

The Strength of Direct Ties:

Evidence from the Electronic Game Industry

Jörg Claussen

Oliver Falck

Thorsten Grohsjean

Discussion paper 2010 – 08

August 2010



Munich School of Management University of Munich

Fakultät für Betriebswirtschaft Ludwig-Maximilians-Universität München

Online at http://epub.ub.uni-muenchen.de

The Strength of Direct Ties:

Evidence from the Electronic Game Industry

Jörg Claussen

Oliver Falck

ICE, LMU Munich Schackstr. 4/III, 80539 Munich, Germany j.claussen@lmu.de Ifo Institute for Economic Research, Poschingerstr. 5, 81679 Munich, Germany <u>falck@ifo.de</u> Thorsten Grohsjean

ICE, LMU Munich Schackstr. 4/III, 80539 Munich, Germany <u>t.grohsjean@lmu.de</u>

August 2010

Abstract: We analyze the economic effects of a developer's connectedness in the electronic game industry. Knowledge spillovers between developers should be of special relevance in this knowledge-based industry. We calculate measures for a developer's connectedness to other developers at multiple points in time. In a regression with developer, developing firm, publishing firm, and time fixed effects, we find that the number of a developer's direct ties, i.e., common past experience, has a strong effect on both a game's revenues and critics' scores. The intensity of indirect ties makes no additional contribution to the game's success.

Keywords: network analysis, game industry, knowledge spillovers

JEL Classification: L14, L86, D83

Acknowledgements: We thank Pascal Kober for his excellent research assistance.

1. Introduction

In his seminal work, Granovetter (1973, 1983) distinguishes between strong and weak ties when describing an actor's social interactions. In a close network in which actors are directly connected by strong ties, everyone knows everyone else and information is quickly shared. However, such a close network might not work so well in terms of gaining new information. By contrast, a wide network that indirectly but weakly links actors from the close network to outside actors offers new sources of information and "whatever is to be diffused can reach a larger number of people, and traverse greater social distance" (Granovetter 1983, p. 1366).

Using measures from social network analysis, we study the economic effects of a developer's connectedness in the fast-growing electronic game industry.¹ The game industry is an intensely knowledge-based industry in which knowledge spillovers via the social networks among developers are probably very relevant. We use the 'degree centrality' measure to count a developer's direct connections to other developers. A direct connection is defined as forming when two or more parties jointly worked on a project, thus having common experience. Degree centrality thus measures how many strong ties a developer has. The 'closeness' measure is the mean geodesic distance from one developer to any other developer and thus measures the average intensity of a developer's ties.

To test the theory we compiled a unique dataset derived from two sources. We use MobyGames, a comprehensive electronic game documentation project, as a source of information about the members of game development teams.² These data allow us to calculate the (cumulative) degree centrality measure and the (cumulative) closeness measure for a developer at any point in time at which he or she was involved in a project since the early days of the game industry in 1972. We link these social network measures with revenue information from the NPD database, which includes information for every electronic game commercially released in the United States between 1995 and 2007. Along with revenue, we also use critics' scores from MobyGames as an alternative indicator of a game's success.

Given the special features of our data, we can include in our analysis a whole set of fixed effects at different levels of aggregation, including developer, developing firm, and publishing firm fixed effects. These fixed effects help us isolate the effect of social interaction on a certain outcome from other confounding influences (Manski 1993) of unobserved time-persistent developer, developing firm, or publishing firm factors. One problem not addressed by the fixed effects framework is the

¹ In 2007, the electronic game industry grew 43%, reaching total sales of U.S.\$ 18 billion.

² Developer networks are also analyzed by Fershtman and Gandal (2009) for the case of open source software. The analysis of co-authorships (Goyal et al. 2006) is also similar to our work.

reciprocal nature of social interaction that likely introduces simultaneity problems when using contemporaneous social network measures. We solve this problem by lagging our social network measures. However, this approach ignores the additional value of the developer's contemporaneous connectedness, which may result in an underestimate of social interaction (Hanushek et al. 2003).

Based on more than 150,000 observations, we find in our fixed effects specification a significantly positive effect of a developer's (lagged) degree centrality measure on a game's success. The result is robust to the inclusion of several control variables, including a time trend, team size, tenure of the developer, and co-developers' social network measures. We also find evidence of heterogeneity of this effect between lead and non-lead developers. By contrast, the developer's closeness measure contributes no additional explanatory power. These results suggest that direct ties foster local sharing of knowledge and thus strongly contribute to the success of a game, whereas the intensity of indirect, weak ties has no significant influence on the game's success.

The remainder of the paper is organized as follows. Section 2 briefly describes central features of the electronic game industry. In Section 3, we set out our estimation strategy, introduce our data, and report the results. Section 4 concludes.

2. The Electronic Game Industry

2.1. Industry Background

The electronic game industry encompasses both video and computer games. Video games are developed for game or handheld consoles; computer games are developed for personal computers. There are two main 'players' when it comes to the software side of the electronic game industry: the developing firm designs, creates, and codes the game; the publishing firm provides financing, packaging, marketing, and manages relationships with retailers and console providers. Even though the first electronic game was created in 1952 at the University of Cambridge, the electronic game industry did not really start gathering steam until the launch of the first video game console, the Magnavox Odyssey, in 1972, and only began to flourish with the introduction of personal computers in 1976 (Kent 2001).

The video game industry has evolved over what can be thought of as seven generations, each encompassing two to five different game consoles having similar, but steadily increasing, computational power. First-generation games cost anywhere from U.S.\$ 1,000–10,000 to develop; currently, this cost ranges between U.S.\$ 5–30 million (Hight and Novak 2008). The increase in development costs is driven by technological progress in gaming devices, leading to bigger development teams. In the early years of the industry, a game development team usually consisted of two people: a designer and a programmer. As graphics were poor, art-related work was mostly

done by the designer. However, with the introduction of compact discs as a storage medium and the development in 1995 of 3D graphics by Sony, artists became increasingly important to the process. To make the game look realistic, it became necessary to use the talents of various specialists, such as object or environment modelers, and team sizes increased correspondingly, now ranging, on average, 30 to 80 members (Hight and Novak 2008). The latest development in the electronic game industry occurred in 2005 with the introduction of the seventh generation of consoles. As these consoles include Internet connectivity, the computer and video game segments converged, resulting in a new type of electronic games, the so-called Massively Multiplayer Online Games that can accommodate hundreds of thousands of individuals playing simultaneously in a virtual world.

2.2. Composition of Game Developer Teams

The composition and size of game development teams evolved in step with technological change and the consequent increase in game complexity. At the same time, increased team sizes resulted in the hierarchical separation of the team into lead and non-lead members, with lead members fulfilling mostly supervisory and managerial functions, and non-lead members mostly being involved in implementation. The hierarchical structure of the team depends on the complexity of the game and the overall structure of the developing firm. For a simple game or a small developing firm, the same team member can perform multiple tasks, whereas in the case of a complex game or a larger developing firm, each team member is responsible for a single, clearly defined task.

Typically, a development team is comprised of four main occupations: producer, game designer, artist, and programmer (Chandler 2009). Producers manage and track the game development process and ensure that the game is released on time and within budget. Game designers develop the main story, characters, and levels, and set the rules of the game (Novak 2008). Artists create the concept art and graphics for the game, e.g., characters, vehicles, and buildings. Their tasks include drawing, modeling, texturing, and animation (Chandler 2009). Programmers create the game code and develop the tools that the designers and artists need for their work (Novak 2008). Other parts of the game development process include audio design, game testing, and quality assurance, but these tasks are typically outsourced (Novak 2008). We focus on producers, game designers, artists, and programmers when building our social network measures as these positions interact a great deal during the creation of a game.

2.3. Developers' Networks in the Game Industry

The organizational structure of most firms in the electronic game industry can best be described as decentralized and project based with a high level of autonomy. The producer puts together a team that will temporarily work together to create a single game, after which the team members are usually individually assigned to other projects. That is the team does not stay together for more than

one project, although, depending on the size of the firm, there is often some overlap. Although large developing firms try to retain talented people with attractive HRM practices, employee turnover is still very high in the gaming sector (Cadin et al. 2006). The project-based structure of the firms, the highly interdependent development process, and the high employee turnover rate lead to a lot of exchange between game developers, making this industry a suitable and interesting environment in which to study knowledge spillovers.

3. The Connectedness of a Developer and Success of a Game

3.1. Identification of Social Network Effects

History matters when identifying social network effects because members of a network have common past experience and thus are also most likely to share many omitted historical factors that might bias the effect of social network effects on an outcome. Furthermore, when we measure the impact of social network effects on current outcomes — in our case, the impact of a developer's connectedness on a game's success — there are also many omitted current factors that influence both the success of a game and the size and quality of a developer's current social network. One very relevant example of an omitted or not fully observable factor is the resources spent by the publishing firm for the game's development. These resources could have a direct impact on the success of a game, and will also be somewhat determinative of the size and composition of the project team, and, eventually, the connectedness of a developer. This might result in an important upward bias of the impact of social network effects on the success of a game.

To circumvent the problem of not fully knowing the amount of resources dedicated to a game's development, one could simply use lagged social network measures of the developer. However, if social networks are persistent over time, this strategy will not solve the problem because even lagged social network measures will be correlated with the current error term. Thus, one has to additionally consider fixed effects on different levels, i.e., the developer, the developing firm, or the publishing firm, in order to extract fixed components that do not vary over time. However, this approach ignores the additional value of the developer's contemporaneous connectedness, which may lead to an underestimation of social network effects.

Against this background, our estimation equation is:

$$S_{igdpt} = \alpha_i + \alpha_d + \alpha_p + \beta_1 D_{igdpt-1} + \beta_2 C_{igdpt-1} + C V_{igdpt} \gamma + \varepsilon_{igdpt}$$
(1)

S is a measure of success for game g of developing firm d and publishing firm p. Our network measures are on the level of the individual developer *i*. Thus, the outcome variable is the same for all developers in a game project. We consider this nested structure of our data by clustering the

error term ε_{igdpt} on the game level. α_i are developer fixed effects. Thus, we can consider only those developers that were engaged in at least two game projects over time t. α_d are fixed effects for the developing firm that usually decides on hiring the team. α_p are publishing firm fixed effects. The publishing firm decides on the resources to be spent for development and marketing of a game. α_t is a full set of dummies for the year a game was launched. These time dummies control for macroeconomic influences or changes in preferences toward electronic games in general. The time dummies also account for the increasing size of development teams and technological progress in gaming devices. Further control variables are included in the matrix CV_{igdpt} , including, among others, tenure of the developer and size of the project team, as well as dummies for licensed titles, genre, release month, and platform.

To measure the connectedness of the individual developer, we use two lagged network measures: the degree centrality measure *D* and the closeness measure *C*, both of which are well established in social network analysis (for a review, see Freeman 2006). Degree centrality is a measure for the number of direct connections a developer has. A direct connection is defined as forming when two (or more) developers jointly work on a game project. It is thus a proxy for a developer's strong ties. We calculate degree centrality relative to the size of the network:

$$D_{igdpt} = \frac{direct \ connections \ to \ other \ network \ members}{number \ of \ network \ members-1}$$
(2)

The closeness measure is the inverse of the average length of paths from one developer to all other developers in the game industry, whereby the developers are again connected by having worked on joint game projects. Closeness is thus a measure of the intensity of the ties, i.e., weak or strong ties:

$$C_{igdpt} = \left(\frac{cumulated \ path \ to \ other \ network \ members}{number \ of \ network \ members-1}\right)^{-1}$$
(3)

The shorter the average path length from the focal developer to all developers, the higher the value of the measure. Conditional on the degree centrality measure, β_2 gives us the additional impact of the intensity of weak ties on a game's success. Calculation of the network measures is explained in greater detail in the data section of the paper.

3.2. Data from the Electronic Game Industry

Our data are derived from two sources: MobyGames and the NPD database. MobyGames is the largest and most detailed video game documentation project in the world, containing comprehensive information on more than 16,000 games published between 1972 and 2009.³ All information is provided by users of the site on a voluntary basis. To ensure accuracy, MobyGames

³ For more details, see <u>http://mobygames.com</u>.

has a strict set of coding instructions and requires all entries to be peer reviewed before they are published. For most games featured in MobyGames, we have information on the platform, release date, and the individuals and firms that developed and published the game (credits). We use the dataset from the beginning of the industry in 1972 up to 2007 to calculate our social network measures.

We use the data from MobyGames to calculate our two social network measures, i.e., degree centrality and closeness. The MobyGames data include information on all developers who participated in the development of a game. Based on these data, we create one-mode networks in which two developers are directly connected if they have worked together on a project.⁴ We construct one-mode networks for every year from 1995 to 2007, with the networks becoming larger over time. That is, the 1995 network contains all developers and their connections in 1972 as well as all connections formed from games released in 1995, as well as every year in between. The 1996 network includes all connections initiated up till 1996 and so on. We thus calculate cumulative network measures.⁵

The MobyGames data are then matched with revenue data collected by NPD, a market research firm. The NPD dataset covers the electronic game industry since 1995.⁶ NPD's retail tracking service monitors retail sales of electronic games and consoles in the United States, covering all distribution channels, including online sales.⁷ From NPD, we calculate the *commercial success* of a game, measured as the revenue generated by a game within the first 12 months after its release.⁸ The diffusion of an electronic game follows an L-shaped curve. The average game in our sample makes 80% of its revenues in the first 12 months after release instead revenues in a given year means we are not making the mistake of comparing apples to oranges, i.e., games in different stages of their diffusion. Our revenue data are for the period January 1995 to December 2008. Our sample thus includes all games that were released between January 1995 and December 2007.

⁴ We use the program *Pajek* to calculate the network measures (available at <u>http://pajek.imfm.si</u>).

⁵ We thus implicitly give direct ties that formed from having worked on a joint project 10 years ago the same weight as ties formed one year ago. We thus ignore the possibility of forgotten or now impossible (due, e.g., to death) ties (Holan and Phillips 2004).

⁶ The NPD database is also used by other researchers (e.g., Shankar and Bayus 2003; Venkatraman and Lee 2004; Clements and Ohashi 2005; Stremersch et al. 2007).

⁷ Online sales are covered as their importance has grown. However, as Wal-Mart stopped providing data to all research companies in 2002, Wal-Mart sales are projected by NPD only until 2002.

⁸ Revenues are deflated to 1995 U.S.\$. Total revenues of the game industry are driven by blockbuster products (McGahan 2004). For example, the best-selling game in 2008, "Wii Sports," made more than U.S.\$ 400 million; however, another top 10 game, "New Super Mario Bros," made only about a quarter of that (see Figure A.1). To account for this skewness in revenue distribution, we use the natural logarithm of revenues in our analysis.

In addition to commercial success, we use critics' scores as a measure of *qualitative success*. Game critics are opinion leaders for hardcore gamers, but they also have some influence on casual gamers through specialized magazines and websites. We use critics' scores that MobyGames has collected from the leading game magazines and websites.⁹ Critics' scores range from 0 to 100. However, since critics' scores are subjective and may systematically differ between scorers, we normalize the scores by subtracting the critic's mean score over all games and then dividing by the critic's standard deviation over all games. For a single game, we then derive our variable—i.e., critics' score—as the mean of all normalized critics' scores judging the respective game.

We also include the following control variables.¹⁰

Leading Position. This dummy variable indicates whether a person occupies a leading position on the development team and is thus chiefly involved in management, or whether the person is an ordinary team member and is therefore mainly active in the actual implementation of the game.

Tenure. We measure the tenure of a person as the number of years between the year the person was first involved in game development and the year the game under study was introduced.

Team Size. As more complex games with detailed and realistic graphics require larger teams, the size of the developer team might have a positive influence on game performance. Hence, we control for team size in our regression.

Licensed Game. Since "blockbusters" play such a huge role in the electronic game industry, more and more frequently developing firms are using intellectual property from movies or books (e.g., Harry Potter or Indiana Jones) or from sports leagues and player associations (e.g., NFL or FIFA) in an attempt to appeal to the mass market.¹¹ To control for external intellectual property, we include a dummy that is equal to unity if a game is based on external intellectual property.

Release Month. Due to the high seasonality of the electronic game industry, with its demand and supply peaks occurring during the holiday season and during the important trade fairs, we include a dummy for the month in which the game is released.

Genre. Like movies and books, electronic games can be classified into genres, such as role-play games or first-person-shooter games. We use the genre classification from the NPD data, which distinguishes between 50 different categories. We control for genre as it can heavily influence market potential and, therefore, the success of a game.

⁹ We use only those magazines and websites that have rated a minimum of 10 games.

¹⁰ Descriptive statistics and pair-wise correlations for all variables are reported in Table 1 and Table 2, respectively.

¹¹ Electronic Arts 2005 Annual Report, <u>http://analist.be/reports/electronic_arts-2005.pdf</u>.

Platform. Since an electronic game is designed for one or multiple platforms, its success will depend on the diffusion of the targeted platform(s). Thus, games developed for more popular platforms have higher market potential, but also face stiffer competition. Hence we include dummies for each of the 23 platforms observed in our sample.

INSERT TABLE 1 HERE

3.3. The Impact of a Developer's Connectedness on a Game's Success

Based on the estimation strategy introduced in Section 3.1, Table 3 and 4 report our estimation results with cluster (game) robust standard errors. Table 3 report results with a game's commercial success as the outcome measure; Table 4 reports results with critics' scores as the outcome measure. In all specifications, we include fixed effects for the developer, developing firm, publishing firm, and time, as well as a set of controls (cf. Section 3.2).

INSERT TABLE 3 HERE

INSERT TABLE 4 HERE

In Columns (3-1) and (4-1), social network measures are contemporaneous. There is a significant positive association of degree centrality with both success measures, but no additional explanatory power from the closeness measure. Taking the results from Column (4-1) as an example and assuming that we can interpret our results as causal effects, all else equal, a one standard deviation increase in a game developer's direct ties increases the game's revenue in the first year by about 0.02 percentage points. For a top 10 game, which might generate revenues of more than U.S.\$ 100 million, this translates into an increase in revenue of more than U.S.\$ 20,000. The development team for a top 10 game can include as many as 50 members, meaning that if degree centrality of the average team member increases by one standard deviation, revenues will increase by more than U.S.\$ 1 million.

In Columns (3-2) and (4-2), social network measures are lagged, and yet there is still a significant positive coefficient for our degree centrality measure. The coefficient is somewhat smaller compared to the results in Columns (3-1) and (4-1), which is what we expected since this approach ignores the additional value of the developer's contemporaneous connectedness. The coefficient for lagged closeness is not significantly different from zero.

In Columns (4-3), (4-4), (5-3), and (5-4), we also control for average (lagged) degree centrality and average (lagged) closeness of the developer's co-developers in the game project. Again, we find a significant positive association of the individual developer's degree centrality measure. The coefficient for closeness remains insignificant.

When looking at the results for our control variables, we find no significant influence from tenure, but do see a strongly significant positive influence of team size on both success measures. Interestingly, licensed games generate higher revenues but receive lower critics' scores. Perhaps this is because licensed content appeals to the mass-market, resulting in higher revenue, but critics find original and creative ideas of more value.

3.4. The Importance of Connectedness for Lead Developers

In a next step, we take advantage of our data as to whether a developer is in a leading position and therefore chiefly engaged in management, or whether he or she is mainly active in game implementation. We allow the variable "leading position" to interact with our social network measures so as to be able to identify differences between leading and non-leading developers.

Estimation results with standard errors clustered on the game level are reported in Table 5. In our analysis, we focus on the main effect of degree centrality, which is the effect non-leaders can benefit from, and the linear combination of degree centrality and the interaction between leading group and degree centrality, which is the effect leaders can benefit from. When using revenue as measure of success, non-leaders do not benefit significantly from high degree centrality, whereas there is strong evidence that leaders do. In contrast, when critics' score is the dependent variable, leaders do not particularly benefit from higher degree centrality.

INSERT TABLE 5 HERE

4. Conclusion

In this paper, we investigate the extent to which a developer's connectedness to other developers influences the success of a project in the knowledge-based electronic game industry. Given the

knowledge intensity of the electronic game industry, knowledge spillovers between developers should be of special relevance. Based on a comprehensive dataset covering the electronic game industry since its infancy, we calculate developers' connectedness measures at different points in time. We find that the number of direct ties a developer has (degree centrality), i.e., the number of other developers a developer has worked with on joint game projects, has a strong and economically meaningful impact on the success of a game, measured by revenues and critics' scores. We also find evidence for the heterogeneity of this effect between lead and non-lead developers. By contrast, we do not find an additional impact from the intensity of a developer's ties to other developers (closeness). These results suggest that direct ties are indeed important in the game industry, but that the intensity of indirect ties is not. We argue that our results, which are derived from fixed effects regressions with lagged connectedness measures, plausibly can be interpreted as causal effects of a developer's connectedness on a game's success.

Ever since the seminal contributions by Jaffe et al. (1993) and Audretsch and Feldman (1996), it is common knowledge that knowledge spillovers are regionally bound, and this is also confirmed for the game industry, evidenced by the regional clustering of developing and publishing firms in Montréal, Canada (Cohendet et al., 2010). Due to government grants, tax allowances, and the reputation for creativity of its bilingual, multicultural workforce, Montréal has developed into one of the most important sites of the electronic game industry, home to more than 40 developing firms. Thus, a natural next step will be to incorporate a regional dimension to our analysis.

References

- Audretsch, David B. and Feldman, Maryann P. 1996. "R&D Spillovers and the Geography of Innovation and Production." *American Economic Review*, 86(3), pp. 630–40.
- **Cadin, Loic; Guérin, Francis and Defillippi, Robert.** 2006. "HRM Practices in the Video Game Industry: Industry or Country Contingent?" *European Management Journal*, 24(4), pp. 288–98.
- **Chandler, Heather M.** 2009. *The Game Production Handbook*. Sudbury, MA: Jones and Bartlett Publishers.
- **Clements, Matthew T. and Ohashi, Hiroshi.** 2005. "Indirect Network Effects and the Product Cycle: Video Games in the U.S., 1994–2002." *Journal of Industrial Economics*, 43(4), pp. 515–42.
- **Cohendet, Patrick; Grandadam, David and Simon, Laurent.** 2010. "The Anatomy of the Creative City" *Industry & Innovation*, 17(1), pp. 91-111.
- Fershtman, Chaim and Gandal, Neil. 2009. "R&D Spillovers: The 'Social Network' of Open Source Software." mimeo.
- Freeman, Linton. 2006. The Development of Social Network Analysis. Vancouver: Empirical Press.
- **Goyal, Sanjeev M.; van der Leij, Marco J. and Moraga-Gonzalez, José L.** 2006. "Economics: An Emerging Small World." *Journal of Political Economy*, 114(2), pp. 403–12.
- Granovetter, Mark S. 1973. "The Strength of Weak Ties." American Journal of Sociology, 78(6), pp. 1360–80.
- **Granovetter, Mark S.** 1983. "The Strength of Weak Ties: A Network Theory Revisited." *Sociological Theory*, 1, pp. 201–33.
- Hanushek, Eric A.; Kain, John F.; Markman, Jacob M. and Rivkin, Steven G. 2003. "Does Peer Ability Affect Student Achievement." *Journal of Applied Econometrics*, 18(5), pp. 527–44.
- **Hight, John and Novak, Jeannie. 2008.** *Game Development Essentials: Game Project Management.* Clifton Park, NY: Thomson Delmar Learning.
- Holan, Martin de and Phillips, Nelson. 2004. "Remembrance of Things Past? The Dynamics of Organizational Forgetting." *Management Science*, 50(11), pp. 1603–13.
- Jaffe, Adam B.; Trajtenberg, Manuel and Henderson, Rebecca M. 1993." Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." *Quarterly Journal of Economics*, 108(3), pp. 577–98.
- Kent, Steven L. 2001. The Ultimate History of Video Games. New York: Three Rivers Press.
- Manski, Charles F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *Review of Economic Studies*, 60(3), pp. 531–42.
- **Novak, Jeannie.** 2008. *Game Development Essentials: An Introduction*. Clifton Park, NY: Thomson Delmar Learning.
- Shankar, Venkatesh and Bayus, Barry L. 2003. "Network Effects and Competition: An Empirical Analysis of the Home Video Game Industry." *Strategic Management Journal*, 24(4), pp. 375–84.
- Stremersch, Stefan; Tellis, Gerard J.; Franses, Philip H. and Binken, Jeroen L. G. 2007. "Indirect Network Effects in New Product Growth." *Journal of Marketing*, 71(3), pp. 52–74.
- Venkatraman N. and Lee, Chi-Hyon. 2004. "Preferential Linkage and Network Evolution: A Conceptual Model and Empirical Test in the U.S. Video Game Sector." Academy of Management Journal, 47(6), pp. 876–92.

Figures and tables

Table 1: Summary statistics

VARIABLE	Ν	Mean	SD	Min	Max
In(Revenue)	151677	14.958	1.701	4.264	19.440
Critics score	146675	0.007	0.781	-3.831	2.223
Degree centrality D_{igdpt}	148627	0.001	0.002	0.000	0.041
Closeness C _{igdpt}	148627	0.205	0.038	0.052	0.338
Leading Position	151677	0.213	0.410	0	1
Tenure	151677	3.871	4.254	0	28
Team size	151677	65.780	53.234	1	297
Licensed game	151677	0.362	0.480	0	1

Table 2: Pair-wise correlations

VARIABLE		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
In(Revenue)	(1)	1.000							
Critics score	(2)	0.375	1.000						
Degree centrality D_{igdpt}	(3)	-0.009	0.016	1.000					
Closeness C_{igdpt}	(4)	0.022	-0.079	0.212	1.000				
Leading Position	(5)	-0.070	-0.049	-0.092	0.003	1.000			
Tenure	(6)	0.040	-0.023	-0.053	0.062	0.236	1.000		
Team size	(7)	0.280	0.150	-0.034	0.254	-0.136	0.015	1.000	
Licensed game	(8)	0.055	-0.210	-0.023	0.056	0.001	0.026	0.086	1.000

INDEPENDENT	(3-1)	(3-2)	(3-3)	(3-4)	
VARIABLES	DEPENDENT VARIABLE: In(Revenue)				
Degree centrality D_{igdpt}	8.494*	8.029*	7.281**	6.512*	
	(4.468)	(4.342)	(3.321)	(3.644)	
Closeness C _{igdpt}	-0.137	-0.307	-0.105	-0.223	
	(0.201)	(0.217)	(0.155)	(0.174)	
Coworker degree c. \overline{D}_{-igdpt}			40.20	56.53	
			(60.77)	(45.38)	
Coworker closeness $ar{C}_{-igdpt}$			-0.548	-3.122	
			(3.059)	(2.567)	
Tenure	0.0170	0.0612	0.0236	0.0676	
	(0.0618)	(0.0886)	(0.0664)	(0.0932)	
Team size	0.00447***	0.00396***	0.00446***	0.00394***	
	(0.000937)	(0.000990)	(0.000938)	(0.000991)	
Licensed game	0.192***	0.172**	0.193***	0.171**	
	(0.0720)	(0.0771)	(0.0721)	(0.0774)	
Network Measures Lagged	No	Yes	No	Yes	
Observations	151484	94597	151443	94388	
Number developers	56944	30993	56937	30956	
Within-developer R ²	0.635	0.638	0.635	0.638	
Between-developer R ²	0.802	0.742	0.798	0.736	
Overall R ²	0.736	0.689	0.734	0.684	

Table 3: Baseline regression results with revenue as success measures.

Notes: Fixed-effect OLS point estimates with standard errors clustered on the project-level in parentheses. As the panels are not nested within the clusters, a degree of freedom adjustment is conducted, producing conservative results for the standard errors. Asterisks denote significance levels (*** p<0.01, ** p<0.05, * p<0.1). All specifications control for fixed effects on the level of the developer, the developing firm, the publishing firm, the release year, the release month, the genre, and the platform, but results are not reported here.

INDEPENDENT	(4-1)	(4-2)	(4-3)	(4-4)	
VARIABLES	DEPENDENT VARIABLE: Critics score				
Degree centrality D_{igdpt}	4.043**	3.880*	2.889*	3.175*	
	(2.047)	(2.143)	(1.623)	(1.845)	
Closeness C _{igdpt}	0.0113	-0.150	0.0170	-0.109	
	(0.0998)	(0.110)	(0.0795)	(0.0890)	
Coworker degree c. \overline{D}_{-igdpt}			50.71*	20.70	
			(29.32)	(21.34)	
Coworker closeness $ar{C}_{-igdpt}$			0.570	-1.492	
0 1			(1.555)	(1.312)	
Tenure	-0.0248	0.0198	-0.0254	0.0219	
	(0.0300)	(0.0423)	(0.0323)	(0.0444)	
Team size	0.00203***	0.00180***	0.00203***	0.00180***	
	(0.000502)	(0.000524)	(0.000503)	(0.000526)	
Licensed game	-0.276***	-0.265***	-0.274***	-0.264***	
	(0.0363)	(0.0389)	(0.0363)	(0.0390)	
Network Measures Lagged	No	Yes	No	Yes	
Observations	146522	91897	146481	91703	
Number developers	55843	30635	55835	0.722	
Within-developer R ²	0.542	0.540	0.543	0.541	
Between-developer R ²	0.708	0.723	0.706	0.722	
Overall R ²	0.654	0.663	0.654	0.661	

Table 4: Baseline regression results with critics score as success measures.

Notes: Fixed-effect OLS point estimates with standard errors clustered on the project-level in parentheses. As the panels are not nested within the clusters, a degree of freedom adjustment is conducted, producing conservative results for the standard errors. Asterisks denote significance levels (*** p<0.01, ** p<0.05, * p<0.1). All specifications control for fixed effects on the level of the developer, the developing firm, the publishing firm, the release year, the release month, the genre, and the platform, but results are not reported here.

	DEPENDENT VARIABLES						
INDEPENDENT	(5-1) (5-2)		(5-3)	(5-4)			
VARIABLES	In(Revenue)		Critics score				
Degree centrality D_{igdpt}	5.746	4.573	4.058*	2.856			
	(4.938)	(3.786)	(2.249)	(1.846)			
Closeness C _{igdpt}	-0.116	-0.0885	0.0168	0.0174			
	(0.217)	(0.172)	(0.108)	(0.0886)			
Leading position	-0.0385	-0.0432	-0.0123	-0.0189			
	(0.0758)	(0.0756)	(0.0405)	(0.0405)			
Leading position * D_{igdpt}	10.14	9.944	-0.0909	0.0775			
	(6.490)	(6.455)	(3.532)	(3.551)			
Leading position * C _{igdpt}	-0.0332	-0.0159	-0.0184	0.00451			
	(0.301)	(0.300)	(0.161)	(0.161)			
Coworker degree c. \overline{D}_{-iqdpt}		40.71		50.85*			
		(60.75)		(29.32)			
Coworker closeness \bar{C}_{-igdpt}		-0.546		0.567			
igupt		(3.059)		(1.555)			
Tenure	0.0171	0.0237	-0.0248	-0.0253			
	(0.0617)	(0.0664)	(0.0300)	(0.0323)			
Team size	0.00445***	0.00445***	0.00203***	0.00202***			
	(0.000937)	(0.000938)	(0.000502)	(0.000503)			
Licensed game	0.192***	0.193***	-0.275***	-0.274***			
	(0.0720)	(0.0721)	(0.0363)	(0.0363)			
Network measures lagged	No	No	No	No			
Observations	151484	151443	146522	146481			
Number developers	56944	56937	55843	55835			
Within-developer R ²	0.635	0.635	0.542	0.543			
Between-developer R ²	0.803	0.800	0.706	0.706			
Overall R ²	0.737	0.734	0.653	0.653			
Degree centrality D_{igdpt} +	15.89**	14.52**	3.967	2.933			
(Leading position * D _{igdpt})	(6.213)	(5.694)	(3.310)	(3.124)			

Table 5: Results for interactions of the network measures with leading position

Notes: Fixed-effect OLS point estimates with standard errors clustered on the project-level in parentheses. As the panels are not nested within the clusters, a degree of freedom adjustment is conducted, producing conservative results for the standard errors. Asterisks denote significance levels (*** p<0.01, ** p<0.05, * p<0.1). The last two lines are not part of the regression results but represent the coefficient of a linear combination together with the respective standard error in parentheses. All specifications control for fixed effects on the level of the developer, the developing firm, the publishing firm, the release year, the release month, the genre, and the platform, but results are not reported here.

Appendix (not intended for publication)

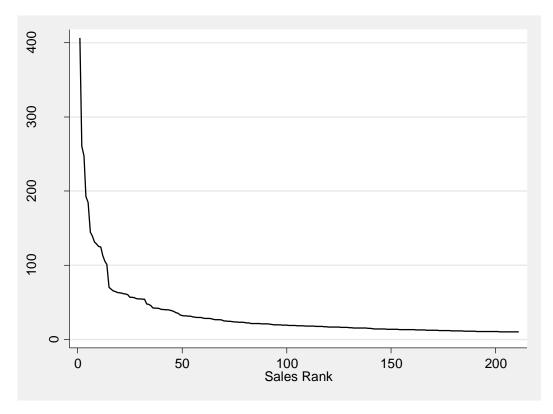


Figure A. 1: Revenue and sales rank for all electronic games in the United States in 2008

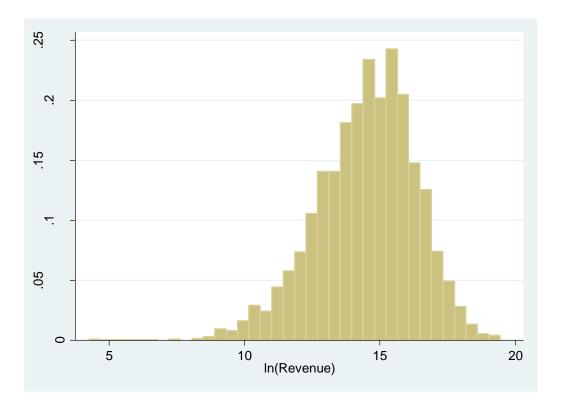


Figure A. 2: Histogram for dependent variable In(Revenue)

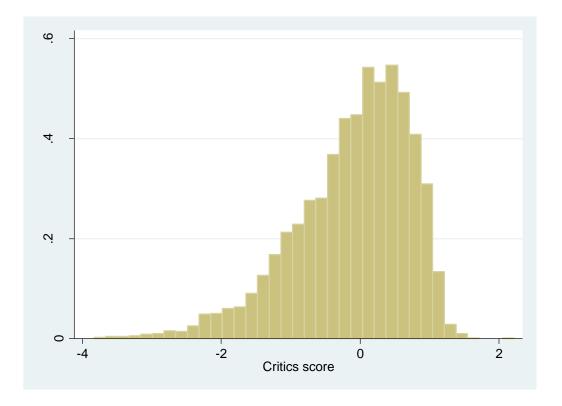


Figure A. 3: Histogram for dependent variable critics score

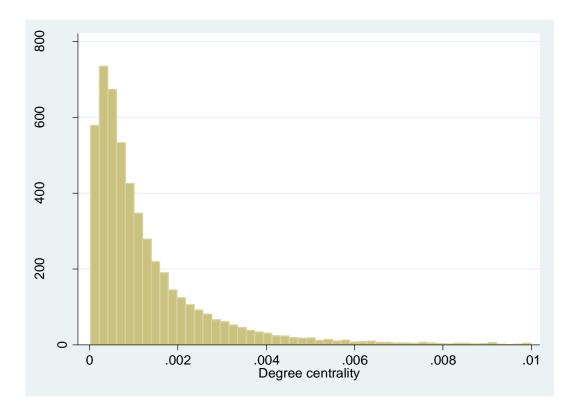


Figure A. 4: Histogram for independent variable degree centrality

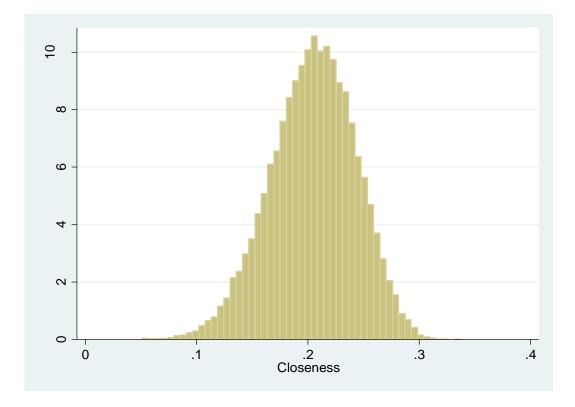


Figure A. 5: Histogram for independent variable closeness

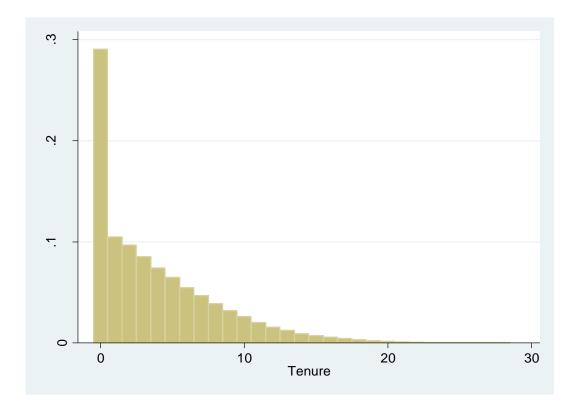


Figure A. 6: Histogram for the control variable tenure

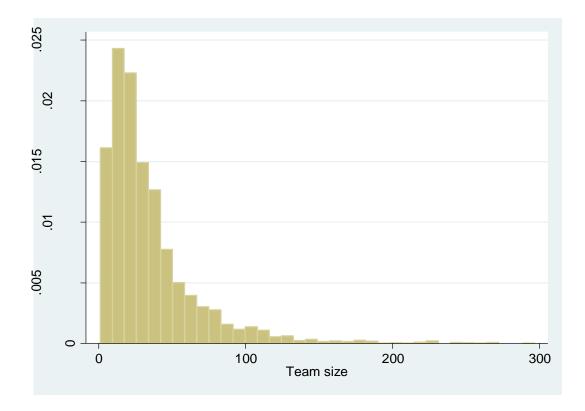


Figure A. 7: Histogram for the control variable team size