Journal of Economic Geography Advance Access published August 28, 2012

*Journal Of Economic Geography* (2012) pp. 1–25 doi:10.1093/jeg/lbs023

# The dynamics of interfirm networks along the industry life cycle: The case of the global video game industry, 1987–2007

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## Abstract

In this article, we study the formation of network ties between firms along the life cycle of a creative industry. We focus on three mechanisms that drive 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 attributes of firms and (iii) individual characteristics which refer to the heterogeneity in the capabilities of firms to exploit external knowledge. The article employs a stochastic actor-oriented model to estimate the – changing – effects of these mechanisms on the formation of the interfirm network in the global video game industry from 1987 to 2007. Our findings indicate that, on average, the direction of the effects of the three mechanisms are stable over time, but that their weights change with the degree of maturity of the industry. To an increasing extent, video game firms tend to prefer to partner over short distances and with more cognitively similar firms as the industry evolves.

**Keywords:** Network dynamics, industry life cycle, proximity, creative industry, video game industry, stochastic actor-oriented model
**JEL classifications:** D85, B52, O18
**Date submitted:** 22 July 2011 **Date accepted:** 20 June 2012

## 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. Recently, scholars have started to investigate how interfirm network formation, as a result of tie initiation patterns, takes place (e.g. Rosenkopf and Padula, 2008; Ahuja et al., 2009; Cassi and Plunket, 2010; Balland, 2012; Broekel and Boschma, 2012), but applied research on the spatial and temporal dimension of network patterns remains sparse (Ter Wal, 2011). In this article, we analyze the formation of an interfirm network by using longitudinal data which allows us to investigate the changing nature of network formation patterns.

Our main objective is to provide a detailed account of the underlying mechanisms of network dynamics along the life cycle of an industry (Audretsch and Feldman, 1996; Klepper, 1996; Agarwal and Gort, 2002). Following this objective, we aim to make three contributions. First, we aim to shed light on the changing nature of collaboration patterns among firms. While the industry life cycle approach has provided a rich account of the changing nature of competition among firms, 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) and the forces that drive network structures (Balland, 2012; Broekel and Boschma, 2012), but there is still little understanding of whether the effect of these mechanisms changes or remains stable along the industry life cycle (Ter Wal, 2011). Second, we aim to disentangle the three main mechanisms that have been argued to underlie the formation of networks: network endogeneity, proximity between firms and individual firm characteristics. Until now, these three mechanisms have been studied in isolation, and integrative approaches have remained sparse (Rivera et al., 2010). By doing so we are able to empirically and theoretically integrate the various schools and academic traditions that originally accommodated the literature on these three different mechanisms. Finally, we aim to contribute to the literature on networks in creative industries. Creative industries are inherently characterized by cycles of fads and fashions and the constant demand for novelty, which gave rise to the project-based organization of production, continuous renegotiation of value(s) and the importance of local buzz (Grabher, 2001; Storper and Venables, 2004; Stark, 2009). By means of investigating a particular creative industry, we test which mechanisms are crucial in network formation, and whether these effects change as the industry evolves, both in time and space.

The context of our research is the global video game industry from 1987 to 2007. The video game industry is often referred to as a creative industry. Typically creative industries are characterized by its project-based production system in which multiple economic actors are responsible for the co-production of new products (Caves, 2000). In the video game industry, new video games tend to be produced by a developer and a publisher. Based on the co-participation in video game production projects we construct the interfirm networks used throughout the article. 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. The analyses are conducted for the total population of firms that developed or published one or more video games for a video game console. We analyze these collaboration patterns based on games produced for four generations of video game consoles, starting in 1987. Yearly relational matrices are constructed for analyzing underlying mechanisms of network dynamics within each generation: 1987–1992, 1993–1998, 1999–2004 and 2005–2007.

The article focuses on two research questions: (i) which proximity dimensions, among other factors, drive the formation of network ties in the global video game industry? and (ii) do the effects of these driving forces increase or decrease as the industry evolves? We employ a stochastic actor-oriented model (SAOM, Snijders, 2001) to analyze the evolution of the interfirm collaboration network. This approach allows for the simultaneous evaluation of three sets of driving forces: (i) relational structures that display endogenous structural mechanisms, reproducing themselves over time;

(ii) similarity between attributes of firms (e.g. being proximate in cognitive or geographical terms) and (iii) individual characteristics which affect, for instance, the capacity to exploit external knowledge (Cohen and Levinthal, 1990). 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 prefer to partner over short distances and with more cognitively similar firms as the industry matures.

The article is organized as follows. Section 2 presents a brief literature review on the main drivers of interfirm network dynamics and industrial dynamics. Then, Section 3 describes the data collection and provides descriptive statistics of the longitudinal network database. The statistical 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

### 2.1. Interfirm networks and proximity

There is increasing attention for a relational approach in economic geography (Dicken et al., 2001; Bathelt and Glückler, 2003; Yeung, 2005). While the earlier work on relational issues in economic geography has generated rich and contextual narratives of the spatial processes at hand, various scholars have recently identified flaws in this literature by criticizing its lack of formalization and its metaphorical accounts of relational processes (see e.g. Giuliani and Bell, 2005; Cantner and Graf, 2006; Grabher, 2006; Glückler, 2007; Sunley, 2008). We argue that 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 (Murdoch, 1999; Grabher and Ibert, 2006; Bergman, 2009; Ter Wal and Boschma, 2009). One of the main research questions is: what drives the emergence of a network tie? A first important aspect of network formation is that it can be influenced by endogenous structural network effects (Glückler, 2007). 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, in which new nodes entering the network tend to form ties with incumbent nodes according to their degree distribution (Barabási and Albert, 1999).

Apart from the path dependent, endogenous drivers of network evolution, scholars in economic geography have stressed the fact that interactive learning and collaborations are easier when firms have similar attributes (Boschma, 2005). 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

(McPherson et al., 2001). We follow the terminology of proximity introduced by the French proximity school in the context of innovation activities (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 (Balland, 2012).

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. 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, which could be strongly correlated with geographical proximity (Breschi and Lissoni, 2001). 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; Sorenson et al., 2006; Ponds et al., 2007; 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 characteristic that may be an important determinant of interfirm collaboration 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 are more likely to be able to identify fruitful collaborations and attract potential collaborators.

When analyzing the forces responsible for 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, 2012). Little attention has been devoted so far to the changing nature of network formation over time (Powell et al., 2005; Glückler, 2007; Boschma and Frenken, 2010; Hoekman et al., 2010). One reason that causes this lack of attention is that it requires complete network data over a long period of time. Another reason is that statistical models to handle such data have been developed only very recently (Snijders et al., 2010). In economic geography, a few studies have started to explore the network dynamics in a spatial setting, like the dynamics in knowledge networks in a Chilean wine cluster (Giuliani, 2010), and the dynamics in co-inventor networks in French genomics (Cassi and Plunket, 2010) and German bio-tech (Ter Wal, 2011).

## 2.2. 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; Agarwal and Gort, 2002; 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), pharmaceuticals (Orsenigo et al., 2001) or biotech (Gay and Dousset, 2005), 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 the 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 toward 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.

### 2.3. 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 on 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. Rather, creative industries are subject to fads and fashions and cycles in which high premiums are available for novelty.

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 (Scott, 1997; Pratt, 2000; 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.

### 2.4. Synthesis

In summary, we have identified three main drivers of interfirm network formation (i.e. structural endogenous network structures, proximity mechanisms and individual characteristics). 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 integrate insights provided by the industry life cycle approach and insights from network analysis. Moreover, though our empirical context is the video game industry, we argue that we are able to unravel more of the subtleties that are specific to creative industries in general. 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, 169) by providing programming skills, artistic designs and insights on the gameplay,[1] 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, technology and commercialization, 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. 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, >75% of all video games are produced by at least two companies, while the rest is produced by one company.

The analyses in this article are based upon a unique, newly constructed database that contains information on all firms that developed or published one or more video games[2]

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

2 Throughout 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.

**Table 1.** Collaboration patterns along the video game industry life cycles

| | 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 |
| No. of games involving | | | | | | |
| 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 |

for a video game console worldwide.[3] We collected firm level data such as years of production, number of games produced, location, ownership structures[4] 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 Mobygames.[5] 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 Datenbank.[6] This online database is complementary to the Mobygames database in that it provides more detailed information on the location of companies and backgrounds of entrepreneurs. In the rare case that neither of the two

3 A video game console is an entertainment computer that is built with the main purpose of allowing its users to play video games. Video game consoles are different from PC's and other multi-purpose computers because they are solely/mainly designed for playing video games. 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.

4 We 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.

5 The 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

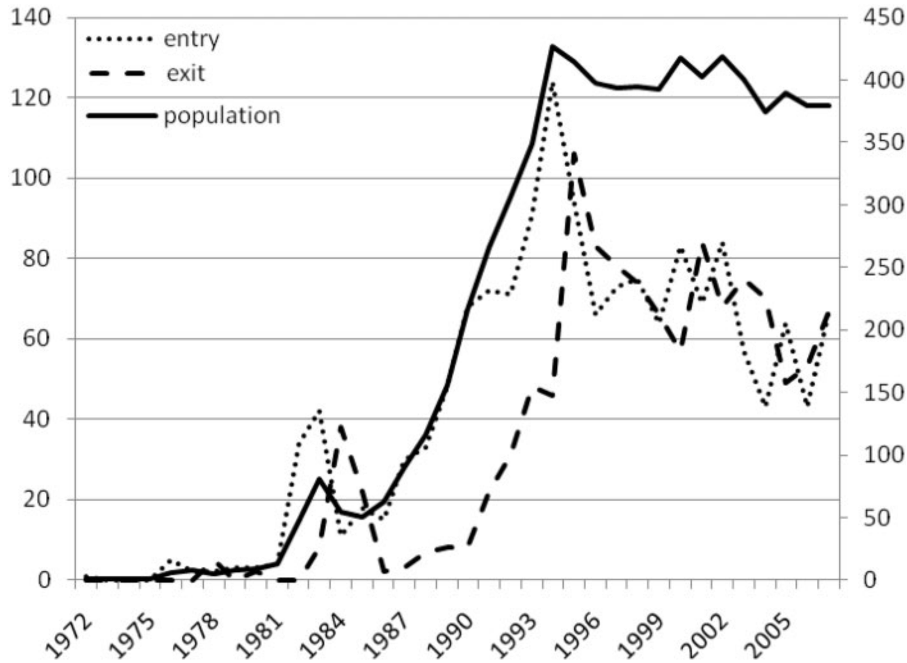


**Figure 1.** Entry. exit and population totals in the video game industry.



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. While the technological specifications of the video game consoles within a generation show a strong resemblance, the technological specifications of consoles from different generations are highly dissimilar. Each subsequent generation 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 generation. In other words, the introduction of a new generation 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 firms[7] in the video game industry. Until the mid-1990s, the population of firms grew rapidly, after which the population has remained largely stable.

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,

7 This figure only includes headquarters.

**Table 2.** Network dynamics: relational and composition change

| Observed period | Ties created | Ties dissolved | Ties Maintained | Firms entry | Firms exit |
|---|---|---|---|---|---|
| Generation 3 | | | | | |
| 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 |
| Generation 4 | | | | | |
| 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 |
| Generation 5 | | | | | |
| 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 |
| Generation 6 | | | | | |
| 2005–2006 | 508 | 526 | 300 | 17 | 16 |
| 2006–2007 | 594 | 504 | 304 | 0 | 32 |

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 level of stability[8] of the network was too low.[9] 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, ex-post, how the multiple partners are actually connected through the collaboration. 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 marginal[10] during the period considered, we opted for excluding them from the analyses. The final data set used for our empirical examination comprises 21,314 games involving 1358 unique firms from 1987 to 2007.

8 Proportion of ties that are maintained from one observed moment (year) to another.
9 Achieving such a level of stability would have required additional assumptions on the length of ties.
10 See Table 1: 5.1% of the total of games developed from 1987 to 2007 (1092/21,314).

**Table 3.** Network structural descriptive statistics

| Observed year | Number of firms | Number of ties | Average degree | 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 |

The resulting network involves $n$ actors and can be represented as a $n \times n$ matrix $x = (x_{ij})$, where $x_{ij} = 1$ represents the joint production of a video game by firm $i$ and firm $j$ ($i$, $j = 1, \ldots, n$). The network dynamics within the four different generations are analyzed separately. For the construction of the longitudinal relational database, we assume that ties are active during the year of release of a given video game. Thus, if a game is released in 2005 by actor $i$ and actor $j$ (regardless of the month), then we assume that a relation exists 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 are also dichotomized,[11] 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 $n \times n$ 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 network.[12]

The resulting network dynamics are summarized in Table 2. The statistics show 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

11 The statistical model used can only run dichotomized networks.

12 We 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.

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 indicating that firms not only produce more games (Table 1), but also collaborate with an increasing number of different partners. Density, which is the ratio of the number of observed links and the total number of possible links, fluctuates only marginally.

## 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 procedures like OLS and logistic regressions that assume independence among observations. Correlation between observations can lead to unreliable estimations of parameter coefficients and SEs (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, SAOMs are the most promising class of models allowing for statistical inference of network dynamics (Snijders et al., 2010). In this article, we use SAOM implemented in the SIENA[13] statistical software (Ripley et al., 2011). A brief description of the general principles of SAOM and details of the model specification follows below.

### 4.1. The statistical model

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 to analyze the dynamics of global and regional knowledge networks (Ter Wal and Boschma, 2009; Giuliani, 2010; Balland, 2012; Maggioni and Uberti, 2011; Ter Wal, 2011).

SAOM are based on three principles which are 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

13 This 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/.

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 are 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 $\lambda_i$ 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 $x_{ij}$, 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):

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

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, 2012; 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 function.[14] 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 ($x^0$), the potential new state ($x$), individual attributes[15] ($v$) and proximity ($w$):

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

As proposed by Snijders (2001), the estimation of the different parameters $\beta_k$ 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

14 In other specifications, one actor can impose unilaterally the creation of a tie to another one.
15 For the analysis, individual and proximity variables are centered around the mean.

**Table 4.** Operationalization of the variables

| 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 in km (natural log) |
| Organizational proximity | Same group of firms (dummy) |
| Social proximity | Number of games previously produced together |
| Cognitive proximity | Similar genres of video games |
| Profile similarity | Similarity of profile (developers/publishers) |
| Size | Number of games previously produced (natural log) |
| Experience | Number of years since entry |

simulates the evolution of the network and estimates the parameters $\beta_k$ 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 SEs.

## 4.2. 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 earlier, we consider three sets of drivers of network formation: (i) structural effects (i.e. density, transitivity, preferential attachment); (ii) individual characteristics of actors (i.e. profile, size, experience) and (iii) proximity mechanisms (i.e. geographical, organizational, institutional, cognitive, social) which will be discussed one by one below (see Tables 4 and 5).

## 4.3. 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, density 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., 2001). Density is measured by the out degree of firms:

$$D_i = \sum\nolimits_j x_{ij}$$

A second structural property, transitivity, is included in our analyses to account for the tendency toward 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

**Table 5.** Descriptive statistics of the dyadic and individual variables

| | Generation 3 | | | | Generation 4 | | | | Generation 5 | | | | Generation 6 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Min | Max | Mean | SD | Min | Max | Mean | SD | Min | Max | Mean | SD | Min | Max |
| Institutional proximity | 0.341 | 0.474 | 0 | 1 | 0.284 | 0.451 | 0 | 1 | 0.241 | 0.428 | 0 | 1 | 0.225 | 0.417 | 0 | 1 |
| Geographical proximity | 2.660 | 2.940 | 0 | 10 | 2.402 | 2.639 | 0 | 10 | 2.204 | 2.411 | 0 | 10 | 2.012 | 2.115 | 0 | 10 |
| Organizational proximity | 0.001 | 0.028 | 0 | 1 | 0.001 | 0.021 | 0 | 1 | 0.001 | 0.027 | 0 | 1 | 0.001 | 0.037 | 0 | 1 |
| Social proximity | 0.010 | 0.307 | 0 | 78 | 0.014 | 0.340 | 0 | 49 | 0.014 | 0.387 | 0 | 133 | 0.052 | 1.229 | 0 | 251 |
| Cognitive proximity | 1.612 | 2.334 | 0 | 10 | 2.546 | 2.848 | 0 | 10 | 2.405 | 2.721 | 0 | 10 | 3.423 | 2.930 | 0 | 10 |
| Profile similarity | 0.552 | 0.333 | 0 | 1 | 0.570 | 0.373 | 0 | 1 | 0.612 | 0.406 | 0 | 1 | 0.586 | 0.419 | 0 | 1 |
| Size | 1.775 | 1.086 | 1 | 7 | 2.385 | 1.271 | 1 | 7 | 2.432 | 1.331 | 1 | 7 | 3.283 | 1.510 | 1 | 8 |
| Experience | 3.702 | 3.267 | 0 | 16 | 5.796 | 4.479 | 0 | 22 | 7.211 | 5.912 | 0 | 28 | 9.945 | 6.930 | 0 | 31 |

times an actor $i$ is tied with two actors that are partners themselves (Ripley et al., 2011):

$$T_i = \sum\nolimits_{j<h} x_{ij} x_{ih} x_{jh}$$

Preferential attachment is the tendency of actors with a large number of relations to attract even more partners. We measure this tendency by including the number of relations of actor $j$ 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:

$$PA_i = \sum\nolimits_j x_{ij} \sqrt{\sum_h x_{jh}}$$

## 4.4. Proximity dimensions

We follow the analytical distinction in five dimensions of proximity proposed by Boschma (2005). *Institutional proximity* measures whether two firms are exposed to the same institutional context. We expect that similarity in the exposure to formal or informal institutions increases the likelihood of actors to start a partnership. In the case of the video game industry, the national level is especially important because it refers to –but is not per se limited to – common intellectual property right regimes, languages and video game culture. These three dimensions of the institutional context are largely bounded by national borders.[16] 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 kilometers. More precisely, we obtained a maximum of 10 and a minimum of 0 by computing the natural logarithm

16 One may argue that neighboring countries are more likely to be similar in terms of their institutional characteristics. This fraction of variance will likely be picked up by the geographical proximity measure, rather than the institutional similarity measure. A possible solution to account for this variance is to specify a model that accounts for spatial autocorrelation. However, this will further complicate the model and the benefits of doing so are unlikely to outweigh the costs.

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:

$$PG_{ij} = 10 - \ln(dist_{ij} + 1)$$

*Organizational proximity* is defined as membership of a larger business group. We generated 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. We collected information on all firm ownership structures allowing us to distinguish between the main office (headquarters) of each firm, its subsidiaries and any historical changes in these structures. As a result, we were able to identify whether two organizations involved in the production of a video game were owned by the same legal actor.

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.

*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 proximity.[17] We follow Balland et al. (2012) 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.

## 4.5. 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 5 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).

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

**Table 6.** Estimation results: parameter estimates and SDs

| | Gen 3 | | Gen 4 | | Gen 5 | | Gen 6 | |
|---|---|---|---|---|---|---|---|---|
| | $N=349$ | | $N=664$ | | $N=724$ | | $N=479$ | |
| | $\beta$ | SD | $\beta$ | SD | $\beta$ | SD | $\beta$ | SD |
| Density | −1.957** | 0.022 | −2.209** | 0.015 | −2.456** | 0.021 | −2.362** | 0.043 |
| Transitivity | 0.654* | 0.331 | 0.653** | 0.045 | 0.632** | 0.031 | 0.700** | 0.067 |
| Institutional proximity | 0.098** | 0.038 | 0.140** | 0.025 | 0.133** | 0.023 | −0.042 | 0.046 |
| Geographical proximity | 0.017** | 0.003 | 0.026** | 0.002 | 0.025** | 0.002 | 0.045** | 0.005 |
| Organizational proximity | 1.854** | 0.100 | 1.533** | 0.096 | 1.450** | 0.071 | 1.104** | 0.135 |
| Social proximity | 0.186** | 0.038 | 0.079** | 0.011 | 0.081** | 0.011 | 0.044** | 0.010 |
| Cognitive proximity | −0.002 | 0.003 | 0.002 | 0.002 | 0.023** | 0.003 | 0.025** | 0.006 |
| Profile similarity | −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 |

Coefficients are statistically significant at the $*p<0.05$; and $**p<0.01$ level.

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 involved.[18] We multiplied this ratio by 10, 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 publishers:[19]

$$PS_{ij} = 1 - \left(\left|v_i - v_j\right|\right)/r_v$$

## 5. Empirical results

Results of parameter estimations are presented in Table 6.[20] The network dynamics of the video game industry from 1987 to 2007 is 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 1000 simulation runs, and convergence of the approximation algorithm is excellent for all the variables of the different models[21] ($t$-values < 0.1). The parameter estimates of SAOM can be interpreted as

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

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

20 Under the null hypothesis that the parameter value is 0, statistical significance can be simply tested with $t$-statistics following a standard normal distribution.

21 Convergence 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.

non-standardized coefficients obtained from logistic regression analysis (Steglich et al., 2010). Therefore, the $\beta$ 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. To obtain odds ratios, one can simply compute the exponentiated form of the coefficients of each predictor.

The coefficients are not standardized, which makes them easier to interpret, but it is important to note that the magnitude of the parameter estimates is therefore sensitive to the scale of the input variables. For instance, the coefficient for geographical proximity will be systematically smaller if measured in kilometers than in miles, or systematically higher if measured in kilometers than in meters, because it expresses how the dependent variable changes with one unit changes in the independent variable. If the scale of the input variable does not change over time, we can compare the coefficients of the same variable across generations, but we cannot compare the weight of different predictors, like the coefficient of geographical proximity with the coefficient of organizational proximity, for instance.[22]

In order to test if the difference between coefficients along the different generations was statistically significant, we plotted a 95% confidence interval for the different coefficients (see Figure 2). As a general result, 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 in terms of direction ($\pm$) and significance, 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. There is a strong tendency toward transitive closure, which indicates that firms are more likely to produce video games with partners of partners. Moreover, this effect appears to be very 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. Here, we evaluate whether the likelihood of firms to collaborate is associated with the geographical, cognitive, social, organizational or institutional proximity between these firms (Boschma, 2005; Balland, 2012). The effect of 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 slightly decreasing after generation 4, and is not significant anymore in the last generation.[23] This could suggest that national institutional contexts are converging over time, and that therefore exposure to

22 Even if we standardize the coefficients, it is still difficult to interpret a result, such as 1 SD of geographical proximity being stronger/smaller than 1 SD of organizational proximity for instance.

23 The correlation between institutional proximity and geographical proximity is ~0.7, which may affect the sign of institutional proximity in the last generation. When we run the models without one the two

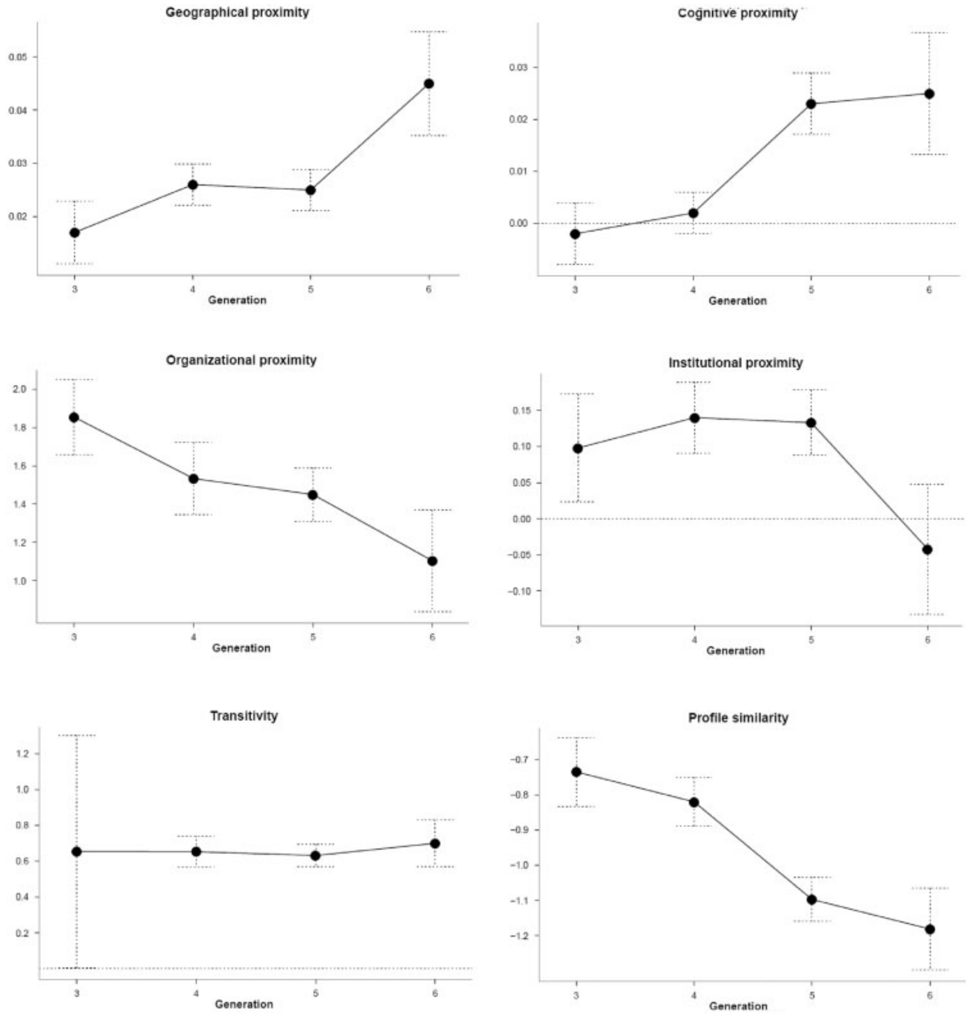


**Figure 2.** Drivers of network dynamics along the industry life cycle.

similar institutional contexts does no longer act as a force that brings firms together. Interestingly, we find a positive and significant impact of geographical proximity for all generations. Moreover, the weight of this effect is even increasing over time. This finding in the context of the global video game industry contradicts the result found at the national level in German co-inventor networks in biotech, which showed a deceasing 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, such a process is unlikely to take place in a creative industry like the video game industry, which relies much less on the emergence of dominant designs than other industries. An additional explanation might be that video games have become

variables, however, the trend we observe remains the same, i.e. the effect of institutional proximity slightly decreases over time and the effect of geographical proximity clearly increases.

technologically more complex which puts a premium on interfirm collaboration to take place over short geographical distances (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. This effect is very strong, since it indicates in generation 3 for instance that, all else being equal, collaborations between firms of the same organizational group are up to six times[24] more likely to occur than collaborations across groups of firms. Nevertheless, it is interesting to note that this effect is strongly decreasing over time, because in generation 6, firms are three times (odds ratio = 3.01) more likely to choose a partner that is close in organizational terms compared to a firm which is not. This pattern can possibly be explained by the fact that business groups tend to diversify over time. Social proximity is also a strong predictor of the likelihood that two firms will co-produce a video game. In generation 3, for instance, an increase of one unit (i.e. producing one additional video game together in the past 5 years) increases the probability to produce a video game in the subsequent year by 20% (odds ratio = 1.20). At first glance, the importance of social proximity seems to decreases over time (odds ratio = 1.05), but this observation is sensitive to the scale of the variable that increases over time, since the average number of games produced increases in later generations. After standardization of the coefficients of social proximity for each generation,[25] we observe in fact a very stable effect of social proximity over time.

The effect of cognitive proximity seems to be strongly influenced by the stage of 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, which can be attributed to the fact that large firms are more likely to have more partners than small firms. Experience is not significant for the early stages of the industry, but it becomes a clear advantage at later stages. Experienced firms are more likely to choose partners and to be chosen to produce video games as the industry evolves.

## 6. Conclusion and discussion

In this article, we have analyzed the network dynamics in an evolving industry, a topic that is still relatively unexplored. We have employed a SAOM to analyze the evolution of drivers of interfirm network formation in the global video game industry. By bringing together the literature on industrial dynamics, network theory and economic

24 In generation 3, the parameter estimate for organizational proximity is equal to 1.85, so the odds ratio for organizational proximity is equal to $\exp(1.85) = 6.38$.

25 To test if the trend we observe is robust to the changing scale of the social proximity variable, we standardized the coefficients by multiplying the parameter estimates by the SD of the input variable.

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 and cognitive proximity and being experienced, but to a lesser extent of organizational and institutional proximity.

The increasing effect of geographical proximity clearly shows that firms are more likely to partner with firms over short 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 short geographical distances (Sorenson et al., 2006). Interestingly, while the effect of geographical proximity became more important as the video game industry evolved, the effect of institutional proximity at the national level decreased and even lost its significance over time. The national institutional regime seems to have 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.

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 network 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 and the role of more informal personal ties in video gaming (Grabher and Ibert, 2006). 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 to external shocks (Neffke et al., 2011). In other words, we need more understanding what these types of networking really mean for the economic performance of firms and regions.

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