discuss first in this section is the local centrality measure, degree centrality. This is perhaps one of the most important control variables in this study due to its high correlation with both closeness centrality and flow betweenness (see Table 5.2). Of course, in the area of social science we can never control for "everything", but if we had excluded this parameter we would never have known to what extent the predictive effects from the other centrality measures were merely produced as a correlate of the focal actors' direct ties. Accordingly, I argue that this represents a major strength in this study.

Models 6 and 7 (Table 5.3) included degree centrality and we observe strong and significant effects on the dependent variable. We furthermore observe that the explained variance was high and strongly significant in these two models. Moreover, in an unreported model where I only included degree centrality, the adjusted R-square was 47% and highly significant ($p<.001$). Therefore, I conclude that local network centrality had a genuine effect on venture success. This is also in accordance with a number of other contributions investigating the relationship between the focal actor's portfolio of direct ties and performance (Ahuja 2000a; Baum, Calabrese and Silverman 2000; e.g. Baum and Oliver 1991; Choonwoo, Lee and Pennings 2001; Shan, Walker and Kogut 1994; Smith-Doerr, Owen-Smith and Powell 1999; Stuart 2000; Stuart, Hoang and Hybels 1999). It is also worth noting that modeling degree centrality as a 2^{nd} degree polynomial in Model 7 (Table 5.3) produced an insignificant non-linear effect, whereas the positive linear trend remained strongly significant. This rejects previous arguments that suggested a possible negative marginal effect from additional ties beyond a certain maturation point.

Yet as I have described, when we compare the interaction effects between degree centrality and the nominal niche variable in Table 5.8, we observe that the interaction effect between flow betweenness and the niche parameter produced a better model fit (Model 17, Table 5.3). I therefore conclude that whereas local network centrality most likely had a genuine effect on venture success, it seems that there was no interaction effect between this variable and the niche to which the entrepreneur was embedded.

There were not only strong and significant correlations between degree centrality and closeness centrality and between degree centrality and flow betweenness (Table 5.2); I also argue that the causality went in the direction illustrated in Figure 5.4. Thus, degree centrality predicted both flow betweenness and closeness centrality, but not the other way around. My reasoning behind this line of thinking is that with regard to either possessing an overall central position in the field or accessing non-redundant information from disparate parts of the system, such positions can only be acquired through the focal actor's direct external ties, whereas the opposite is impossible.

In addition, the double-headed line between degree centrality and the niche variable illustrates that actors within Niche 2 were more active overall in their local network than their colleagues were in Niches 1 and 3 (Model 2, Table 5.10). Previously described contrast effects show that actors in Niche 2 had a significantly higher degree centrality score than entrepreneurs in Niche 1 and Niche 3 had, respectively. Note, however, as with the described relationship between the niche variable and closeness centrality, I do not claim any particular causal direction between the observed relationships, and that is the reason for having included a double-headed arrow also in Figure 5.4.

Moreover, Figure 5.4 illustrates a relationship between degree centrality and the size of the plant, but as I have discussed earlier, the causality can go both ways, therefore the double-headed arrow. Being active in the local network could spur enthusiasm for micro-power and accordingly motivate the entrepreneur to attempt a larger plant than initially planned, but start-ups that decided to attempt relatively large (and expensive) plants could also feel a need to reduce the risk they had taken by gaining as much knowledge as possible through their local network.

Formal Education. The correlation matrix (Table 5.2) and Models 2 and 3 (Table 5.3) gave directional but insignificant support for a positive relationship between formal education and venture success. However, if we considerer Tables 5.9 and 5.11, it also looks as if level of education could have an indirect effect on electricity production per capital invested. Highly educated entrepreneurs seemed to have a propensity to approach the center of the field, and as long as they did not become "too" central (in terms of closeness centrality), this would have had a positive influence on venture success. I have no good rationalization for why there was a significant relationship between formal education and the propensity to approach the center of the field, but a tentative explanation could be that years of schooling inspired the entrepreneurs to behave in more "professional" manner, which in turn induced them to approach the more established, well-known and "reputable" vendors and other micro-power plants.

Educated actors were overall also likely to build large plants and I have earlier portrayed how this might spur the entrepreneur to become more active in the network, which in turn was related to venture success. As I have said previously, the better educated the entrepreneur was, the better scientific skills he would possess. Consequently, this would enable him to better calculate and predict the outcome from different sizes of hydro turbines, and altogether reduce the risk of attempting relatively large investments. Entrepreneurs with a low formal education, on the other hand, would face a higher risk and uncertainty of the outcome due to lack of formal competence, and would accordingly feel inclined towards smaller (and less expensive) solutions.

Early versus Late Adopters. Previously, I have discussed how being an early or late adopter seemed to affect venture success and the size of the plant, but from Table 5.11 we furthermore observe that the parameter seemed to affect the closeness centrality variable. I have no ready explanation for this pattern, but a plausible reason might be that a small number of vendors, consultants and perhaps also previously established micro-power plants had appeared as the most visible operators in the emerging field. Such a kind of implicit branding has in turn been a motivational factor for new entrants to approach these central actors. Note that in the described step-wise procedure where degree centrality was the dependent variable, start-up year did not qualify as independent variable at all. This – I argue – supports my above argument. Late adopters did not seem to access a higher closeness centrality score as a result of being more active in their local network, but as a result of approaching previously established actors that had an overall more strategic position in the emerging field.

Conclusion

In this chapter I have tested the hypotheses that were developed in Chapter 3. After presenting and discussing the results of the statistical analyses, I have given emphasis to other potentially interesting findings that were not necessarily reflected in the hypotheses. In the last section of the chapter, I have given a lengthy discussion of the findings throughout this study.

6. Conclusion of the Dissertation

This chapter concludes the dissertation. As opposed to the latter part of the previous chapter, the discussion has now been narrowed down to deal with – in light of what the statistical analyses have revealed – the research question from Chapter two and the hypotheses that I developed in Chapter three. Thus, I refer to what I believe is the core contribution from this research project, namely whether the concept of social capital can be inferred as a multilevel phenomenon or not.

In addition, the chapter discusses the interplay between network research and institutional issues such as population density (Hannan 1986) and mimetic behavior (DiMaggio 1991). I believe that the dissertation – if not fully and comprehensively –has given us a clue that these different approaches can reveal more about social phenomena when combined than when treated separately.

In the latter part of the chapter, I portray a few practical implications from the findings in this study, discuss some limitations, and also point out avenues for further research.

Contribution

The limited focus I conduct in this concluding chapter is perhaps best illustrated in Figure 6.1. As compared to Figure 5.4, a great number of both variables and relationships have been deleted, and we now only observe one dependent variable, namely venture success. The niche effect, flow betweenness, and closeness centrality remain as network predictors on the dependent variable. Moreover, the upper part of the figure is similar to Figure 2.9 in Chapter 2, which summed up the research question. As the closeness centrality variable, the niche effect and the interaction effect between the niche variable and flow betweenness portray, this study has taught us in particular that social capital appears to be both a cross-level and mixed determinant phenomenon. The parameter "early or late adopter" reflects Hypotheses 5 and 5alt, and below I discuss these different issues in turn and in combination.

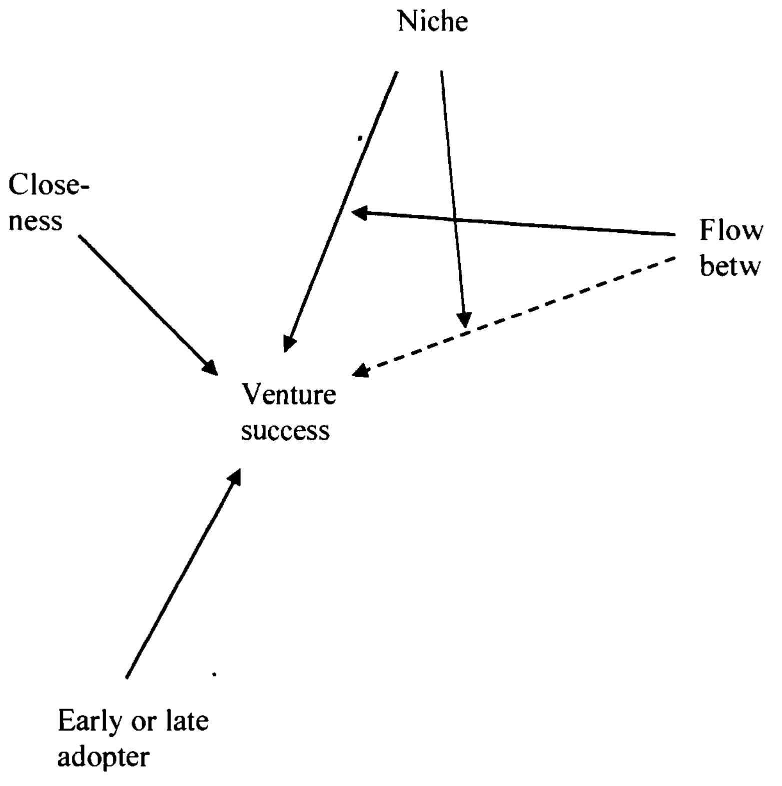

Figure 6.1 Simplified empirical model.

Contribution to the Concept of Social Capital and Network Research

Aldrich (1978), Knoke and Rogers (1979) referred to the tendency of inter-organizational networks to develop "stable action sets" or "central cores" of dominant organizations, whereas DiMaggio and Powell (1983: 471) referred to *"the emergence of sharply defined interorganizational structures of domination and patterns of coalition"* in the development of organizational fields. Thus, partition of corporate and organizational actors is often desirable on practical grounds as a means of representing complex relational patterns with clarity (Aldrich and Whetten 1981: 385). Partition is moreover considered to be of importance for research on flows of innovation (DiMaggio and Powell 1983), personnel (Baty, Evan and Rothermel 1971), or information (Boorman and Levitt 1983).

DiMaggio (1986) held that a preferable way to partition an organizational field is to identify what Burt and Talmud (1993) defined as ecological niches of structurally equivalent actors. Structural-equation approaches can: indicate roles distributed among actors according to similarity in communication structures (Greve and Salaff 2001), discern patron-client patterns at the subpopulation level, identify occupants of positions in center-periphery structures where outliers transact only with dominant actors (Meyer 1979), and elucidate brokerage or agency structures (White 1983). Structural equivalence also indicates groups of actors with shared cognitions (Carley 1986; Galaskiewicz and Burt 1991). In this research project, I have applied the block-modeling technique Concor (Convergence of iterated correlations) (White, Boorman and Breiger 1976; White, Breiger and Boorman 1976) to identify subsets of structurally equivalent actors in the emerging hydroelectric micro-power field in Western Norway.

Cross-level models predict, implicitly or explicitly, that individual group members can respond to a group-level characteristic in a disparate, rather than homogenous fashion. The model's independent variable can accordingly be homogenous within groups, but the dependent variable is not; it varies both within and between groups (Klein, Danserau and Hall 1994). In other words, characteristics of individual group members moderate the relationship of the group characteristic to individual behavior or outcome. Group members for whom the moderator is high respond to the group characteristic in one way, whereas group members for whom the moderator is low respond in a different fashion (Bedeian, Kermery and Mossholder 1989; Bryk and Raudenbush 1992; Tate 1985).

In this dissertation, independent characteristics for individuals are analogous to characteristics of the focal actor's external ties. Among other things, external ties can provide him with access to non-redundant information, and in this study I have operationalized the concept by applying Freeman, Borgatti et al.'s (1991) centrality measure of flow betweenness. Niches of structurally equivalent start-ups are analogous to the group level aggregate, and in this study, the extent to which each niche was densely or sparsely connected identified relational characteristics for the collectives. Tables 4.1- 4.8 show that a certain degree of clustering took place within the 3 identified niches with micro-power start-ups. However, the intensity of contacts was relatively low in Niche 1 and high in Niches 2 and 3. Accordingly, I have portrayed Niche 1 as sparsely connected and Niches 2 and 3 as densely connected.

Models 12 and 17 (Table 5.3) – including the interaction terms between the niches the entrepreneurs belonged to (i.e. higher level aggregate) and the focal actor's access to non-redundant information (i.e. lower level aggregate) – illustrate that the lower level parameter behaved differently on venture success, dependent upon to which niche the entrepreneurs belonged. In Model 17 (Table 5.3), we furthermore observe that this effect was significant. The parameters did not always behave perfectly in accordance with what I hypothesized, but the results indicate that cross-level issues are at play in predicting venture success. The Florentine case from Chapter 2 gained further empirical support for the cross-level issue; it was when the interaction term of different level aggregates was included in the model (Model 4, Table 2.5) that we first observed a dramatic increase in explained variance.

Mixed-determinant models suggest that predictors at a variety of levels can influence a criterion of interest. For instance, market characteristics (e.g. the availability of jobs), group characteristics (e.g. diversity within the group), and individual characteristics (e.g. job satisfaction) have all been hypothesized to influence employee turnover (Hulin, Roznowski and Hachiya 1985). Thus, whereas the interaction term in cross-level models produces combined effects on individual behavior or outcome from homogenous group characteristics and independent individual characteristics, mixed-determinant models generate additive effects from the same (or other) levels. In this study, a mixed-determinant approach implied that the higher level aggregate (niche effect) and the lower level aggregate (e.g. focal actor's access to non-redundant information) would have an additional effect on venture success. In addition, the regression analyses in Table 5.3 largely show us that we were also dealing with mixed-determinant network predictors of venture success. Start-ups in Niche 1 seemed to be inferior in performance, start-ups in Niche 2 superior, whereas their colleagues in Niche 3 fell somewhere between the other niches – at least according to the latter models.

The focal actor's network distance to the center of the field was another variable that comprised the lower level aggregate and was operationalized by applying Freeman's (1979) closeness centrality measure. A number of models in Table 5.3, including the 2^{nd} degree polynomial effect of this parameter, showed significant effects on venture success. This is in accordance with Hypothesis 1, which suggested that entrepreneurs approaching either the margins or the center of the field would be low performers, whereas actors positioning themselves in intermediate positions would be high performers. The robustness of this result, even after controlling for the higher level aggregate, niche effect, gave us further indication that we were dealing with an empirical phenomenon that was mixed determinant in nature.

Multilevel issues admittedly go far beyond the simple cross-level and mixed-determinant model that I have developed and tested in this dissertation, but the findings clearly indicate that valuable information can be lost by not simultaneously considering multiple levels in network- and social capital studies.[34] From Table 2.5 we learn that when cross-level terms between actor centrality (i.e. lower level aggregates) and which niche the Florentine families belonged to (i.e. higher level aggregate) were first included, we observed that the different level aggregates also had genuine additive (i.e. mixed-determinant) effects on family wealth. Table 5.3 reveals similar findings; the niche effect first became significant when we controlled for lower level aggregates, i.e. the focal actor's network distance to the center of the field (Model 9). Whereas some models indicate that access to non-redundant information had no genuine effect on venture success, the interaction term with the niche variable nonetheless shows that the effect was contingent upon characteristics of higher level aggregates.

To summarize, we can state that the concept of social capital is (at least) a cross-level and mixed-determinant phenomenon. It is tempting to claim that the term can be identified only as long as we observe a positive outcome for the subject under study, in our case, electricity production per capital invested (in real terms) at the focal micro-power plant. However, as I have previously described, Lin (2001: 28) warned that such a view *"may implicate a tautology...It would be impossible to build a theory in which causal effectual factors are folded into a singular function...... [and] incorrect to allow the outcome variables to dictate the specification of the causal variable."* To my knowledge, there has not yet been developed a coherent and agreed-upon theory of social capital, but seminal works of both Granovetter (1973) and Burt (1992a) have stimulated researchers to consider the actor's access to non-redundant information when (explicitly or implicitly) dealing with the concept. Despite the fact that the causal agent behind their argument diverges – Burt maintained that the player

[34] For an excellent and comprehensive review of level issues in the field of social science, see Klein, Danserau et al. (1994).

gains access to non-redundant information by spanning structural holes, whereas Granovetter emphasized the bridging of weak ties to disparate parts of the system – both agreed upon the importance of non-redundancy.[35]

In this study, a major contribution to our understanding of the concept of social capital is that the focal actor's access to non-redundant information seemed to be dependent on the higher level aggregate; i.e. the niche effect. Accordingly, I argue that the attempt to build a coherent social capital theory should consider the interplay between non-redundant information and relational characteristics for collectives. The dissertation has argued that perhaps the best way to identify collectives of actors within a larger network structure is to apply block modeling techniques in order to uncover niches of structurally equivalent actors. I am, however, not dogmatically claiming that researchers should always undertake such an approach. The research question as well as the methodological issues might encourage scholars to consider natural boundaries (e.g. departments or project teams within a firm, organizational [or other] actors within a given geographical area), cohesion techniques or other approaches, for instance.

Moreover, I am careful not to maintain that density levels within identified collectives or higher level aggregates should be the only causal agents to be considered. On the contrary, the density approach that I have undertaken in this research project is both a simplistic and rough measure, and it can very well be that future contributions, applying more sophisticated lines of attack, will uncover possible reasons for why the interaction effects in this dissertation only gained partial support for Hypothesis 4. In addition, the characteristics for collectives could go beyond merely investigating the distinctiveness *within* these structures to also focusing on relationships *between* the higher level aggregates identified. I slightly touched upon this issue in the discussion of the Florentine case in Chapter 2, where I questioned if Burt's (1992a)

[35] The reason for applying the Freeman, Borgatti et al. (1991) centrality measure of flow betweenness in this paper rather than Burt's (1992a) measure of structural holes, is that I have dealt with a connected graph that considered all nodes in the network. Burt's approach, on the other hand, merely dealt with the players' egocentric network, i.e. it focused on the focal actor and to what extent his immediate network ties were connected to each other. In a number of unreported models, I applied Burt's network measure of structural holes instead of flow betweenness. The findings were mostly in line with what has been reported throughout this paper, but the explained variance was much lower.

structural holes theory or Granovetter's (1973) weak tie argument was manifest at different levels of analyses. For instance, density of contacts between niches can give us information about to what extent there are strong or weak ties between different collectives, and the degree to which different niches are connected to other niches that are disconnected can teach us which collective or collectives possess brokering positions (for further details, see Scott 2000; Wasserman and Faust 1994). Altogether, I argue that a variety of approaches in how to identify collective actors as well as relational characteristics for these higher level aggregates can provide a fruitful, comparable insight to our understanding of social capital as a multilevel phenomenon.

If we now flip the coin, another contribution in this dissertation is the discovery that relational characteristics for collectives not only affected individual performance or outcome per se; individual characteristics such as the focal actor's access to non-redundant information seemed to interact with these higher level aggregates. After having identified the given collectives of organizational actors, it was not sufficient to merely identify general relational characteristics within or between these structures. This study has revealed that researchers would most likely gain fuller insight if they also undertake the task of examining how the different actors are connected to other actors both within and beyond the identified collective or collectives.

A further important contribution in this dissertation, I argue, is that there is not necessarily a positive linear relationship between being close to the center of the field and outcome. Despite the fact that Freeman (1979), in his influential contribution on network centralities, did not explicitly relate the different measures to the concept of social capital, his work has had strong influence in relating actors' network position to power and performance. To the extent that a theorist could claim that social capital can be operationalized and measured as the focal actor's network distance to the center of the field, an implication from this study – along with Greve, Golombek et al.'s (2001) contribution from the Norwegian pulp and paper industry – is that access to social capital is not necessarily positive per se. By comparing actors at the margins or intermediate positions of the network, we see that social capital had a positive effect on performance, but by comparing actors in intermediate positions with colleagues at the very center of the field, we learn that "too much" social capital hampered outcome.

A significant contribution of this study is the discovery that access to non-redundant information interacted with the niche factor on venture success, whereas neither the focal actor's network distance to the center of the field (closeness centrality) nor local network centrality (degree centrality) seemed to be contingent upon relational characteristics for the identified collectives. This teaches us that whereas some network characteristics at the focal actor level were likely to interact with higher level aggregates, other lower level characteristics seemed to predict the dependent variable in a consistent manner, independent of to which niche the entrepreneurs belonged. Thus, if a theorist intends to build a social capital theory which treats the concept as a multilevel phenomenon, a lesson from this study is that one individual network characteristic – i.e. access to non-redundant information – interacted with higher level aggregates, whereas others – i.e. network distance to the center of the field and local network centrality – probably did not.

In line with the discussion above, I believe that another important contribution is the inclusion of different centrality measures in the regression analyses. Despite that the correlation matrix in Table 5.2 indicates high correlation between degree centrality, closeness centrality, and flow betweenness, the concepts are considerably distinctive in conceptual content. Thus, by applying these different measures in separate models (and to some extent also simultaneously), we furthermore learn that they behaved quite differently on the dependent variable. Not only was there a difference in the interplay with the higher level aggregate, as described above, but we also observe that the relationship between closeness centrality and the dependent variable was non-linear with the shape of a negative 2nd degree polynomial, whereas the relationship between degree centrality and the same effect variable was positive and linear.

As I have warned a number of times throughout this dissertation, including parameters that are highly correlated, which is the case between degree centrality and closeness centrality, can cause severe multicollinearity problems in the analyses. Yet, visual inspection of the data-plots in JMP (2003) indicated no such problems in any of the described models. In this regard, I hold that the different outcomes from the applied centrality measure can give us a hint that it is misleading to assume that items or parameters, which load on the same factor, necessarily imply that they portray the same theoretical concept. This contribution, on the other hand, has illustrated that such an approach could lead to significant loss in the information that we gain from our statistical analyses.

The Interplay with the Institutional Approach

If we now look beyond the very concept of social capital, a final important contribution in this dissertation is the inclusion of institutional issues such as network density and mimetic behavior. From Chapter 3, we remember that I hypothesized that late adopters would outperform early adopters as a result of the increased density of micro-power start-ups (Hannan 1986). An alternative hypothesis, on the other hand, suggested that the relationship might be the other way around due to mimetic behavior among late adopters (DiMaggio 1991).

Initial analyses (Models 13 and 14, Table 5.3) gave partial support for both hypotheses and in particular, we remember from Table 5.6 and Figure 5.2 that between 1995 and 1998 the trend was negative, supporting the argument behind mimetic behavior (DiMaggio 1991). From this year on, however, the curve became positive, indicating support for the density argument (Hannan 1986). It thus seems that late entrepreneurs were benefiting from the overall increase in learning and competence being established throughout the emerging hydroelectric micro-power field. We accordingly observe the contours of a non-linear relationship with the shape of a positive 2nd degree polynomial between start-up year and venture success, where 1998 was the turning point (this is also statistically significant in Model 13, Table 5.3). The most likely interpretation of this finding is that both of the opposing causal forces were at play. In the early years, it seems that the negative effect from mimetic behavior was superior in predictive power, whereas the increased competence and learning that was developed throughout the field more than outweighed this negative trend beyond 1998.

However, we learn in later models (Models 15-17, Table 5.3) that the inclusion of network variables changed the picture described. The positive polynomial effect faded away, and a genuine negative and significant linear trend between start-up year and venture success appeared. The way I have interpreted this picture is that to gain from the increased level of organizational learning that had taken place in the emerging field, it was essential to acquire competence through certain network constellations. If not, the entrepreneur faced the risk of low performance as a result of the mimetic processes.

Thus, the latter models in Table 5.3 reveal in a way what happened to predictors reflecting institutional forces when we controlled for the focal actor's access to social capital through his network ties. To my knowledge, this is the first attempt where two such divergent approaches in the area of organization studies have been simultaneously tested against each other. So despite the application of a very simplified empirical approach to network density and mimetic behavior (i.e. modeling start-up year as independent variable), I believe that these findings can spur an avenue of further research in a dual context that is ripe to provide increased insight in the area of organization studies.

Practical Implications

Above, I have implicitly pointed out some practical implications from the findings in this study, and in this section my intention is to explicitly portray a few such considerations.

We can begin with the novel entrepreneur in the process of building a micro-power plant. As are the majority of organizational actors, he is of course interested in building an efficient and profitable plant. So, in terms of gaining the best competence achievable for micro-power systems, what should he do? The regression analyses in this dissertation (Models 13 and 14, Table 5.3) indicate that a certain level of knowledge has been developed throughout the emerging field, but this competence per se will not automatically benefit the focal actor; it must be gained through certain network constellations. Thus, in order to become a successful entrepreneur he has to access the right players, with the right knowledge at the right time; but who are these? First of all, the strong and significant relationship between local network centrality and venture success indicates that it is far better to collaborate with a number of other actors than with merely a few, no matter whom they are. A plausible explanation for this relationship may be that many direct ties to a larger extent provide the entrepreneur with rich information from both successful and not so successful colleagues and also from competent and not so competent vendors and consultants. It is well established knowledge that we not only learn from successful others, but also from those who are not so successful (as well as we learn from our own successes and failures). If an actor possesses only one or a few ties, he is less likely to access overall knowledge. Instead, he risks accessing only superior knowledge (constraining him from knowledge about which pitfalls he is vulnerable to) or inferior knowledge (constraining him from knowledge about better and more efficient solutions at hand). Thus, my first practical advice is: be active in your local network and try to learn as much as possible from as many others as possible.

Another finding from this research project is that the most successful entrepreneurs seem to be positioned in network positions intermediate to the center of the field, whereas inferior entrepreneurs operate at the margins or the very center of the field. Remember that this effect was only significant after controlling for local network centrality or the niche effect, and a plausible explanation from this finding could be that there are possibly one or a few highly profiled vendors in the field. Their visibility is in turn correlated with their overall central network position since many other nodes are likely to approach them. Everything else being equal, if a start-up wishes to collaborate with this (or these) central actor(s), this will, in turn, give him an overall central position (as compared to collaborating with less central vendors). Furthermore, as I described in Chapter 3, a possible reason that venture success for such start-ups can be depressed is that the most high-profile vendors and consultants charge a premium price for their products due to asymmetric knowledge and power between the involved actors.

Perhaps the best way to exemplify this issue is to take another look at the network structure in the emerging field, which I illustrated in Figure 4.2. For the years 1995 and 1997 in particular, we observe that there was at least one very central actor, and examination of the raw-data shows that this was a vendor of micro-power systems (and not a micro-power start-up). Cautious advice to a potential start-up would be that it is not necessarily the best decision to try to get the first and best systems this vendor – or other highly central and well-known vendors – provides. At least, it would be highly recommendable to carefully compare the products, services, and competence this actor offers with other solutions available throughout the field.

The dissertation has also revealed that structurally equivalent start-ups in densely connected niches are likely to outperform their colleagues in a sparsely connected niche, and in particular, this seems to be the case if the focal actor accesses non-redundant information. It is of course unrealistic to expect a potential start-up to undertake the task (which I have conducted in this thesis) of identifying and examining different ecological niches, but a more reasonable undertaking would be to investigate if there is some level of collaboration and information-sharing among a given set of actors that the entrepreneur would like to approach. If the answer is yes, the next step would be to not only focus on this identified collective, but also to approach one or more actors that are disconnected from the identified group.

If we now look beyond the emerging micro-power field and ask if the results from this research project could also be applicable to other sectors, the answer to this question is: only by replications of this study on other organizational actors. Nevertheless, I believe that the recommendations described above are also applicable for entrepreneurs in other emerging fields such as shellfish farming, for instance.

Limitations and Further Research

As the previous section has emphasized, this dissertation has by no means intended to develop or empirically test a comprehensive social capital theory. The intention has rather been to focus on the concept of social capital as a multi-level phenomenon and furthermore inspire a greater awareness of the interplay between structural network research and institutional issues such as population density (Hannan 1986) and mimetic behavior (DiMaggio and Powell 1991). I therefore hope that the contribution can spur further research in these areas. In the last section of this dissertation, I discuss possible avenues where I believe fruitful knowledge is most likely to be acquired. Nevertheless, as with all research, this project has been constrained with certain limitations, and I will first debate some of these issues.

Limitations

With regard to relational characteristics for collectives, this dissertation has merely focused on niche density, and as previously described, this is a rather rough measure, which can partly mask other possible causal mechanisms. Tables 4.2 - 4.8 reveal that some clustering had taken place within all three niches from 1995, and that there seemed to be a consistently higher degree of density in Niches 2 and 3 as compared to Niche 1. We do not know, however, if the niche factor was constant on venture success throughout the early life of the emerging field. Thus, is it arbitrary for a micro-power plant to start electricity production in a given niche any year, or could it be that the density factor is particularly important in the early years of the emerging field, whereas the overall increase in knowledge and competence in the latter years deflates this effect? Controlling for start-up year partly accounts for this possible effect, but the relatively low number of observations in this study did not allow me to simultaneously include the interaction effects between the niche factor and flow betweenness, and the niche factor and start-up year.[36]

In Chapter 4, I mentioned that the total number of actors within each niche – including micro-power start-ups, vendors and consultants – was 23 in Niche 1, 15 in Niche 2 and 9 in Niche 3. In other words, Niche 1 – which was sparsely connected – had substantially more nodes than the relatively densely connected Niches 2 and 3. Wasserman and Faust (1994: 413) held that it is useful to consider the relative size of the identified blocks when examining the tendency of network ties within (and between) collectives. We remember that this dissertation has identified network density as the number relations *(l)* among *(n)* actors compared to the maximum possible number of relations, $l/[n(n-1)/2]$. Using some algebra, it can be shown that $(N_a-1)/(N_b-1)$ can be used as a baseline for evaluating the tendency for the density of ties within niche a, N_a, relative to niche b, N_b (for further details, see Wasserman and Faust 1994: 414).

Thus, the size of the niches can influence network density, and after applying the above baseline, the relationship in size between Niches 1 and 2 was 1.571, between Niches 1 and 3 it was 2.750, and between Niches 3 and 2 it was .571. At the same time, the relationship in density between Niches 2 and 1 was 2.402, between Niches 3 and 1 it was 1.815, and between 2 and 3 it was 1.323.[37] If we now account for niche size when comparing the relationship in densities between the three niches, we get the following scores: 1.529 between Niches 2 and 1, .660 between Niches 3 and 1, and 2.316 between Niches 2 and 3.

The above revised calculations reveal some interesting issues. First, we observe that even after accounting for niche size, Niche 2 is still more densely connected than Niche 1. Niche 3, on the other hand, actually seems to be less connected than Niche 1 when accounting for

[36]Nevertheless, in unreported models where I included interaction effects between start-up year and niche, instead of interaction effects between flow betweenness and niche, the effects were insignificant.

[37] Niche densities were adapted from Table 4.1.

niche size. In other words, the relatively high density level in Niche 3 compared to Niche 1 can be explained as a result of the large difference in niche size, whereas the difference in density level between Niches 1 and 2 seems to be robust. If we now look back the findings from this study, we remember that comparisons between Niches 1 and 2 to a large extent were in accordance with what Hypothesis 2 predicted; start-ups in the densely connected Niche 2 were generally better entrepreneurs than their colleagues were in the sparsely connected Niche 1. On the other hand, there were less clear findings when considering Niche 3 – where start-ups fell somewhat between their colleagues in Niches 1 and 2, which we can possibly explain as a lack of "genuine" high density level within this niche. However, from the above calculations we observe that after accounting for niche size, Niche 2 appears to be more than twice as densely connected than Niche 3 (2.316 times more connected, to be precise), and this can also explain why actors in Niche 2 were more productive than their colleagues in Niche 3.

Another liability regarding the identified niches is that I did not manage to find a particular saturation level in explained variance when deciding on the number of splits in Concor (White, Boorman and Breiger 1976; White, Breiger and Boorman 1976). In the Florentine case, I discovered a steady increase in explained variance when I increased the number of splits from one (i.e. two identified niches) to two (i.e. four identified niches), whereas the increase in explained variance was substantially lower when I increased the number of splits from two to three. The network identified for the emerging micro-power field, however, revealed a linear trend in explained variance when increasing the number of splits. Since no other particular saturation level was identified, I therefore decided to conduct two splits. As previously stated, a relatively low number of splits is in accordance with Wasserman and Faust (1994: 378) who argued that *"[t]heory and interpretability of the solution are the primary considerations in deciding how many... [partitions] to produce."* They furthermore held that making too many splits can lead to unstable correlations, due to the small number of elements.

The number of splits that I have applied is open to interpretation, and – as we have observed – clearly indicates that a certain degree of clustering had taken place within a number of the niches, yet with varying density levels. Moreover, statistical analyses illustrated that by applying two splits I have identified niches that clearly portray both cross-level and mixed-determinant effects on focal actor venture success within the emerging field. Thus, conducting two splits was not only easily interpretable, but the identified niches seemed to make sense empirically as well.

The "perfect" network study should have collected data on relationships between all identified nodes, yet this represents a great challenge for the researcher since it is not always obvious how to define the natural boundaries of a given network structure. In this dissertation, my intention was to overcome this obstacle by applying what have been described as snowball sampling techniques (for further details, see the methodological section in Chapter 4). Nevertheless, by conducting this procedure I have focused on gathering relevant data on relationships between the micro-power start-ups and data on relationships between micro-power start-ups and vendors and consultants (plus ties to small scale hydro-power plants). An advantage to applying this procedure was that I gained information on relationships that went beyond the boundaries of the population of micro-power start-ups. The "perfect" network study, on the other hand, should also have gathered network data from all nodes that were included in this study. The problem, however, was where to draw the line, and the number of nodes could possibly have exploded if I had approached all the reported players. In this dissertation, I have accordingly focused on the micro-power start-ups and the relational ties between themselves and to vendors and consultants (plus ties to "somewhat" larger plants). This represents the very core of the emerging field, and the high explained variance from a number of models in Table 5.3, including network variables, indicates that I have been able to identify the essential part of the network structure.

With regard to gathering network data, another limitation in this study is that I asked the respondents to report, not only about present ties, but also about the history and the eventual termination of different relationships. An ideal solution (but impossible ex post facto) would have been to follow the emerging field throughout its life span and gather network data from the relevant plants on a regular basis, for instance once every year. This would possibly have given a larger degree of accuracy in reporting the history of different network constellations. Nevertheless, the strong and significant relationship between different network measures and venture success in a number of models again seems to indicate that respondents have managed to be fairly accurate in reporting the history of their network ties. As described earlier, previous research has shown that people are good at recalling regularly occurring relations as opposed to ad hoc contacts (Freeman, Romney and Freeman 1987). The procedure applied of gathering data on a longitudinal and dynamic network structure is also in accordance with scholars' recommendations (Burt 1992a; Podolny and Baron 1997).

Moreover, analyzing a network structure that has been dichotomized is a simplistic approach in how to uncover how different network configurations affect venture success. From Chapter 4, we remember that I asked the respondents to indicate a variety of characteristics regarding the different contacts. Therefore, it would have been interesting to dig further into the embedded structure of multiplexity in relationships. This could have been done by modeling layers of network structure that differed in content, and I could have conducted a variety of network analyses on these different matrices of contacts to examine how they varied or diverged in the regression analyses. As the data collection instrument reveals (Appendix I), I furthermore asked the respondents to report how different relationships had changed over time. The major reason for not conducting the above strategies, however, was the increased complexity this would have represented in the network analyses. Since the network was relatively sparsely connected – at least in the earlier years of the emerging field – I would most likely have also encountered the problem of unconnected graphs, a well-known problem for network scholars.

The dependent variable that I applied in this study was average yearly electricity production per capital invested (discounted in real terms), and personally, I hold that this is both an informative and relevant measure for venture success. Nevertheless, I by no means hold that it is a perfect performance measure.[38] If, for instance, we assume that the price of electricity on the whole has been relatively high throughout the life of the emerging field (as compared to previous years), the entrepreneur at a large micro-power plant with low production per capital invested, could still perceive his project to be a success, whereas a colleague at a small plant with high production per capital invested would perhaps consider his investment to be a failure. The reason is that the "low performing" large plant will sell more electricity than the small "high performing" plant, and the higher the electricity price, the less the "too high" investments at the large plant and the "low" investments at the small plant matter. In particular, this will be the case if the electricity remains high indefinitely. Having said this, if

[38] For an interesting discussion of the use of "performance" as the dependent variable in organization studies, see March and Sutton (1997).

we had included the price of electricity when modeling the dependent variable, this would also have included a causal factor of venture success that could be considered exogenous and which is also highly volatile. The distinction between a successful and a not-so-successful entrepreneur could therefore have been rather arbitrary.

It is moreover worth noting that the applied sample, from which I have accessed both network variables and autonomous characteristics, was relatively low. Thus, having only conducted statistical analyses on 20 start-ups, we should of course be cautious in the interpretations from the statistical analyses. As we have observed, in a number of models I merely gained directional support for certain hypotheses. Nevertheless, despite relatively few observations, we definitely observed significant parameters in a number of models, along with high explained variance. In particular, this was the case after controlling for start-up year. I therefore argue that we are dealing with an empirical phenomenon that is both strong and robust in nature. The Florentine case from Chapter 2 – where we observed a dramatic increase in explained variance on family wealth when interaction terms between centrality and niche variable were included – gave further empirical evidence to my conception of social capital as a cross-level and mixed-determinant phenomenon.

From the statistical analyses in Table 5.3 (Models 13 and 14), we remember that there was a negative trend in start-up success in the early years of the emerging field (between 1995 and 1998), and I have previously described this as a possible effect of mimetic behavior. However, we must bear in mind that there is (at least theoretically) a limited access to rivers where it is feasible and economically defendable to establish micro-power plants. Over the time span, we can therefore expect that the cost of investments will increase, not necessarily as a result of inferior competence (or disadvantageous network constellations), but as a result of more complicated and demanding projects. In other words, it is reasonable to assume that micro-power plants will be first established close to the "best" rivers, and that the second wave of adopters will be the entrepreneurs with access to the "second best" rivers, and so forth. At least theoretically, this can give us an alternative (or complementary) explanation of the negative trend in venture success in the early life of the emerging field. Nevertheless, as I described in the introductory chapter, the potential for hydroelectric micro- and miniature plants in Norway is estimated to be about 3 billion kWh in electricity production, whereas the actual production in 2000 was roughly estimated to be 235 million kWh (NVE). This implies that only a marginal fraction of the estimated capacity has been built out, and it is accordingly likely to assume that the above arguments regarding lack of "good" rivers for relatively late adopters are not valid. We furthermore observe a positive trend in venture success beyond 1998 (when not controlling for network variables), which probably would not have been the case if the quality of the remaining rivers was inferior in terms of their hydroelectric potential.

Whereas this study only collected data from entrepreneurs that had actually started electricity production, it is nevertheless reasonable to assume that ex ante consideration of river quality played an important role in the decision to attempt a project or not. We therefore know nothing about potential entrepreneurs who – after extensively examining the possibilities of building a micro-power plant – concluded that such a project involved a risk that was too high. This factor accordingly indicates that there are other causal mechanisms that could explain venture success than those portrayed in this dissertation. For instance, it could be that the different network constellations described throughout this contribution did not merely predict outcome; inferior start-ups might never have started at all if they were positioned in advance in a densely connected niche and at the same time accessed non-redundant information. This could have taught them that their river was perhaps not at all suitable for electricity production, i.e. the investment would be too high compared to what they would obtain from the project in terms of electricity production. Accordingly, more research is needed to uncover such potential causal mechanisms. The ideal situation would be to access network data, not only from "actual" start-ups, but also from all candidates that had ever considered building a micro-power plant. By doing this, we would learn if different network constellations also appeared as selection mechanisms for whether to attempt an entrepreneurial project or not.

Further Research

The previous sections have indicated where I believe future research should go, and now I will discuss some of these issues in detail. First, later contributions should try to include more observations in their analyses than this study achieved. If the number of actors is low, one way of doing this is would be to model panel data – i.e. access repeated observations from the same actors over a time-span.[39] In addition to more robust statistical analyses, this could teach us if there are any learning effects at the plants that were reflected in increased electricity production over the time-span. And given that there are learning effects; do entrepreneurs within densely connected niches learn at the fastest pace for instance, or does access to non-redundant information or other centrality measures predict a similar pattern?

This study has focused on the network constellation at start-up, yet with panel data it would also have been possible to investigate if network ties accessed post start-up had any genuine effect on venture success. Previous contributions have discovered that many network ties in a given time period increased the propensity of accessing more network ties in subsequent time periods (Ahuja 2000b; Gulati 1999; Smith-Doerr, Owen-Smith and Powell 1999; Stuart 1998). To my knowledge, however, we have no clear understanding if such network dynamics actually affect performance. In this regard, it could be interesting to investigate to what extent independent variables at start-up have a persistent effect on the dependent variable when controlling for present or lagged network variables. That is: to what extent will circumstances around start-up forever affect venture success? Is it possible that entrepreneurs with not-so-fortunate network constellations at start-up have possibilities to succeed later if they manage to connect with the "right" players at the "right" time, or will they forever be losers? A problem in my empirical context has been the very way I have modeled the dependent variable. Since venture success was modeled as yearly electricity production per capital invested, the denominator will forever affect the dependent variable. Accordingly, further research addressing the above issues should consider other performance measures.

We remember that this study focused on the very structure of the ties that make up the social network, rather than focusing on the content of these ties. Therefore, later contributions should examine in what way the very content of contacts could create variations in venture success. From the methodological chapter, I described how the respondents were asked to indicate a variety of characteristics regarding the different contacts. It would therefore have been interesting to dig further into the structure of the embedded and multiplex structure in the relationships. This could have been done by modeling layers of network structure that

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[39] In this study, my intention was to conduct panel regression. However, little variance in the variables for each actor constrained me from doing so.

differed in content, for instance. In addition, I could have conducted a variety of network analyses on these different matrices of contacts and examined how they diverged or converged on performance parameters or other autonomous attributes.

The density approach that I have undertaken in this paper is both a simplistic and rough measure, and it can very well be that future contributions that apply more sophisticated lines of attack will uncover possible reasons as to why the interaction effects in this dissertation only granted partial support for Hypothesis 4. Yet as described, one explanation can be the way the size of the identified niches influenced density levels; i.e. the more nodes in a niche the less densely connected it tended to be and vice versa. In addition, characteristics for collectives can also go beyond merely investigating the distinctiveness *within* niches to also focusing on relationships *between* them. I slightly touched upon this issue in the discussion of the Florentine case in Chapter 2, where I questioned if Burt's (1992a) structural holes theory or Granovetter's (1973) weak tie argument were manifest at different levels of analyses. For instance, the density of contacts between niches could provide us with information about to what extent there are strong or weak ties between different collectives. The degree to which different niches are connected to others that are disconnected can furthermore teach us which collective or collectives possess brokering positions (for further details, see Scott 2000; Wasserman and Faust 1994). Altogether, I argue that a variety of approaches in how to both identify collective actors and relational characteristics for these higher level aggregates can provide fruitful and comparable insight to our understanding of social capital as a multilevel phenomenon.

I have stated earlier that the interplay between network predictors of social capital and institutional issues can spur an avenue of further research in a dual context that is ripe to provide us further insight in the area of organizational studies. In this dissertation, I have merely investigated what happens when we simultaneously include different network measures and start-up year as independent variables. I believe that a fruitful path to gain fuller insight in this area would be to investigate if there is any interaction effect between these variables. For instance, is the observed relationship between network distance to the center of the field and venture success constant for all micro-power entrepreneurs no matter what year they started production, or do we observe that start-up year moderates this (or other) network variables? Further contributions should accordingly undertake the task of investigating such issues.

Finally, this dissertation has addressed the concept of social capital as a multilevel phenomenon by modeling network centralities at the focal actor level and niche characteristics at higher level aggregates as the independent variable. The dependent variable, on the contrary, was merely venture success, measured by dividing average yearly electricity production by real investments. In other words, independent variables were multilevel in nature whereas the dependent variable was not. I thus intended to uncover how "good" an entrepreneur is as a consequence of network configurations at different levels of analysis. Yet another approach – which also extends the multilevel issue in network analysis – would be to go beyond the question of how "good" the entrepreneur is and to also ask how "different" he is from his colleagues. Can it be for instance that the closer the network distance between a dyad of start-ups, the more similar venture success? And are dyads of start-ups belonging to the same niche more similar in performance than dyads belonging to different niches? To expand our understanding of social capital as a multilevel phenomenon, further studies should accordingly conduct research where the dependent variable is also examined at different levels of analyses, and this work is under way.

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8. Appendix I: Data Collection Instrument (in Norwegian)

Vegleiing for utfylling

På dei neste sidene har eg lista opp namn på ein del aktørar som opererer innanfor mikro- og minikraft. Første delen inneheld ei oversikt over leverandørar, rådgivarar og liknande, medan fylgjande del presenterer ulike mikro- og minikraftverk. Eg ber Dykk nemne med kven av desse De har (eller har hatt) regelmessig kontakt.

Kolonne 3
Her set De årstalet då kontakten vart etablert for fyrste gong.

Kolonne 4
Har kontakten eventuelt opphøyrd å eksistere, set De årstalet for dette her.

Kolonne 5
I denne kolona set De omtrentleg hyppigheit for eksisterande kontaktar, eller den mest vanlege hyppigheita for avslutta kontaktar. Set inn *eitt* tal.

1. Sjeldnare enn kvar månad.
2. Månadleg.
3. Kvar veke eller oftare.

Kolonne 6
Her ynskjer eg å få reie på den mest vanlege *type* kontakt De hadde *fram til kraftverket vart sett i drift* (for kontaktar oppretta *etter* at drifta kom i gong, set De type kontakt for den *første tida*). Set inn *ein eller fleire* talverdiar:

1. Kontakt i samband med spørsmål som vedkjem lovreguleringar og naturvern.
2. Kontakt i samband med val av produkt, tekniske løysingar og hydrologiske tilhøve.
3. Kontakt i samband med installering/bygging og oppstart.
4. Kontakt i samband med drift og vedlikehald.

Kolonne 7
Her ynskjer eg å få reie på den mest vanlege *type* kontakt De har *i dag* (eller mest vanlege type kontakt De hadde det året den vart avslutta). Set inn *ein eller fleire* talverdiar:

1. Kontakt i samband med spørsmål som vedkjem lovreguleringar og naturvern.
2. Kontakt i samband med val av produkt, tekniske løysingar og hydrologiske tilhøve.
3. Kontakt i samband med installering/bygging og oppstart.
4. Kontakt i samband med drift og vedlikehald.

I tomme rekker ber eg Dykk om føye til andre moglege aktørar De har (eller har hatt) tilsvarande kontakt med. NB! For leverandørar, rådgivarar og andre relevante aktørar som De fører opp, er det viktig å nemne kva *type tenester/produkt* som vert levert.

På dei siste sidene ber eg om informasjon frå kraftverket samt noko anna informasjon.

Dersom De ynskjer å få tilsendt forskingsrapport frå undersøkinga, kan De gje meg e-post adresse eller vanleg adresse: ______________________________

Leverandørar, rådgivarar og andre relevante aktørar	Type tenester og produkt som vert levert	Kontakt sidan (år)	Evt. avslutta (år)	Hyppig-heit	Opphavleg type kontakt	Type kontakt i dag (el. ved avsl.)
Aquaservice AS, Sykkylven	###########					
Bygland Teknologi AS, Bygland	###########					
Energi Teknikk AS, Kvinnherad	###########					
Fossing Tresliperi AS, Kragerø	###########					
Gunnar Ettestøl, Vegårdshei	###########					
Ivar Sægrov, NVE, Førde	###########					
Lier Energi AS, Lier	###########					
Mikrokraft AS/ Kjønståná, Møyskrev Stavanger/ Hjelmeland	###########					
Natur-Energi AS (tidl Miljø-Energi), Stavanger	###########					
Nordic Pipe AS, Sund	###########					
NVK Gruppen Norplan AS, Ski	###########					
Olav Skeie, Norskog, Oslo	###########					
Richard Vanvik, Vindafjord	###########					
Rør og Vannteknikk AS, Steinkjer	###########					
Sintef Energiforskning, Trondheim	###########					
Small Turbine Partner AS, Trondheim	###########					
Tubus AS, Sarpsborg	###########					

Kraftverk	Kommune	Kontakt sidan (år)	Evt. avslutta (år)	Hyppig-heit	Opphavleg type kontakt	Type kontakt i dag (el. ved avsl.)
Bjørsvik	Bergen					
Gjedrem & Holmen Elverk	Bjerkreim					
Vikeså Kraftverk	Bjerkreim					
Dyrstad	Bremanger					
Kaldheim	Etne					
Rimbareid Kraftstasjon	Fitjar					
Vistvik Minikraftverk	Fitjar					
Storelva	Flora					
Strupen	Flora					
Bakkefossen Kraftverk, N Gjerland	Førde					
Gunnar Jan Gjerland	Førde					
Høghagebekken Kraftverk, A Eiane	Forsand					
Grøndal & Krutlet Kraftverk	Forsand					
Øksland Kraftverk	Gaular					
Norvald Hestad, Hestadgrend	Gaular					
DFU Kraftverk	Gjesdal					
Mjåland Kraftverk	Gjesdal					
Byrkjedal Kraftverk	Gjesdal					
Monabekken Kraftverk	Gjesdal					
Dybingen Kraftverk	Gjesdal					
Svandedal Kraftverk	Gjesdal					
Fossheim Kraftverk, Søreide	Gloppen					
Fløtre	Gloppen					
Brattvåg	Haram					
Nesset Kraftverk	Hareid					
Hauskje Kraftverk	Hjelmeland					
Brekke, Ortnevik	Høyanger					
Kinnali kraftverk I & II	Jølster					
Grovane Kraftverk AS	Jølster					
Tveitelvfallet	Kvinnherad					
Kjeldebekken, Dyrkolbotn	Lindås					
Biskopstien Kraftverk, Handeland	Lund					
Moi Elverk	Lund					
Langli	Molde					
Hauan Kraftverk, A Neraas	Nesset					
Møllefossen Kraftstasjon	Osterøy					
Torbjørn Rødstøl	Rauma					
Åfarnes, K Herje	Rauma					
Frisvold, Krokset	Rauma					
Inge Flovik	Rauma					
SAFA	Samnanger					
Dyrhovden, Haga	Samnanger					
Minikraftverk Hisdalen	Samnanger					

Kraftverk	Kommune	Kontakt sidan (år)	Evt. avslutta (år)	Hyppig-heit	Opphavleg type kontakt	Type kontakt i dag (el. ved avsl.)
Risvoldtunet, Aalvik	Sauda					
Øyvind Djuv	Sauda					
Kaupanger, C Knagenhjelm	Sogndal					
Pedek	Solund					
Mehammer	Stord					
Kasper Fjelde	Strand					
Fiskå Mølle	Strand					
Ottar Holta	Strand					
Furset kraftverk	Stranda					
Aaning	Stryn					
Vasstaket Kraftverk, J Hogrenning, Loen	Stryn					
Glomnes Kraft	Stryn					
Tveit Kraftverk	Suldal					
Hamrabø Mikrokraftverk, S Havrevoll	Suldal					
Drarvik	Suldal					
Torstein Mikal Bratland	Suldal					
Bjøråa, K Årnes	Surnadal					
Torjul Mikrokraftverk, R Sørheim	Tingvoll					
Helgøy Kraftverk	Vanylven					
Imsland, Staurland	Vindafjord					
Austefjord, K Ervik, Hjartåbygda	Volda					
Hjartåbygda, OJ Humberset	Volda					
Høydal Kraftverk	Volda					
Heideelva Kraftverk	Volda					
Kleivafoss	Voss					
Vartdal Kraftverk	Ørsta					

Ver venleg og svar på fylgjande spørsmål:

Kraftverket sitt namn, innehavar og kommunenamn: ______________________________

____

Når vart straumproduksjonen sett i gong ved kraftverket? mnd/år: ____________

Månadleg brutto (total) straumproduksjon i kWh frå kraftverket (legg eventuelt ved utskrift/utskrifter):

	Jan	Feb	Mars	April	Mai	Juni	Juli	Aug	Sept	Okt	Nov	Des
1995												
1996												
1997												
1998												
1999												
2000												
2001												
2002												

Fyll inn dei opplysningar De kjenner til ved kraftverket: Maksimal yting (kW): __________

Slukeevne (m3/s): ____________

Brutto fall (m): ______________

Storleik på inntaksdam (m3): _____

Nedslagsfelt (km2): ___________

Har De oppdemt magasin i nedslagsfelt? Dersom ja, om lag kor stort er dette? m3: ________

Er det andre tilhøve som kan påverke straumproduksjonen (bruk evt. baksida av arket)? _____

____

Namn og kommunenamn til næraste vêrstasjon: ______________________________

Om lag kor store investeringar har De til saman hatt ved bygging av kraftverket? kr: _______

Om lag kor mykje av desse investeringane har evt. gått med til å knyte seg til kraftnettet?

kr:__________

Om lag kor store driftskostnader har De per år? ______________________________

Har kraftverket vore råka av uføresette hendingar/ulykker (t.d. lynnedslag)? Dersom ja, i kor mange månader stansa dette straumproduksjonen? ______ (bruk baksida av arket til å nemne *kva* som hende)

Alt i alt, i kor stor grad meiner De at kraftverket har vore vellukka? (set *eitt* kryss)

I svært stor grad: ___

I nokså stor grad: ___

I nokon grad: ___

I nokså liten grad: ___

I svært liten grad: ___

Her ynskjer eg nokre opplysningar om De som har bygd kraftverket (dersom fleire personar enn Dykk sjølv har vore med på prosjektet, set De tilsvarande opplysningar for den eller dei *til høgre* for Dykk sjølv).

Kjønn: ________ ________ ________ ________

Fødselsår: ________ ________ ________ ________

Kor mange år med yrkeserfaring har De? ________ ________ ________ ________

Lengd på utdanning

grunnskule:	___	___	___	___
vidaregåande skule:	___	___	___	___
1-3 år på universitet/høgskule:	___	___	___	___
4 år eller meir på universitet/høgskule:	___	___	___	___

Innanfor kva område har De høgst utdanning?

teknisk/naturvitskapleg	___	___	___	___
landbruk/skogbruk	___	___	___	___
økonomisk/administrativ	___	___	___	___
anna	___	___	___	___

Eventuelt namn på formell utdanning:

____________ ____________ ____________ ____________

Har De vore med på å bygge andre kraftverk før De bygde Dykkar eige kraftverk? Dersom ja, til saman kor mange? ________

Har De (eller har De hatt) jobb innanfor kraftbransjen utanom Dykkar eige kraftverk? Dersom ja, kva type jobb? ______________________________ (bruk evt. baksida av arket)

Dersom fleire enn Dykk sjølv har vore med på å bygge Dykkar eige kraftverk. Har nokon av desse personane vore med på å bygge kraftverk tidligare? Dersom ja, kor mange kraftverk har dei til saman vore med på å bygge? ________

Kjenner De til nybygde mikrokraftverk (mindre enn 100 kW) som allereie er i drift i fylka Rogaland, Hordaland, Sogn og Fjordane eller Møre og Romsdalen som ikkje er med på lista? Dersom ja, før opp namn/innehavar og kommunenamn (bruk evt. baksida av arket):

____

Hjarteleg takk for hjelpa! All innhenta informasjon vert handsama konfidensielt. Innan kort tid tek eg kontakt for å avtale eit telefonintervju. Skjemaet kan eventuelt fyllast ut på eiga hand, returnerast i frankert svarkonvolutt eller faksast på nummer 5595 9430.

Med venleg helsing Jarle Aarstad!

9. Appendix II: Syntax Files

Table 2.2

Model 1: Fit Model(Y(:Outcome), Effects(:Centrality), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:Outcome << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 2: Fit Model(Y(:Outcome), Effects(:Niche), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:Outcome << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 3: Fit Model(Y(:Outcome), Effects(:Centrality, :Niche), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:Outcome << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 4: Fit Model(Y(:Outcome), Effects(:Centrality, :Niche, :Centrality * :Niche), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:Outcome << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Tables 2.3 and 2.4

```
CONCOR
------------------------------------------------------------------------------
Diagonal:                          Reciprocal
Max partitions:                    2
Input dataset:                     C:\Programfiler\Ucinet
6\DataFiles\Foreløpig\Padgett Ekteskap
```

Table 2.5

Model 1: Fit Model(Y(:WealthLn), Effects(:InfoCentr), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:WealthLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 2: Fit Model(Y(:WealthLn), Effects(:Niche), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:WealthLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 3: Fit Model(Y(:WealthLn), Effects(:InfoCentr, :Niche), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:WealthLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 4: Fit Model(Y(:WealthLn), Effects(:InfoCentr, :Niche, :Niche * :InfoCentr), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:WealthLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Tables 4.1 to 4.8

CONCOR

```
--------------------------------------------------------------------------
Diagonal:                    Reciprocal
Max partitions:              2
Input dataset:               C:\Programfiler\Ucinet
6\DataFiles\Foreløpig\Mikroakt 5 år tom 2001
```

Table 5.3

Model 1: Fit Model(Y(:MeanProdLn), Effects(:Size of the plant), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 2: Fit Model(Y(:MeanProdLn), Effects(:Built alone, :Education, :Age of actors, :Head difference, :MeanDevPre%), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 3: Fit Model(Y(:MeanProdLn), Effects(:Size of the plant, :Built alone, :Education, :Age of actors, :Head difference, :MeanDevPre%), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 4: Fit Model(Y(:MeanProdLn), Effects(:nCloseness, :nCloseness * :nCloseness), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 5: Fit Model(Y(:MeanProdLn), Effects(:nCloseness), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 6: Fit Model(Y(:MeanProdLn), Effects(:nDegree, :nCloseness, :nCloseness * :nCloseness), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 7: Fit Model(Y(:MeanProdLn), Effects(:nDegree, :nDegree * :nDegree, :nCloseness, :nCloseness * :nCloseness), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 8: Fit Model(Y(:MeanProdLn), Effects(:Niche), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 9: Fit Model(Y(:MeanProdLn), Effects(:nCloseness, :nCloseness * :nCloseness, :Niche), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 10: Fit Model(Y(:MeanProdLn), Effects(:nFlowBetwLn), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 11: Fit Model(Y(:MeanProdLn), Effects(:nFlowBetwLn, :Niche), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 12: Fit Model(Y(:MeanProdLn), Effects(:nFlowBetwLn, :Niche, :Niche * :nFlowBetwLn), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 13: Fit Model(Y(:MeanProdLn), Effects(:Name("Start-up year")), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 14: Fit Model(Y(:MeanProdLn), Effects(:Name("Start-up year"), :Name("Start-up year") * :Name("Start-up year")), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 15: Fit Model(Y(:MeanProdLn), Effects(:nCloseness, :nCloseness * :nCloseness, :Niche, :Name("Start-up year"), :Name("Start-up year") * :Name("Start-up year")), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 16: Fit Model(Y(:MeanProdLn), Effects(:nCloseness, :nCloseness * :nCloseness, :Niche, :Name("Start-up year")), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 17: Fit Model(Y(:MeanProdLn), Effects(:nFlowBetwLn, :Niche, :Niche * :nFlowBetwLn, :Name("Start-up year")), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Table 5.7

Model 1: Fit Model(Y(:MeanProdLn), Effects(:MeanDevPre%), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Model 2: Fit Model(Y(:MeanProdLn), Effects(:MeanDevPre%, :MeanDevPre% * :MeanDevPre%), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(:MeanProdLn << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));

Table 5.8

```
Fit Model(Y( :MeanProdLn), Effects( :Niche,  :nDegree,  :Niche *  :nDegree,
:Name("Start-up year")), Personality(Standard Least Squares),
Emphasis(Effect Leverage), Run Model( :MeanProdLn << {Plot Actual by
Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));
```

Table 5.9

Model 1:
```
Fit Model(Y( :Size of the plant), Effects( :nFlowBetwLn),
Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(
:Size of the plant << {Plot Actual by Predicted(1), Plot Residual by
Predicted(1), Plot Effect Leverage(1)}));
```

Model 2:
```
Fit Model(Y( :Size of the plant), Effects( :nCloseness),
Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(
:Size of the plant << {Plot Actual by Predicted(1), Plot Residual by
Predicted(1), Plot Effect Leverage(1)}));
```

Model 3:
```
Fit Model(Y( :Size of the plant), Effects( :nDegree),
Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(
:Size of the plant << {Plot Actual by Predicted(1), Plot Residual by
Predicted(1), Plot Effect Leverage(1)}));
```

Model 4:
```
Fit Model(Y( :Size of the plant), Effects( :Name("Start-up
year"),  :Education), Personality(Standard Least Squares), Emphasis(Effect
Leverage), Run Model( :Size of the plant << {Plot Actual by Predicted(1),
Plot Residual by Predicted(1), Plot Effect Leverage(1)}));
```

Model 5:
```
Fit Model(Y( :Size of the plant), Effects( :nCloseness,
:Name("Start-up year"),  :Education), Personality(Standard Least Squares),
Emphasis(Effect Leverage), Run Model( :Size of the plant << {Plot Actual by
Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));
```

Model 6:
```
Fit Model(Y( :Size of the plant), Effects( :nDegree,
:Name("Start-up year"),  :Education), Personality(Standard Least Squares),
Emphasis(Effect Leverage), Run Model( :Size of the plant << {Plot Actual by
Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));
```

Table 5.10

Model 1:
```
Fit Model(Y( :nDegree), Effects( :Size of the plant),
Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model(
:nDegree << {Plot Actual by Predicted(1), Plot Residual by Predicted(1),
Plot Effect Leverage(1)}));
```

Model 2:
```
Fit Model(Y( :nDegree), Effects( :Niche), Personality(Standard
Least Squares), Emphasis(Effect Leverage), Run Model(Profiler(1, Confidence
Intervals(1), Term Value(Niche(8.90104241143398e-307))),  :nDegree << {Plot
Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect
Leverage(1)}));
```

Table 5.11

Model 1: `Fit Model(Y( :nCloseness), Effects( :Name("Start-up year"), :Education, :Age of actors), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model( :nCloseness << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));`

Model 2: `Fit Model(Y( :nCloseness), Effects( :Niche), Personality(Standard Least Squares), Emphasis(Effect Leverage), Run Model( :nCloseness << {Plot Actual by Predicted(1), Plot Residual by Predicted(1), Plot Effect Leverage(1)}));`