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Abstract:

In this paper, we study the formation of network ties between firms along the life cycle of a creative industry. We focus on three drivers of network formation: i) network endogeneity which stresses a path-dependent change originating from previous network structures, ii) five forms of proximity (e.g. geographical proximity) which ascribe tie formation to the similarity of actors' attributes; and (iii) individual characteristics which refer to the heterogeneity in actors capabilities to exploit external knowledge. The paper employs a stochastic actor-oriented model to estimate the – changing – effects of these drivers on inter-firm network formation in the global video game industry from 1987 to 2007. Our findings indicate that the effects of the drivers of network formation change with the degree of maturity of the industry. To an increasing extent, video game firms tend to partner over shorter distances and with more cognitively similar firms as the industry evolves.

JEL codes: D85, B52, O18

Key words: network dynamics, industry life cycle, proximity, creative industry, video game industry, stochastic actor-oriented model

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1 Introduction

Interfirm networks have increasingly become the focus of study in economic geography (Grabher, 2001; Morrison, 2008; Bergman, 2009; Ter Wal and Boschma, 2009; Boschma and Frenken, 2010; Vicente et al., 2011). While research on interfirm networks as a means to explain firm performance and regional competitiveness has grown exponentially, relatively little is known about how interfirm networks come into being, how their structure changes over time, and how spatial patterns affect this process. Scholars have started to investigate how interfirm network formation in terms of tie initiation takes place (e.g. Rosenkopf and Padula, 2008; Ahuja et al., 2009; Cassi and Plunket, 2010; Balland, 2011; Broekel and Boschma, 2011), but applied research on the spatial and temporal dimension of network formation remains sparse (Ter Wal, 2011). In this paper, we analyse the formation of an interfirm network by using longitudinal data and adopting a long-term perspective.

Our main objective is to provide a detailed account of the underlying mechanisms of network dynamics along the life cycle of an industry (Klepper, 1996; Audretsch and Feldman, 1996). We aim to make three contributions. First, the industry life cycle approach has provided a rich account of the changing nature of competition among firms, but questions about the changing nature of collaboration have been left unanswered (Malerba, 2006; Ter Wal and Boschma, 2011). A few studies have investigated the dynamics in network structure (e.g. Bonaccorsi and Giuri, 2001; Orsenigo et al., 2001, Gay and Dousset, 2005), but not the driving forces. Second, scholars have argued that the level of similarity between attributes of actors is crucial in the process of tie formation (McPherson et al., 2001). We build on the French proximity school to investigate which forms of proximity (like geographical proximity) that drove the formation of the interfirm network (Boschma and Frenken, 2010). Although it has been shown empirically that different forms of proximity influence network formation (Balland, 2011; Broekel and Boschma, 2011), it is crucial to investigate whether the effect of these drivers changes or remains stable along the industry life cycle (Ter Wal, 2011). And finally, we aim to contribute to the literature on networks in creative industries. Creative industries are characterized by project-based production in which local buzz is considered to be highly important (Grabher, 2001). By means of investigating a particular creative industry, we test which drivers are crucial in network formation, and whether these effects change as the industry evolves in space.

In this paper, we analyze network formation in the global video game industry from 1987 to 2007. The analyses are conducted for the total population of firms that developed or published one or more video games for a video game console and the co-production of a video game is what represents the formation of a network tie. The video game industry is often referred to as a creative industry. Typical to such a creative industry is its project-based production in which new video games are jointly developed (Caves, 2000). Also, the video game industry has a 35 years long history which allows us to track and follow tie formation processes from the very beginning of the industry. We analyze collaboration in the production of video games for four generations of video game consoles, starting in 1987. Yearly relational matrices are constructed for analysing underlying mechanisms of network dynamics within each generation: 1987-1992, 1993-1998, 1999-2004, 2005-2007.

The paper focuses on two research questions: (1) which proximity dimensions, among other factors,

drive the formation of network ties in the global video game industry?; and (2) do the effects of these driving forces increase or decrease as the industry evolves? We employ a stochastic actor-oriented model (Snijders, 2001) to analyze the evolution of the interfirm collaboration network. This approach allows for the simultaneous evaluation of 3 sets of driving forces: (1) individual characteristics which affect, for instance, the capacity to exploit external knowledge; (2) relational structures that display endogenous structural mechanisms that reproduce themselves over time; and (3) similarity between attributes of firms (like being proximate in cognitive or geographical terms). Our findings indicate that the forces that drive the formation of network ties are indeed dependent on the state of development of an industry. Firms tend to partner over shorter distances and with more cognitively similar firms as the industry matures.

The paper is organized as follows. Section 2 presents a brief literature review on the main drivers of interfirm network dynamics. Then, section 3 describes the data collection and provides descriptive statistics of the longitudinal network database. The stochastic actor-oriented model, the different variables and the model specification are detailed in section 4. In section 5, we present the main empirical results. Section 6 concludes and discusses implications for further research.

2 Drivers of the Interfirm Network along the Industry Life Cycle

Interfirm networks and proximity

There is increasing attention for a relational approach in economic geography (Bathelt and Glückler, 2003). While the earlier work on relational issues in economic geography has generated very rich and contextual narratives of the spatial processes at hand, various scholars have recently identified flaws in this literature by criticizing its lack of formalisation, and its metaphorical accounts of relational processes (e.g. Giuliani and Bell, 2005; Grabher, 2006; Cantner and Graf, 2006; Glückler, 2007; Sunley, 2008). We argue that social network analysis, which allows for a quantitative investigation of interorganizational interactions, provides a framework to deal with these flaws.

In the last decade, network analysis has gained an increasing amount of attention from scholars in economic geography (Ter Wal and Boschma, 2009). One of the main research questions is: what drives a network tie? Traditionally, one looks at the similarity of actors' attributes, in which the similarity between connected actors is compared with the similarity between non-connected actors (McPherson et al., 2001). Sociologists refer to the term homophily for explaining the tendency of social groups to form around actors that have similar tastes, preferences, ethnic background or social status. We follow the terminology of proximity introduced by the French proximity school (Rallet and Torre, 1999; Carrincazeaux et al., 2008), and we link proximity to the formation of network linkages (Boschma and Frenken, 2010). Boschma (2005) proposed an analytical distinction in five dimensions of proximity, in which cognitive, organizational, institutional, social and geographical proximity reduce collaboration costs or risks, and do therefore increase the likelihood of actors to form partnerships. That is, actors are more likely to collaborate with others when they have similar knowledge bases, when they share

similar norms and values, when they belong to the same business group, when they are embedded in the same social context, or when they are located in the same geographical area.

It is not necessarily true that all forms of proximity act as important drivers of network formation. In economic geography, a crucial question is whether geographical proximity influences the likelihood of tie formation (Morgan, 2004). By employing Boschma's (2005) proximity framework, one can isolate the effect of geographical proximity from other forms of proximity, as geographical proximity is just one potential driver of network formation, and not necessarily the most important one (Boschma, 2005). Although a great deal of interactions take place between agents that are geographically proximate (see e.g. Weterings, 2005; Suire and Vicente, 2009; Hoekman et al., 2010), this might be caused by other forms of proximity. Moreover, other forms of proximity may act as substitutes for geographical proximity in network formation, as studies have empirically demonstrated (see e.g. Singh, 2005; Agrawal et al., 2006; Ponds et al., 2007; Sorenson et al., 2006; Breschi et al., 2010).

In addition to these proximity dimensions, the literature has argued that individual characteristics of organizations may also influence the likelihood to collaborate (Cassiman and Veugelers, 2002). Indeed, changes in the network result from decisions of organizations with heterogeneous characteristics such as age or size. Organizations establish relationships in order to access resources that they do not have themselves. For example, larger firms are often argued to be better able to gain access to financial resources, while smaller firms are often argued to be more flexible. As a result, large organizations might turn to smaller organizations to respond more rapidly to unexpected situations, while smaller firms might turn to larger firms to gain access to financial resources. Another important determinant of collaborations is the experience of the firm. The more experience a firm accumulates over the years, the richer its functional knowledge base and the more valuable its knowledge about potential partners. As a result, experienced firms will be more likely to be able to identify fruitful collaborations and attract potential collaborators.

Apart from proximity and individual characteristics, network formation may also be influenced by endogenous structural network effects. Endogenous or path-dependent network formation describes how current network structures influence its future evolution. Two of the most prominent structural effects are transitivity and preferential attachment. Transitivity – or triadic closure – is a local network force that induces two unconnected nodes that are connected to one common node to connect themselves (Davis, 1970; Holland and Leinhardt, 1971). Positive transitivity implies that organizations that have a partner in common are more likely to partner themselves, thereby effectuating triadic closure. The role of the common partner here is crucial. The partner can provide information to both partners in order to reduce uncertainty about the competences and the trustworthiness of the potential partner (Uzzi, 1996; Cowan et al., 2007). Preferential attachment describes the attractiveness of central actors comparatively to others. It has been shown recently that new nodes entering the network indeed tend to form ties with incumbent nodes according to their degree distribution (Barabási and Albert, 1999).

When analyzing the driving forces behind interfirm network formation, scholars often adopt a static approach, explaining the structure of the network at one point in time (e.g. Autant-Bernard et al., 2007; Rosenkopf and Padula, 2008; Ozman, 2009; Ahuja et al., 2009; Glückler, 2010; Broekel and Boschma,

2011). Little attention has been devoted so far to the changing nature of network formation over time (Powell et al., 2005). One reason that causes this lack of attention is that it requires complete network data over a long period of time and complex statistical models. Therefore, research on the spatial and temporal dimension of network formation has remained sparse (Glückler, 2007; Boschma and Frenken, 2010). Only very recently, studies focus on network dynamics in a spatial setting, like the dynamics in knowledge networks in a Chilean wine cluster (Giuliani, 2010), or the dynamics in co-inventor networks in French genomics (Cassi and Plunket, 2010) and German bio-tech (Ter Wal, 2011).

Industry Evolution

To study network dynamics, we believe that the industry life cycle approach provides a useful framework. This is not because the industry life cycle approach has fully incorporated network dynamics in their models. On the contrary, the industry life cycle approach has mainly been preoccupied with firm population dynamics in which the evolution of competitive structures over an industry's lifespan is examined and how these relate to the nature of the products that are produced in these industries (Gort and Klepper, 1982; Abernathy and Clark, 1985; Klepper, 1997; Neffke et al., 2011). Typically, the evolution of the population of firms in an industry follows an S-curve, starting by just a few firms entering the industry, followed by a period of strong growth in the number of new entrants which, after some time, levels off and eventually decreases. However, while entry and exit of firms and the changing nature of competition are inextricably interwoven with changing network structures, this domain of research has remained largely unexplored (Malerba, 2006; Ter Wal and Boschma, 2011). There are a few studies that have investigated dynamics in networks structures in the aircraft-engine industry (e.g. Bonaccorsi and Giuri, 2001) and pharmaceuticals (Orsenigo et al., 2001), but these studies have not analyzed the driving forces behind the network dynamics.

Changes in the pattern of entry and exit of firms and the nature of competition along the industry life cycle mark some implications for the study of network evolution. Due to the entry and exit of firms, the nodes in a network come and go, and relationships are created and dissolved (Boschma and Frenken, 2010). In order to fully capture and understand the forces that drive formation of network ties, an understanding of the changing industrial settings and the interaction between firm population and industry setting is required. According to Orsenigo et al. (2001), the network of strategic alliances in biotechnology is characterized by stable core-periphery patterns during the industry life cycle, because the formation of new alliances depends on the network of prior alliances, among other factors. And when the nature of competition in an industry changes from product innovation to price cuts, firms tend to collaborate with similar partners to secure efficient and smooth interactions. Such a pattern is frequently observed in various industries, as mimetic isomorphism within the population of firms tends to guide the industry towards the establishment of a dominant design (DiMaggio and Powell, 1983; Utterback and Suárez, 1993). The emergence of a dominant design allows production to become more standardized and firms to exploit scale economies. This type of competition requires very specialized, industry-specific knowledge, skills and machinery, and little access to new and diverse sources of knowledge (Neffke et al., 2011).

If industries are subject to continuous flows of new firms entering the industry resulting from

disruptive technological change (Rosenkopf and Tushman, 1994; Rosenkopf and Padula, 2008), interfirm network structures are likely to be less stable. Also, the patterns of tie formation between new entrants and incumbent firms in the industry are argued to be decisive in determining firms' success rates. For example, incumbent firms can increase the size of the population of firms that have adopted a specific technology by entering into a partnership with new entrants (Chandler, 1997; Rosenkopf and Padula, 2008). Another feature of partnerships between incumbents and new entrants is that innovations are often introduced by new entrants which exert pressure on the yet existing pool of firms. Incumbent firms can team up with the new entrants in order to gain access to the innovative product or technology.

Network formation in creative industries

The aforementioned studies on interfirm networks concern either engineering industries, with a focus on vertical networks between suppliers and buyers, or high-tech industries (biotech, telecommunications) in which the focus is strategic alliance networks. The insights provided by these studies are unlikely to apply to creative industries, because in creative industries collaboration patterns are extremely important but less subject to processes of knowledge codification and product standardization.

Production in creative industries is highly dependent on the interaction between multiple autonomous agents (Caves, 2003). Industries such as feature film production (Mezias and Mezias, 2000), advertising (Grabher, 2001) and book publishing (Heebels and Boschma, 2011) are based on project-based production systems involving creative and business-oriented entrepreneurs. Success of these entrepreneurs is dependent on their embeddedness in interfirm networks, communities and scenes (Grabher, 2001). Within each project, the functional activities are distributed over the firms involved. The firms involved are continuously updating each other, exchanging ideas and negotiating decisions. The products that come out of these projects are unique: each product differentiates itself by introducing more or less novel – stylistic – elements.

Interfirm collaborations in creative industries serve not only as conduits of information flows but also as hierarchies of reputation and status (Currid, 2007; Heebels and Boschma, 2011). Reputation and status are extremely important in the production of cultural products. The main reason is that cultural production is associated with great uncertainty. Nobody knows a priori whether a cultural product will be accepted or rejected by the larger audience (Caves, 2003), and hits can easily be followed by flops. Gaining access to partners with high levels of status is likely to enable firms to capture the attention and fulfill the needs of a large audience.

While various scholars have argued that the weightlessness of ideas is likely to diminish the role of geography (Friedman, 2005), others have stressed the overall importance of space and place because of the symbiotic relationship between place, culture and economy (Pratt, 2000; Scott, 1997; Johns, 2005). The latter strand of literature argues that geographical proximity, urban culture and local buzz are extremely important for cultural industries and are likely to set apart the spatial organization of cultural industries from other industries. Scott (2004) argues that a large share of all interfirm partnerships in creative industries can be found in larger cities.

Synthesis

In summary, we have identified three main drivers of interfirm network formation (i.e. proximity mechanisms, individual characteristics and structural endogenous network structures). We will test which ones have been responsible for the formation of the co-production network in the global video game industry, and we will explicitly focus on the (in)stability of these forces as this industry evolves. By doing so, we reconcile insights provided by the industry life cycle approach and insights from network analysis. Moreover, though our focus on the video game industry, we will be able to unravel more of the subtleties that are specific to creative industries. In that respect, we see this study as an explorative and early attempt to provide insights on the dynamics of network formation over the life cycle of a creative industry.

3 Empirical Setting

The video game industry is typically referred to as a creative industry to stress the importance of both creative human capital in the production process and the one-off nature of the final product (Tschang, 2007). Each video game differentiates itself from any other video game by introducing new gameplays, new perspectives, new genre combinations, new characters or enhanced graphics. Therefore all video games are essentially novel and its success depends on whether consumers are prepared to pay for the quality of the product innovation (Delmestri et al., 2005).

Like other creative industries, the video game industry is made up of firms that generate creative content and firms that recognize, finance and market the creative content (Tschang, 2007). The production of a video game is carried out as a project involving a development company and a publishing company, although some development companies publish their own games and some publishing companies set up in-house development studios. Developers "... are charged with the creative development of a game code" (Johns, 2005, p. 169) by providing programming skills, artistic designs and insights on the gameplay¹, while publishers are responsible for managing, funding and marketing the video game project by providing the project management, market insights, marketing skills and financial capital (Tschang, 2007). The production of video games is organized in temporal projects in which employees of the developer and the publisher gather to create a new video game. The production process of a video game is characterized by the coalescence of art and technology and involves character designers, graphic artists, programmers, and managers, project leaders and marketers.

We define two firms as having a network tie if both firms were involved in the production of a video game. In most cases, such a network tie is established through the co-production of video games involving a firm with a clear profile as a publisher and a firm with a clear profile as a developer. As shown in table 1, more than 75 % of all video games are produced by at least two companies, while the rest is produced by one company.

The analyses in this paper are based upon a unique, newly constructed database that contains

¹Gameplay is "the formalized interaction that occurs when players follow the rules of a game and experience its system through play" (Salen and Zimmerman, 2003, p. 303).

	Gen 1	Gen 2	Gen 3	Gen 4	Gen 5	Gen 6
Years covered	1972-1981	1982-1986	1987-1992	1993-1998	1999-2004	2005-2007
Number of firms	21	166	510	1035	1029	757
Number of games	212	916	2526	5525	8406	4857
Games per firm (mean)	10.095	5.518	4.953	5.338	8.169	6.416
<i>No. of games involving:</i>						
-A single firm	128	508	806	1394	1112	455
-Two firms	84	398	1659	3937	6841	4018
-Three firms	0	10	58	188	437	355
-Four firms	0	0	3	6	15	16
-Five firms	0	0	0	0	1	8
-Six firms	0	0	0	0	0	5

Table 1: Collaboration patterns along the video games industry life cycles

information on all firms that developed or published one or more video games² for a video game console³. We collected firm level data such as years of production, number of games produced, location, ownership structures⁴ and game level data such as co-production partners, production year, computer platform compatibility and genre. The data was collected starting from the inception of the industry in 1972 until 2007. The data is a compilation of various data sources. The starting point was the Game Documentation and Review Project Mobygames⁵. The Mobygames website is a comprehensive database of software titles and covers the date and country of release of each title, the platform on which the game can be played, and the name of the publisher and developer of the game. The database goes back until the inception of the industry in 1972, and the project aims to include all games that have ever been developed and published in the video game industry. To obtain data on entry, exit, and location of firms and to control and monitor the quality of the Mobygames data we also consulted the German Online Games Datenbank⁶. This online database is complementary to the Mobygames database in that it provides more detailed information on the location of companies and backgrounds

²Throughout the paper, the term ‘video games’ is used to describe games played using a video game console linked to a television or monitor, rather than PC (Personal Computer) games or other digital hardware.

³A video game console is an interactive entertainment computer or electronic device that produces a video display signal which can be used with a display device (a television, monitor, etc.) to display a video game. The term video game console is used to distinguish a machine designed for consumers to buy and use solely for playing video games from a personal computer, which has many other functions, or arcade machines, which are designed for businesses that buy and then charge others to play" (http://en.wikipedia.org/wiki/Video_game_console, 04/23/2010). The consoles in the database include the Odyssey, Channel F, Atari 2600, Odyssey 2, Intellivision, Atari 5200, ColecoVision, Vectrex, NES, Sega Master System, Atari 7800, TurboGrafx-16, Genesis, TurboGrafx CD, Neo Geo, SNES, CD-I, Sega CD, 3DO, Amiga CD32, Jaguar, Neo Geo CD, PC-FX, Saturn, Sega 32X, PlayStation, Nintendo 64, Dreamcast, GameCube, PlayStation 2, Xbox, Xbox 360, PlayStation 3, and Wii.

⁴We collected data not only for the headquarters of each firm, but also its subsidiaries. Throughout the text we will refer to these subsidiaries as firms and in the empirical modeling we will use the legal relation between headquarter and its subsidiaries as a factor that explains their collaboration.

⁵The Game Documentation and Review Project Mobygames can freely be consulted at <http://www.mobygames.com>. The Mobygames database is a catalog of ‘all relevant information about electronic games (computer, console, and arcade) on a game-by-game basis’ (<http://www.mobygames.com/info/faq1#a>). The information contained in MobyGames database is the result of contribution by the website’s creators as well as voluntarily contribution by Mobygames community members. All information submitted to MobyGames is checked by the website’s creators and errors can be corrected by visitors of the website.

⁶“Online Games Datenbank” can freely be consulted at <http://www.ogdb.de>

of entrepreneurs. In the rare case that neither of the two databases provided this information or in the rare case that the information in the two databases was contradicting, other online or hardcopy resources were consulted.

Video games are produced for one or more video game consoles such as the XBOX 360. Each of the video game consoles introduced in the industry can be categorized into chronological generations (GEN). While the technological specifications of the video game consoles within a GEN show a strong resemblance, the technological specifications of consoles from different GENs are highly dissimilar. Each subsequent GEN of consoles shows a significant improvement in technological specifications and allows the producers of video games to produce games that are significantly different than the games produced for the prior GEN. In other words, the introduction of a new GEN of consoles leads to a change in the design rules for video games (Baldwin and Clark, 2000).

The introduction of new video game consoles, innovation in the production of video games and other industry-specific dynamics have generated high levels of turbulence in the industry. In figure 1, we plotted the entry and exit of all firms⁷ in the video game industry. Until the mid 1990s, the population of firms grew rapidly, after which the population has remained largely stable.

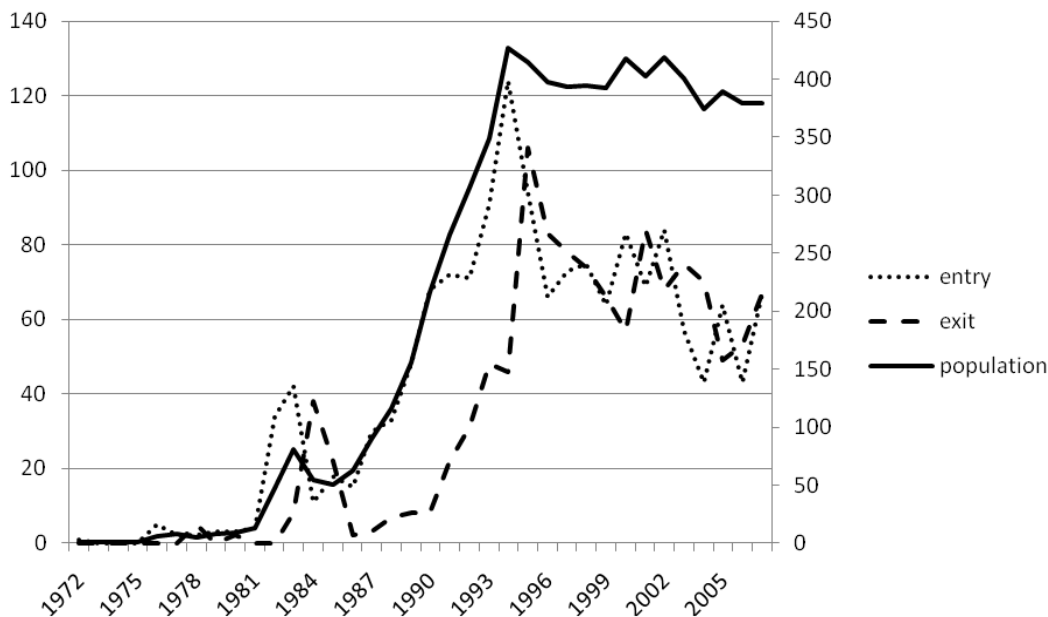


Figure 1: Entry, exit and population totals in the video game industry

For the empirical analyses, we set the start of a new generation at the year in which the first game of a new generation is released. Generation 1 covers the years 1972-1981, generation 2 covers the years 1982-1986, generation 3 covers the years 1987-1992, generation 4 covers the years 1993-1998, generation 5 covers the years 1999-2004, and generation 6 covers the years 2005-2007. In our analyses, we focus on generations 3, 4, 5 and 6. We exclude generation 1 and 2 from the empirical analysis, because the

⁷This figure only includes headquarters.

Observed period	Ties created	Ties dissolved	Ties maintained	Firms entry	Firms exit
1987-1988	132	92	28	52	1
1988-1989	242	114	46	45	0
1989-1990	402	180	108	45	4
1990-1991	412	368	142	20	7
1991-1992	492	394	160	0	23
1993-1994	734	566	282	61	14
1994-1995	554	800	216	54	42
1995-1996	584	572	198	42	46
1996-1997	648	546	236	25	49
1997-1998	478	628	256	0	51
1999-2000	754	468	324	55	10
2000-2001	566	770	308	56	23
2001-2002	872	502	372	35	37
2002-2003	762	794	450	26	53
2003-2004	678	796	416	0	65
2005-2006	508	526	300	17	16
2006-2007	594	504	304	0	32

Table 2: Network dynamics : relational and composition change

level of stability⁸ of the network was too low⁹. Such instability keeps the approximation algorithm we use to model the network dynamics from converging, which will produce unreliable results. In order to improve the stability for generation 3, 4, 5 and 6, we excluded firms that developed only one game in the entire sample of games. In addition, we limited our analysis to the games produced by two firms. Including games developed by more than two firms would have generated two problems. First, it is impossible to assess which partners are actually collaborating. We would have to assume that all partners are equally connected which might not always be the case. Second, each game produces a clique in which all firms involved are fully connected. This could artificially increase the level of network closure and bias the estimation of transitivity. Because such games are marginal¹⁰ during the period considered, we opted for excluding them from the analyses. The final dataset used for our empirical examination comprises 21,314 games involving 1,358 unique firms from 1987 to 2007.

The resulting network involves n actors and can be represented as a $n * n$ matrix $x = (x_{ij})$, where $x_{ij} = 1$ represents the joint production of a video game by firm i and firm $j (i, j = 1, \dots, n)$. The network dynamics within the four different generations are analyzed separately. For the construction of the longitudinal relational database, it is assumed that ties are active during the year of release of a given video game. As such, if a game is released in 2005 by actor i and actor j (regardless of the month), then we assume that a relation exist between i and j for the year 2005, and only for this year. It means that the tie will be dissolved in 2006 if i and j do not release a game together again. Moreover, relations are not directed because we assume that ties are always reciprocated. All relations

⁸Ties that are maintained from one observed moment (year) to another.

⁹Achieving such a level of stability would have required additional assumptions on the length of ties.

¹⁰See table 1 : 5,1% of the total of games developed from 1987 to 2007 (1092/21314).

Observed Year	No of Firms	Number of Ties	Average degree	Network Density
1987	187	120	0.642	0.003
1988	238	160	0.672	0.003
1989	283	288	1.018	0.004
1990	324	510	1.574	0.005
1991	337	554	1.644	0.005
1992	314	652	2.076	0.007
1993	482	848	1.759	0.004
1994	529	1016	1.921	0.004
1995	541	770	1.423	0.003
1996	537	782	1.456	0.003
1997	513	884	1.723	0.003
1998	462	734	1.589	0.003
1999	552	792	1.435	0.003
2000	597	1078	1.806	0.003
2001	630	874	1.387	0.002
2002	628	1244	1.981	0.003
2003	601	1212	2.017	0.003
2004	536	1094	2.041	0.004
2005	462	826	1.788	0.004
2006	463	808	1.745	0.004
2007	431	898	2.084	0.005

Table 3: Network structural descriptive statistics

are also dichotomized¹¹, which means that $x_{ij} = 1$ even if the number of games produced by i and j is > 1 during a given year. For technical reasons, each generation corresponds to a set of yearly matrices with the same $n * n$ size, with $n = 349$ for generation three, $n = 664$ for generation four, $n = 724$ for generation five, and $n = 479$ for generation six, but actors are allowed to leave or enter the network¹².

The resulting network dynamics are summarized in table 2. We can observe that the network becomes more stable over time, because the proportion of ties maintained compared to the number of ties created or dissolved from one year to another is increasing. Table 3 provides some descriptive statistics about the longitudinal network data, including the number of firms and the number of ties for each year included in the statistical analysis. The number of firms is increasing, but also the average degree. This means that firms not only produce more games (table 1), but also collaborate with an increasing number of different partners.

4 Modeling Network Dynamics

The empirical investigation of network dynamics is concerned with complex relational structures that require specific statistical models (Snijders, 2001). A fundamental property of network structures is the existence of conditional dependencies between observations, especially between dyads that have actors in common (Rivera et al., 2010). By nature, such network dependencies violate standard statistical

¹¹The statistical model used can only run dichotomized networks.

¹²We used the method described in Huisman and Snijders (2003) to represent actors entering/leaving the industry. We also used the method of structural zeros (Ripley et al., 2011) as a robustness check which led to the same results.

procedures like OLS and logistic regressions that assume independence among observations. Correlation between observations can lead to unreliable estimations of parameter coefficients and standard errors (Steglich et al., 2010). Therefore, a class of statistical network models based on Markov random graph has been developed to model structural dependencies. Although the first generation of statistical network models was restrictive in terms of effects (Wasserman and Pattison, 1996), more realistic models have been implemented with recent advances in Markov chain Monte Carlo simulation procedures. So far, Stochastic Actor-Oriented Models (SAOM) are the most promising class of models allowing for statistical inference of network dynamics (Snijders et al., 2010). In this paper, we use SAOM implemented in the SIENA¹³ statistical software (Ripley et al., 2011). A brief description of the general principles of SAOM and details of the model specification follows below.

Stochastic Actor-Oriented Models (SAOM)

Besides explicitly representing network dependencies, SAOM are dynamic models that offer the possibility to include a variety of effects related to the heterogeneity of actors or their proximity. SAOM have been identified as a promising model in economic geography (Ter Wal and Boschma, 2009; Maggioni and Uberti, 2011), and applied to analyze the dynamics of global and regional knowledge networks (Giuliani, 2010; Balland, 2011; Ter Wal, 2011).

SAOM are based on three principles that can appear more or less realistic depending on the nature of the network analyzed. First, the evolution of network structures is modeled as the realization of a continuous-time Markov chain, i.e. a dynamic process where the network in $t + 1$ is generated stochastically from its configuration in t . Since change probability depends on the current state of the network and not on its past configurations, relevant information about joint history or intensity of collaborations can be included as an exogenous variable to make this assumption more realistic (Steglich et al., 2010). Second, time runs continuously between observations, which means that observed change is assumed to be the result of an unobserved sequence of micro steps. In each step, actors can change only one tie variable at a time, inducing that a group of actors cannot decide to start relationships simultaneously. Third, and more importantly, it is assumed that network dynamics is the result of choices of actors based on their preferences and constraints, i.e. the model is "actor-oriented". Network structures change because actors develop strategies to create ties with others (Jackson and Rogers, 2007), based on their awareness of the network configuration. This assumption is plausible in the context of the video game industry in which firms are able to determine their strategic decisions, and information on collaborations of other firms is available for intellectual property rights purposes.

In SAOM, actors drive the dynamics of networks because at stochastically determined moments they can change their relations with other actors by deciding to create, maintain or dissolve ties. More formally, these opportunities are determined by a rate function in which opportunities to collaborate occur according to a Poisson process with rate λ_i for each actor i . Given that an actor i has the opportunity to make a relational change, the choice for this actor is to change one of the tie variables

¹³This class of models is often referred to directly as SIENA models. SIENA stands for "Simulation Investigation for Empirical Network Analysis". The RSiena package is implemented in the R language and can be downloaded from the CRAN website: <http://cran.r-project.org/web/packages/RSiena/>.

x_{ij} , which will lead to a new state $x, x \in C(x^0)$. At this stage, a traditional logistic regression is used to model choice probabilities (Snijders et al., 2010):

$$P \{X(t) \text{ changes to } x \mid i \text{ has a change opportunity at time } t, X(t) = x^0\} \\ = p_i(x^0, x, v, w) = \frac{\exp(f_i(x^0, x, v, w))}{\sum_{x \in C(x^0)} \exp(f_i(x^0, x', v, w))} \quad (1)$$

When actors have the opportunity to change their relations, they choose their partners by trying to maximize their objective function, with random perturbations. For the analysis of non-directed networks, different types of models are implemented in SIENA. We model the creation of linkages by using the unilateral initiative and reciprocal confirmation model, which is the most realistic for analyzing collaboration networks (Van de Bunt and Groenewegen, 2007; Balland, 2011; Ter Wal, 2011). In a first stage, actor i can only attempt to maximize its objective function by trying to produce a video game with actor j , but this collaboration is only realized if actor j accepts on the basis of its own objective function¹⁴. Thus, changes in network ties are modeled according to a utility function at the node level which is the driving force of network dynamics. The objective function describes preferences and constraints of firms: to be linked with others that are geographically proximate might be one (Carayol and Roux, 2009). More formally, collaboration choices are determined by a linear combination of effects, depending on the current state, the potential new state, individual attributes¹⁵ and proximity :

$$f_i(x^0, x, v, w) = \sum_k \beta_k S_{ki}(x^0, x, v, w) \quad (2)$$

As proposed by Snijders (2001), the estimation of the different parameters β_k of the objective function is achieved by the mean of an iterative Markov chain Monte Carlo algorithm based on the method of moments. The stochastic approximation algorithm simulates the evolution of the network and estimates the parameters β_k that minimize the deviation between observed and simulated networks. Over the iteration procedure, the provisional parameters of the probability model are progressively adjusted in a way that the simulated networks fit the observed networks. The parameter is then held constant to its final value, in order to evaluate the goodness of fit of the model and the standards errors.

Model specification

A major strength of SAOM is that a large variety of variables can be included in the specification of the objective function to model preferences and constraints of actors. As discussed above, we consider three sets of drivers of network formation: (1) structural effects (i.e. density, transitivity, preferential attachment); (2) individual characteristics of actors (i.e. profile, size, experience); and (3) proximity mechanisms (i.e. geographical, organizational, institutional, cognitive, social) which will be discussed one by one below (see table 4 and table 5).

¹⁴In other specifications, one actor can impose unilaterally the creation of a tie to another one.

¹⁵For the analysis, individual and proximity variables are centered around the mean.

Variable	Operationalization
Density	Out degree
Transitivity	Transitive triplets
Preferential attachment	Square root of degree of alter
Institutional proximity	Same country (dummy)
Geographical proximity	Inverse of Physical distance (natural log)
Organizational proximity	Same group of firms (dummy)
Social proximity	Same games produced previously (nb)
Cognitive proximity	Same genres of VG
Profile similarity	Similarity of profile (developers/publishers)
Size	No of Games produced previously (natural log)
Experience	Number of years since entry

Table 4: Operationalization of the variables

	Gen 3				Gen 4				Gen 5				Gen 6			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Inst. prox.	0.3	0.4	0	1	0.2	0.4	0	1	0.2	0.4	0	1	0.2	0.4	0	1
Geo. prox.	2.6	2.9	0	10	2.4	2.6	0	10	2.2	2.4	0	10	2.0	2.1	0	10
Org. prox.	0.0	0.0	0	1	0.0	0.0	0	1	0.0	0.0	0	1	0.0	0.0	0	1
Soc. prox.	0.0	0.3	0	78	0.0	0.3	0	49	0.0	0.3	0	133	0.0	1.2	0	251
Cog. prox.	1.6	2.3	0	10	2.5	2.8	0	10	2.4	2.7	0	10	3.4	2.9	0	10
Prof. sim.	0.5	0.3	0	1	0.5	0.3	0	1	0.6	0.4	0	1	0.5	0.4	0	1
Size	1.7	1.0	1	7	2.3	1.2	1	7	2.4	1.3	1	7	3.2	1.5	1	8
Experience	3.7	3.2	0	16	5.7	4.4	0	22	7.2	5.9	0	28	9.9	6.9	0	31

Table 5: Descriptive statistics of the dyadic and individual variables

- Structural effects

We include three variables that measure the effects of structural network properties and explain how the structure of the video game network influences its further evolution. First, the density effect can be interpreted as the constant term in regression analysis, indicating the general tendency to form linkages. This variable should always be included in SAOM to control for the cost of relations (Snijders et al., 2010), and indicates why all nodes are not able to be fully connected to all others (McPherson et al., 1991). Density is measured by the out degree of firms: $D_i = \sum_j x_{ij}$

Transitivity is an important structural effect for network dynamics, concerned with the tendency towards network closure. It can be measured in several ways, but the most straightforward is based on the number of transitive triplets of actors, i.e. the number of times an actor i is tied with two actors that are partners themselves (Ripley et al., 2011): $T_i = \sum_{j < h} x_{ij}x_{ih}x_{jh}$

Preferential attachment considers that actors with a large number of relations are more attractive. As such, it is measured by the number of relations of the actor to whom i is tied. More precisely, we take the square root of the degree of alter in order to decrease the degree of colinearity with other structural variables: $PA_i = \sum_j x_{ij} \sqrt{\sum_h x_{jh}}$

- Individual characteristics

To control for the heterogeneity of firms in their capacity to collaborate, we include size and experience of actors. Size is based on the natural logarithm of the number of games a firm has produced during the last five years. We consider all the games produced, regardless of the number of partners involved. The experience of a firm is measured by the number of years the firm has been active in the video game industry (i.e. the age of the firm).

Profile similarity is a variable that accounts for the fact that firms perform the role of either publisher or developer in the development process. The tendency to publish is obtained by dividing for each actor i the number of games in which i has the role of publisher, divided by the total number of games in which i was involved¹⁶. We multiplied this ratio by ten, allowing the variable to range from 0 to 10. Thus, we control for the fact that publishing oriented firms are likely to collaborate with developers and developing oriented firms with publishers¹⁷: $PS_{ij} = 1 - (|v_i - v_j|) / r_v$

- Proximity dimensions

We follow the seminal analytical distinction in five dimensions of proximity proposed by Boschma (2005). Institutional proximity measures whether two firms are exposed to the same institutional framework. Sharing similar formal or informal institutions increases the likelihood of actors to start

¹⁶From the date of entry to the date of exit of the industry.

¹⁷Where v is the tendency to publish and R_v is the difference between the highest and the lowest value of the tendency to publish variable.

a partnership. In the case of the video game industry, the national level is especially important as it refers to common intellectual property right regimes, languages and video game culture. As such, we follow previous studies measuring institutional proximity as a binary measure, equal to 1 if the two firms belong to the same country and 0 if not (Hoekman et al., 2009).

Geographical proximity is measured by the inverse of the natural logarithm of the physical distance ('as the crow flies') between two firms in kilometers¹⁸. More precisely, we obtained a maximum of 10 and a minimum of 0 by computing the natural logarithm of the distance between firms. We subtracted the log of distance from 10, in order to have a proximity measure rather than a distance measure. As a result, the variable ranges from 0 for the most distant firms to 10 for the closest ones: $PG_{ij} = 10 - \ln(dist_{ij})$

Organizational proximity is defined as membership of a larger business group. We created a 1-0 dummy variable equal to 1 if the two organizations involved in the production of the video game belong to the same legal entity, and 0 otherwise. In our dataset, we identified all firm ownership structures allowing us to distinguish between the main office (headquarters) of each firm and its subsidiaries. As a result, we were able to identify whether two organizations involved in the production of a video game shared the same owner(s) and did therefore belong to the same legal entity.

Boschma (2005) defined social proximity in terms of socially embedded relations between agents at the micro-level. More in particular, social proximity refers to the extent to which agents share prior mutual relationships. Such relationships carry information about potential future partners, and thereby increase the probability to engage in future collaborations. Social proximity can be measured on the basis of the number of previous collaborations (Ahuja et al., 2009). We count the number of games that two actors have produced together during the five previous years. In order to compute this measure, we also considered games that have been produced by more than two firms. We must note here that social proximity could also be classified as a structural endogenous network formation mechanism. Indeed, prior social interaction is given by the model.

Cognitive proximity refers to the similarity in the distribution of knowledge endowments across two agents (Nooteboom, 1999). Contrary to most empirical studies, we adopt an asymmetric, directed measure of cognitive proximity¹⁹. We follow Balland et al. (2011) who shows that adopting a featural rather than a distance approach allows us to account for the fact that actor i might be more cognitively proximate to j than j to i . To construct such a directed measure of proximity, we rely on information on the stylistic elements used in the video games produced by companies in the 5 years prior to the focal year. Each video game is categorized into one or multiple stylistic elements. Such elements range from genres such as action or simulation to perspectives such as first-person perspective or top-down. The genres that firms have covered represent the cognitive framework upon which firms operate. In order to calculate the cognitive proximity between two firms we measured the number of genres that firm i and firm j share divided by the total number of genres covered by firm i and firm j respectively. As a result the measure will be asymmetric.

¹⁸Not computed for firms at distance 0 but directly replaced by 0.

¹⁹Neffke and Svensson Henning (2008) use a similar argument to conceptualize asymmetric related variety.

5 Empirical results

Results of parameter estimations are presented in table 6. The network dynamics of the video game industry from 1987 to 2007 are modeled separately for each generation (3, 4, 5 and 6), in order to evaluate the changing influence of network drivers over time. All parameter estimations are based on 1,000 simulation runs, and convergence of the approximation algorithm is excellent for all the variables of the different models²⁰ (t-values < 0.1). The parameter estimates of SAOM can be interpreted as non-standardized coefficients obtained from logistic regression analysis (Steglich et al., 2010). Therefore, the β reported in table 6 are log-odds ratio, corresponding to how the log-odds of tie formation change with one unit change in the corresponding independent variable. In order to test if the difference between coefficients along the different generations was statistically significant, we visualize the 95% confidence intervals for the different coefficients (see figure 2). We found little or no overlap of the confidence intervals of generation 3 and generation 6, and confidence intervals of some effects even do not overlap from one generation to another. In sum, our analysis suggests that the influence of drivers of network formation is relatively stable but their weights do significantly change over time as the industry evolves.

The first two rows of table 6 report the effects of the structural network variables density and transitive triads on tie formation. We found a negative and significant impact of the density effect. This variable measures the costs of linkages which inhibit firms to be fully connected. For the transitivity variable, we found a positive and significant effect for all generations. This result indicates that firms are more likely to produce video games with partners of partners. Moreover, this effect appears to be rather stable over time, indicating that transitive patterns do not increase with the degree of maturity of the industry. This is in contrast to Ter Wal (2011), who showed an increasing importance of triadic closure in co-inventor networks in German biotech, which he associated with increasing codification of knowledge in biotech.

Row 3 to 7 in table 6 report the influence of proximity mechanisms on partner selection. We evaluate whether firms tend to collaborate with firms that have similar attributes. Institutional proximity is positive and significant for generation 3, 4 and 5. This means that, even when controlling for physical distance, firms located in the same country are more likely to produce a game together. However, this effect is decreasing after generation 4, and is not significant anymore in the last generation. This suggests that national institutional regimes are becoming less important over time as drivers of network ties. In that context, it is interesting to find a positive and significant impact of geographical proximity for all generations. The weight of this coefficient is even increasing over time. This finding contradicts the result found at a national level in German co-inventor networks in biotech, which showed a decreasing importance of geographical proximity as time passed by (Ter Wal, 2011). While this latter result has been associated with increasing codification of knowledge in biotech, this process is unlikely to take place in a creative industry like video games. An additional explanation is that video games have become more technologically complex which requires more interfirm collaboration at shorter geographical distances

²⁰Convergence check can be used to evaluate the goodness of fit of SAOM, by indicating the deviation between observed values and simulated values. To achieve such a good level of convergence, we excluded preferential attachment from the analysis because this effect was too highly correlated with the other structural mechanisms.

	Gen 3 (N=349)		Gen 4 (N=664)		Gen 5 (N=724)		Gen 6 (N=479)	
	Parameter	SD	Parameter	SD	Parameter	SD	Parameter	SD
Density	-1.957 ***	0.022	-2.209 ***	0.015	-2.456 ***	0.021	-2.362 ***	0.043
Transitive triads	0.654 *	0.331	0.653 ***	0.045	0.632 ***	0.031	0.700 ***	0.067
Institutional prox.	0.098 ***	0.038	0.140 ***	0.025	0.133 ***	0.023	-0.042	0.046
Geographical prox.	0.017 ***	0.003	0.026 ***	0.002	0.025 ***	0.002	0.045 ***	0.005
Organizational prox.	1.854 ***	0.100	1.533 ***	0.096	1.450 ***	0.071	1.104 ***	0.135
Social prox.	0.186 ***	0.038	0.079 ***	0.011	0.081 ***	0.011	0.044 ***	0.010
Cognitive prox.	-0.002	0.003	0.002	0.002	0.023 ***	0.003	0.025 ***	0.006
Profile sim.	-0.735 ***	0.050	-0.820 ***	0.035	-1.097 ***	0.032	-1.181 ***	0.059
Size	0.206 **	0.067	0.206 ***	0.003	0.166 ***	0.009	0.065 ***	0.015
Experience	-0.003	0.005	-0.005	0.014	0.004 ***	0.001	0.020 ***	0.002

Table 6: Estimation results: parameter estimates and standard deviations

(Sorenson et al., 2006).

The results also demonstrate that organizational proximity is an important factor of collaboration: this effect is positive and significant for all generations. Nevertheless, it is interesting to note that this effect is decreasing over time, probably because business groups tend to diversify over time. Social proximity also is a strong predictor of the likelihood that two firms will co-produce a video game. However, this effect is clearly decreasing over time, meaning that previous collaborations is still an important driver of network formation in the video game industry, but to a lesser extent.

The effect of cognitive proximity seems to be strongly influenced by the industry life cycle. While this effect was not significant during generation 3 and 4, it becomes positive and significant for generation 5 and 6. This may reflect the fact that developing new video games has become more technologically complex, and therefore requires more cognitive proximate partners over time, as well as more geographically proximate partners, as noticed earlier.

With respect to the individual characteristics, profile similarity is negative and significant for all generations. It shows that developers are more likely to collaborate with publishers, and vice versa. It is interesting to observe that this negative effect is increasing, showing that actors tend to specialize in their publisher/developer role over the industry life cycle. Size of firms is positive and significant for all generations, but this effect is decreasing. And finally, experience is not significant for the early stages of the industry, but it becomes a clear advantage at later stages.

6 Conclusion and discussion

In this paper, we have analyzed the network dynamics in an evolving industry, a topic that is still relatively unexplored. We have employed a Stochastic Actor-Oriented Model to analyse the evolution of drivers of interfirm network formation in the global video game industry. By bringing together literature on industrial dynamics, network theory and economic geography, we have explored how network

formation in a creative industry is influenced by different forms of proximity, alongside individual characteristics and structural endogenous network structures. Taking a dynamic perspective on networks, we found strong evidence that the effects of the main drivers of network formation changed as the video game industry evolved in the period 1987-2007. Broadly speaking, tie formation became increasingly a function of geographical, cognitive proximity and being experienced, but to a lesser extent to organizational, social and institutional proximity.

The increasing coefficient of geographical proximity clearly shows that firms are more likely to partner with firms over shorter geographical distance as the video game industry evolved. This may reflect the fact that we deal with a creative cultural industry in which local buzz is crucial (Storper and Venables, 2004). The project-based and flexible nature of production makes the video game industry less exposed to processes of standardization and increasing codification of knowledge which might have relaxed the necessity to be geographically proximate. An additional explanation might be found in the increasing technological complexity of video game development which requires more interfirm collaboration at shorter geographical distances (Sorenson et al., 2006). Interestingly, the effect of Institutional proximity decreased and even lost its significance over time, while geographical proximity became more important. Clearly, the national institutional regime has lost its meaning as a driver of network ties as the video game business evolved.

Another important finding is that cognitive proximity was not a determinant of tie formation in the first generations, but the network formation in later generations was clearly driven by similarities in genre portfolios of firms. This may reflect the fact that developing new video games became more technologically complex and therefore required more cognitive proximate partners over time. Another explanation for this finding might be found in the fact that boundaries between video game genres and styles became better defined and video game firms started to specialize over time.

This is in line with another outcome of our analysis. That is, experienced firms were more likely to attract partners than firms with little experience but only so in later generations. A first possible explanation is that the effect of experience on attracting partners is only apparent above a certain threshold. Another explanation might be found on the consumer side of the video game value chain. The ever increasing number of video games that are released each year requires consumers to acquire larger amounts of information in order to assess the quality of all video games available. Rather than acquiring information of all video games, the consumer might rely more on reputation and status of experienced video game producers.

As mentioned earlier, we see this study as an explorative and early attempt to analyze the dynamics of network formation along the life cycle of a creative industry. In that respect, there are a number of challenges for future research. First, we have focused on drivers of network formation based on secondary network data which enabled us, among others things, to focus on networks dynamics from a long-term perspective. What is still needed is to conduct a more qualitative approach based on survey data that could deepen our understanding of the motives behind networking in video gaming. Second, we need more similar studies for other types of industries, and see whether the same drivers of network formation over time hold in these contexts. As discussed earlier, creative industries might

be different from other industries. Third, our study showed that firms find their collaboration mainly within their own region, that they work together with firms with similar portfolios, and that they are likely to partner with experienced firms. While such a pattern might be highly profitable in the short to medium run, in the long run this pattern may cause these firms (and their regions) to become vulnerable for external shocks (Neffke et al., 2011). In other words, we need more understanding what these types of networking really mean for the performance of firms and regions.

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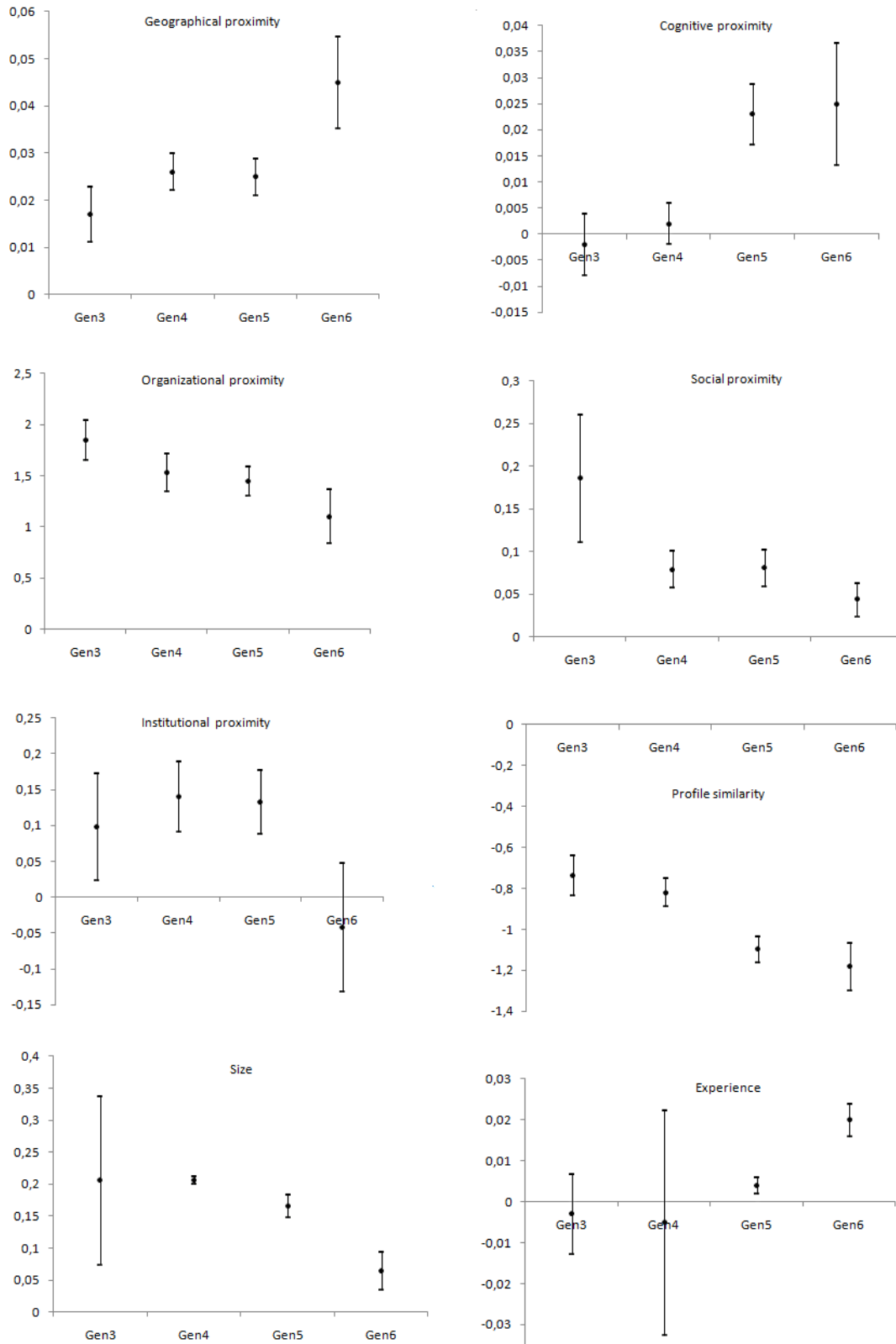


Figure 2: Drivers of network dynamics over the industry life cycle