University of Konstanz
Department of Economics

# Social Capital and Online Games

*Christoph Safferling*

Working Paper Series
2011-32

http://www.wiwi.uni-konstanz.de/workingpaperseries

# Social capital and online games

Christoph Safferling*†

this version: September 2, 2011

**Abstract**

We use data from an online game economy and econometric matching methods to test whether social capital of players has an impact on game success. Membership in a "clan", a voluntary organisation of players, positively impacts game success. Hence, social capital has a positive effect on outcomes. Yet, top performers do not gain from access to this social capital.

JEL Classification: A13, C99, D10, D12

*Address: Universität Wien, Institut für Betriebswirtschaftslehre, Brünner Strasse 72, A-1210 Wien, Austria. Email: `Christoph.Safferling@univie.ac.at`

†I would like to thank Oliver Fabel and Christian Hopp for helpful comments. The original marketplace data from which the players were chosen was part of an earlier research project together with Aaron Lowen of Grand Valley State University. Two KoL players were invaluable for kindly giving me access to their player data. Chris Maloof was very helpful in providing access to his koldb data, and Fryguy for granting access to the DCdb data.

# 1 Introduction

We use data from an online game economy and econometric matching methods to test whether social capital of players has an impact on game success. Membership in a "clan"[1], a voluntary organisation of players, positively impacts game success. Hence, social capital has a positive effect on outcomes. Yet, top performers do not gain from access to this social capital.

The internet has dramatically increased the possibilities of social networking. Sites such as Facebook build their entire business model on facilitating social contacts and interactions. But networking is not only done via social websites: online games have also gained widespread acceptance, with players competing against each other over the internet. In 2009 there were 46 million players of online games, generating an industry revenue of 3.8 billion US$ for the United States alone[2]. According to these numbers, statistically speaking a fifth of the US population participate in online games.

Players meet and form "clan" organisations exclusively online. Socialising increasingly becomes a regular activity for many, just as the internet has long evolved into a regular marketplace to trade all kinds of goods and services. In contrast with the pure exchange of personal information in social networks, online game players are very performance-orientated. Readily available online game data can therefore provide an outlook on future developments and business potential in the internet economy. In this paper, we are specifically interested in investigating the emergence of "virtual" social capital that enhances individual performance.

The remainder of this chapter is structured as follows: Section 2 gives an

[1] "Clans" are commonly known as "guilds" in other online games. This name stems from the medieval namesake; Ogilvie (2004) shows that these medieval guilds did provide valuable social capital to their members in medieval Germany.

[2] Today's Gamers report 09: `http://www.gamesindustry.com/about-newzoo/todaysgamers_graphs_MMO`, accessed March 15, 2010

overview of relevant literature and constructs the hypothesis. Section 3 presents the data and methology, and section 4 the results. Finally, section 5 concludes.

## 2 On Social Capital and Online Worlds

Since Becker's seminal contribution of human capital theory (Becker, 1964), the idea of *social* capital, which offers investment opportunities and returns, has increasingly gained acceptance in the discipline of economics. While human capital equates to *what* you know, social capital represents *whom* you know. Granovetter (1985) imports the notion of social ties and relations as being helpful or harmful from other social sciences, mainly sociology, into economics. Robison et al. (2002) reconcile social capital and economics. Social capital shares the characteristics of capital: In general, investments into it, and returns from it, are possible. Glaeser et al. (2002) develop an investment model supporting[3] this view.

Durlauf (2002) provides a critical account of the existing empirical studies on social capital. He proposes to derive experimental or large-scale survey data to generate a dataset to solve the data problems in the existing empirical literature. Our dataset provides quasi-experimental data from an online game world economy. Moreover, a large number of control variables on the characters in the game can be used to substitute for an in-depth survey. Burt (2011) argues that virtual worlds have "enormous potential" as a research site, especially for social network research. He raises the concern of validity, and confirms that virtual worlds provide valid results for two aspects of social capital: higher outcomes of network brokers, and increased trust between members of the same network.

[3]Not all economists readily agree. For a critical assessment see Sobel (2002), and for an overview see Adler and Kwon (2002) and Durlauf and Fafchamps (2005).

Many would suggest that internet activities reduce social capital: Sitting in front of a computer all day does not lead to new social contacts. Bauernschuster et al. (2011) use data on internet usage in Germany, exploiting the natural experiment of the German Reunification in 1990 to combat endegeneity issues. The study finds that internet usage does not decrease a person's social capital. For some subsamples, mainly younger children, the effect is even positive.

Two studies on social capital are set in online worlds. Focusing on the online world *Second Life*, Fiedler et al. (2011) and Füllbrunn et al. (2011) analyse online trust levels. They find online trust levels to be lower than in comparable real-world experiments. These works conduct economic experiments using an online (non-game) world as a communication medium. In contrast, we study player behaviour in a highly competitive game environment.

In accordance with the third form of social capital of Groot et al. (2007) (membership in unions, or clubs), online game "guilds", or "clans", voluntary groups of players that meet, chat, discuss strategies, or help each other online, constitute social capital. In sociology, Papargyris and Poulymenakou (2005), Ang and Zaphiris (2008), and Ang and Zaphiris (2010) support this argument. Rodrigues and Mustaro (2008) analyse online guilds as social networks. They find that smaller guilds have a higher "density": information can flow more easily to all members.

A (positive) relationship between in-game leadership of guild members and their out-of-game leadership characteristics was shown by Jang and Ryu (2011). In the physical world, social capital has been shown to be advantageous to individuals by Knack and Keefer (1997). It also provides an advantage for firms (Nahapiet and Ghoshal, 1998; Stam and Elfring, 2008).

> **Hypothesis 1:** *(Social Capital) Members of an in-game clan are more successful than lone players.*

McFadyen and Cannella (2004) find social capital exhibits diminishing returns on knowledge creation. Their study uses the network of contacts of an individual as a measure for social capital. Network contacts have inverse U-shaped effects on knowledge creation: at some point, more social contacts actually reduce the marginal benefit. We follow this argument, but from a different perspective: in a competitive game environment, top performers will benefit less from access to social capital than mediocre, or poor, performers. The latter can benefit from easy access to strategies and game information. In contrast, top players do not *access* superior strategies, but *invent* them. They are still able to use social ties for discussion and spillover effects of strategy generation. Yet, the more direct effect of access to better strategies is of no importance, as they already follow the "best" strategies. In effect, bad players are using clans to free-ride[4] on the strategies and game-knowledge of the better players.

Our definition of social capital as group membership leads to a second argument for this effect: peer effects[5]. In their experimental study, Falk and Ichino (2006) find that lower productivity workers benefit from the addition of a high-productivity worker to the group. In contrast, high productivity workers do not exhibit the same magnitude of productivity gain. This effect was also found by Mas and Moretti (2009) in their empiric study of supermarket personnel. Hence, we state our second hypothesis:

> **Hypothesis 2:** *(Peer Effects) The benefits of social capital are lower for high-performing individuals.*

[4]Eisenkopf (2010) confirms in an experimental study the peer effect of "better" students having a positive effect on "worse". Yet, inclusion of top-performers into the group also lowers the motivation of the low-performers.

[5]The idea that the productivity of other group members directly affects the productivity of an individual is quite old. For early economic review see Arnott and Rowse (1987), and Manski (1993). More recent research was made by e.g. Encinosa et al. (2007).

| | nobs | mean | sd | min | max |
|---|---|---|---|---|---|
| lnfastestSC | 9728 | 7.971839 | .9446542 | 5.846439 | 12.10249 |
| lnfastestHC | 8105 | 7.773895 | .5646562 | 6.489205 | 11.40935 |
| clan | 29472 | .5137758 | .4998187 | 0 | 1 |

Descriptive statistics of the independent variables and the dependent variable. Full descriptive statistics including all control variables are in appendix 6.2.

**Table 1:** *Descriptive statistics for the social capital dataset*

# 3 Data and Methodology

We use data from an online roleplaying game called *The Kingdom of Loathing*, henceforth KoL. From April 2004 to October 2006 all in-game item[6] transactions via the in-game market were observed, uniquely identifying buyers and sellers. From these transactions, all players that had bought or sold at least one donation item were selected. A donation item is a valuable item in the game that needs to be bought via a "donation"[7] of 10 US$; the game is otherwise free to play. Selecting only the donation item traders was necessary, as any character who has held a donation item at least once is flagged as *no delete* on the servers and will not be deleted for inactivity. We can thus ensure that data on all characters are still available in all databases.

For these characters, we obtain data on their specific game achievements from the koldb[8]. Koldb is a player-run database of game achievements. It provides a large number of characteristics and achievements of all KoL characters. Table 1 presents the descriptive statistics of the dataset.

Our variables of interest are the outcome and the treatment variables. The treatment variable, `clan`, is a dummy variable equal to 1 if the individual is a member of an in-game clan. Outcome variables are `lnfastestHC` and

[6] In-game goods are called "items" in KoL.

[7] "Donation" is the term that the game designers use. Economically speaking, you of course *buy* a "donation" item for 10$.

[8] `http://www.koldb.com`, accessed March 15, 2010; Chris Maloof was invaluable in his help and willingness to provide us with the koldb data.

`lnfastestSC`, the log of the number of turns the fastest game took to complete (for two possible game modes: normal ("softcore", sc), and "hardcore" (hc)). Hence, lower numbers express better performances. The goal of the game is to ascend as quickly as possible. Completion times are automatically logged and displayed on "leaderboards". There is a large community of players who try to break speed records. After nominally finishing the game, a player can chose to "ascend". He will re-start, receiving one game benefit for his character. The next ascension will then be easier and/or faster.

Control variables are the total number of "ascensions" in each possible game mode, specifically the variables `scnp`, `sct`, `scb`, `sco`, `hcnp`, `hct`, `hcb`, `hco`. These are the two game modes (sc and hc), with optional restrictions (no path "np", teetotaler "t", boozetafarian "b", and oxygenarian "o").

We also know the ID number of the character. This is a proxy for character age: a character generated earlier will have a lower `playerid`. The average level at ascension (`av_lvl_at_asc`) indicates the character level at which, on average, the character opted to ascend. This is a measure of how quickly the player wanted to re-start the game[9]. Wealth for each character is only indirectly measured, as we do not have access to the (private) inventories of the characters. However, each character can opt to install a "display case"[10], a public presentation space for his character. Any item put into the display case is publicly observable. While not a perfect measure of (private) character wealth, there should be a high correlation between the market value of a display case and the market value of the total character inventory.

We use two ranks over the entire playerbase from the koldb: the percentile dedication (`perc_dedic`), ranking players on their number of ascensions, and

[9]There is an amount of high-level content available to characters after finishing the main game.

[10]We have received the display case data from the DCdb (`http://www.jickenwings.org/collections/index.cgi`, accessed March 15, 2010), a database computing all display case data of all characters. We would like to thank Fryguy for his help and willingness to share this data with us.

the percentile speed (perc_speed), ranking players on the speed of the fastest run. These ranks are over the entire KoL player community, not just our dataset. A percentile speed of 0.99 translates into 99% of all players being slower.

The remaining variables capture the trade patterns of the individuals. The number of donation items purchased (mra_buy, iotm_buy) and sold (mra_sell, iotm_sell), and the number of trade "errors" exploited (expl_error) or made (make_error) by the character. Trade errors are trades at less than 1% of the average market price for each good. Appendix 6.1 provides an overview and brief description of all variables.

What kind of individuals chose to play online games, and are thus part of our dataset? Yee (2006) provides survey demographics of online games, and Fnord7 et al. (2006) conducted a survey of the KoL players at the beginning of our data enquiry. Randomly selecting 3,000 of all active players (logged into the game in the past 14 days) and with a response rate of roughly one third, the results are as close to representative of the playerbase as is available. Of those responding, 76% reported to be male, compared to 85% reported by Yee. The players are young, but not uncommonly so: 35% are younger than 18, 48% between 18 and 29 years of age, and 17% are aged 30 or older. The average age reported by Yee is 26.5 years. The vast majority of players, 89%, come from native English-speaking countries: 65% from the US, 10% from the UK, 8% from Canada, and 6% from Australia and New Zealand. The game takes up a lot of the leisure time of the players, with 41% reporting that they play for longer than 2 hours per day, and 43% reporting that they log onto the game daily (while 75% play five days a week). This is in accordance with Yee, stating an average of 22 hours spent per week by the players.

Membership in a clan is voluntary with players self-selecting[11] into the

[11] In fact, there is a double self-selection: players chose the difficulty mode, and membership of a clan. There are no means to show which is chosen first: the difficulty mode, or the clan membership. For our analysis we must assume that choice of a clan has no effect on which difficulty mode

clan. Thus, clan membership is not random, but a strategic, endogenous choice of a player. A standard regression of clan membership on outcome could be biased, since membership and the error term are correlated. We use matching methods to correct for this endogeneity. Our variable of interest, the average treatment effect on the treated (ATT) is generally:

$$\text{ATT} = E[Y(1) - Y(0)|D = 1] = E[Y(1)|D = 1] - E[Y(0)|D = 1]$$

with $D$ as treatment dummy (clan membership, in our case). $Y(1)$ is the outcome of a treated individual and $Y(0)$ the outcome of an untreated (non-clan member) individual. To correctly calculate the ATT, we need an unobservable counterfactual: $E[Y(0)|D = 1]$, the outcome of a non-clan member, given that he or she were member of a clan.

Matching techniques can estimate this counterfactual. The goal is to find individuals that are as alike as possible in all variables, except for the treatment and (possibly) the outcome variable. This matching creates "statistical twins", with one of the twins taking part in the treatment and the other not.

If matching were perfect (all control variables of the two individuals were perfectly identical), the outcome difference between the matched individuals would be an exact estimator. Yet, perfect matching is impossible[12]. In particular, including more control variables yields the so-called "curse of dimensionality": more variables imply a smaller statistical chance of finding a match. There are a number of statistical techniques to overcome this problem. In this paper, we use propensity score matching (PSM) (Rosenbaum and Rubin, 1983; Leuven and Sianesi, 2003) and coarsened exact matching (CEM) (Iacus et al., 2008; Blackwell et al., 2009). PSM derives a propensity score by probit estima-

the players chose. This seems reasonable, as a player will probably choose his preferred game style (difficulty mode), and then realise he needs extra help in achieving goals from a clan.

[12]If there is a single *continuous* control variable, the chances of having two people match with exactly the same value of that control variable is statistically zero.

tion; we estimate the probability to enter the treatment group conditional on all control variables. Individuals are matched if they possess equal probabilities to enter the treatment. With CEM, all observations of a control variable are temporarily coarsened and put into different "bins", in the same way as constructing a histogram. Matching individuals are then found on basis of these bins. The actual regressions use the original variables, with regression weights obtained from the CEM matching.

We set up two matching specifications for CEM. The first uses the total number of hardcore (hc), and the total number of softcore (sc) ascensions to match the individuals. The second uses the percentile dedication of sc and hc ascensions. Recall, the percentile is generated over the entire game population sample, not only our dataset. The number of ascensions of each individual allows matching according to game knowledge and playing preferences. More ascensions signifies a higher game knowledge, and also indicates a preference for playing the game more often. As groups often form from like-minded individuals, this should be the best[13] matching predictor. Our first CEM matching specification turns out inferior to the second one: the overall data imbalance was hardly reduced[14]. The goal of CEM is to reduce the imbalance of the *matched* data: perfectly matched data would not exhibit any imbalances. Our second matching specification using the global, overall, rank of an individual's ascensions provides better results: the imbalances are substantially cut[15], and the loss of observations is lower than in the first model.

We match our PSM models over all variables. PSM techniques need a large enough "overlap" over all control variables between the two groups. When

[13]Additionally adding either wealth or the playerid as a third matching variable lead to an unacceptably high loss of data, and the results did not change where they were still significant.

[14]From an unmatched 0.268 to a matched 0.266 for sc, and from 0.326 to 0.247 for hc; 0 denotes perfect balance, 1 total imbalance. The Scott coarsening algorithm was used, which is more aggressive in finding matches, but leads to a high loss of observation points due to non-matching.

[15]From 0.315 (unmatched) to 0.073 (sc), and from 0.359 (unmatched) to 0.194 (hc).

comparing two matched individuals, these may not differ too much in their control variables. To ensure that the data is on this so-called "common (empirical) support", only the CEM-matched individuals are used for the regressions (Blackwell et al., 2009). The first PSM matching regressions use the first CEM matching specification, and the second PSM regressions use the second CEM specification.

# 4 Results

All regression models[16] provide clear-cut results supporting our first hypothesis. The results for clan membership are listed in Table 2. The OLS regression already shows a significant effect of clan membership on game performance (in both major game modes, hardcore and softcore). As discussed earlier, this result is possibly biased by the strategic choices of clan membership. Yet, PSM and CEM matching methods also show that social capital as measured in clan membership has a positive effect on outcome.

Subsequently we focus on the second hypothesis. We examine individuals within different tiers of achievement. Table 3 shows the regression results with robust standard errors, restricting the sample to different tiers: the 90% slowest, 10% and 5% fastest players. Note, these tier levels were computed from the entire game population, not just our dataset.

Membership in a clan is beneficial for the 90% slowest players, for both difficulty modes. For the top 10%, however, clan membership no longer plays a prominent role: it is insignificant for players of the hardcore difficulty mode, and less significant for the top 10% of the softcore difficulty mode players (and insignificant for the top 5% softcore players as well).

[16] Full regression tables are in appendix 6.3.

| | OLS | CEM(1) | CEM(2) | PSM(1) | PSM(2) |
|---|---|---|---|---|---|
| **Softcore game mode** | | | | | |
| clan | -0.170** | -0.130** | -0.115** | -0.188** | -0.318** |
| | (0.030) | (0.038) | (0.039) | (0.067) | (0.074) |
| Constant | 6.311** | 6.581** | 6.264** | | |
| | (0.050) | (0.058) | (0.057) | | |
| $N$ | 9728 | 7611 | 7966 | 6134 | 6632 |
| adj. $R^2$ | 0.423 | 0.451 | 0.444 | | |
| F | 324.160 | 348.064 | 354.747 | | |
| **Hardcore game mode** | | | | | |
| clan | -0.107** | -0.127** | -0.145** | -0.083 | -0.232** |
| | (0.023) | (0.027) | (0.027) | (0.066) | (0.059) |
| Constant | 7.313** | 7.437** | 7.334** | | |
| | (0.047) | (0.044) | (0.041) | | |
| $N$ | 8105 | 5957 | 7094 | 4957 | 5967 |
| adj. $R^2$ | 0.391 | 0.391 | 0.404 | | |
| F | 162.678 | 213.116 | 267.908 | | |

Significance levels: †: 10%, ∗: 5%, ∗∗: 1%

Dependent (outcome) variable is `lnfastestSC` for the softcore game mode, and `lnfastestHC` for the hardcore game mode. Standard errors (robust for OLS, weighted for CEM) in parentheses. Control variables omitted, see appendix 6.3 for the full regression outputs.

**Table 2:** *Clan membership benefits*

# 5 Conclusion

We have used online game data to verify that social capital exists and has positive effects on individual performance. We have shown that social capital has different effects, depending on the achievement tier of an individual: poor achievers benefit more than those that are already top performers. This second result may well be specific to our definition of social capital: club membership for easy access to profitable strategies. This has been investigated in the peer effects literature before and suggests that a combination of these two fields may lead to new insights.

While our results are clear-cut and robust, we are limited by the sample self-

| | Softcore game mode | | | Hardcore game mode | | |
|---|---|---|---|---|---|---|
| | low 90% | top 10% | top 5% | low 90% | top 10% | top 5% |
| clan | -0.161** | -0.245* | 0.179 | -0.117** | -0.062 | -0.068 |
| | (0.000) | (0.020) | (0.349) | (0.000) | (0.255) | (0.513) |
| Constant | 6.367** | 6.779** | 6.331** | 7.276** | 7.722** | 7.649** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $N$ | 8987 | 741 | 291 | 7250 | 855 | 427 |
| Adj. $R^2$ | 0.398 | 0.353 | 0.423 | 0.374 | 0.200 | 0.164 |
| F | 234.713 | 38.094 | . | 133.167 | 9.550 | 4.177 |
| Significance levels: †: 10%, ∗: 5%, ∗∗: 1% | | | | | | |

Regressions with robust standard errors, $p$-values in parenthesis. Control variables omitted, see appendix 6.3 for the full regression outputs. The $F$-value for the top 5% softcore regression is missing due to a singularity of the outer-products-of-gradients matrix for this regression. Bootstrapped standard errors do not have this limitation, and the $F$-test (actually $\chi^2$) is again highly significant at less than the 1% level. The results for all regressions with bootstrapped standard error did not change qualitatively.

**Table 3:** *Clan membership benefits by tiers*

selection of our dataset: that of online game players. However, we believe that any selection problems are more than compensated for by the unique structure of our data: We have highly competitive outcome variables, allowing us to accurately describe (game) success and the means to rank these outcomes over the entire game population, not only the sample size.

## References


Adler, P. S., Kwon, S.-W., 2002. Social capital: Prospects for a new concept. The Academy of Management Review 27 (1), pp. 17–40.

Ang, C. S., Zaphiris, P., 2008. Social learning in MMOG: an activity theoretical perspective. Interactive Technology and Smart Education 5 (2), 84–102.

Ang, C. S., Zaphiris, P., 2010. Social roles of players in mmorpg guilds. Information, Communication & Society 13 (4), 592–614.

Arnott, R., Rowse, J., 1987. Peer group effects and educational attainment. Journal of Public Economics 32 (3), 287–305.

Bauernschuster, S., Falck, O., Woessmann, L., May 2011. Surfing alone? The internet and social capital: Evidence from an unforeseeable technological mistake. IZA Discussion Papers 5747, Institute for the Study of Labor (IZA). URL `http://ideas.repec.org/p/iza/izadps/dp5747.html`

Becker, G. S., 1964. Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education, 3rd Edition. University Of Chicago Press.

Blackwell, M., Iacus, S., King, G., Porro, G., December 2009. cem: Coarsened exact matching in stata. Stata Journal 9 (4), 524–546.

Burt, R., 07 2011. Structural holes in virtual worlds. Tech. rep., Chicago Booth. URL `http://faculty.chicagobooth.edu/ronald.burt/research/files/SHVW.pdf`

Durlauf, S. N., 2002. On the empirics of social capital. The Economic Journal 112 (483), F459–F479.

Durlauf, S. N., Fafchamps, M., 2005. Social Capital. In: Aghion, P., Durlauf, S. N. (Eds.), Handbook of Economic Growth. Vol. 1, Part 2. Elsevier, pp. 1639–1699.

Eisenkopf, G., June 2010. Peer effects, motivation, and learning. Economics of Education Review 29 (3), 364–374.

Encinosa, W. E., Gaynor, M., Rebitzer, J. B., 2007. The sociology of groups and the economics of incentives: Theory and evidence on compensation systems. Journal of Economic Behavior & Organization 62 (2), 187–214.

Falk, A., Ichino, A., 2006. Clean evidence on peer effects. Journal of Labor Economics 24 (1), pp. 39–57.

Fiedler, M., Haruvy, E., Li, S. X., 2011. Social distance in a virtual world experiment. Games and Economic Behavior 72 (2), 400–426.

Fnord7, Curd, F., Noire, B., 2006. Kol community survey 3/2006.
URL `http://www.brandybuck.com/fnord/survey/survey_results.html`

Füllbrunn, S., Richwien, K., Sadrieh, A., 2011. Trust and trustworthiness in anonymous virtual worlds. Journal of Media Economics 24 (1), 48–63.

Glaeser, E. L., Laibson, D., Sacerdote, B., 2002. An economic approach to social capital. The Economic Journal 112 (483), F437–F458.

Granovetter, M., 1985. Economic action and social structure: The problem of embeddedness. American Journal of Sociology 91 (3), pp. 481–510.

Groot, W., van den Brink, H. M., van Praag, B. M., 2007. The compensating income variation of social capital. CESifo Working Paper Series 1889, CESifo Group Munich.
URL `http://ideas.repec.org/p/ces/ceswps/_1889.html`

Iacus, S., King, G., Porro, G., June 2008. Matching for causal inference without balance checking. UNIMI – Research Papers in Economics, Business, and Statistics 1073, Universitá degli Studi di Milano.
URL `http://ideas.repec.org/p/bep/unimip/1073.html`

Jang, Y., Ryu, S., 2011. Exploring game experiences and game leadership in massively multiplayer online role-playing games. British Journal of Educational Technology 42 (4), 616–623.

Knack, S., Keefer, P., 1997. Does social capital have an economic payoff? A cross-country investigation. The Quarterly Journal of Economics 112 (4), pp. 1251–1288.

Leuven, E., Sianesi, B., April 2003. Psmatch2: Stata module to perform full mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. Statistical Software Components, Boston College Department of Economics.

Manski, C. F., 1993. Identification of endogenous social effects: The reflection problem. The Review of Economic Studies 60 (3), pp. 531–542.

Mas, A., Moretti, E., 2009. Peers at work. American Economic Review 99 (1), 112–45.

McFadyen, M. A., Cannella, A. A. J., 2004. Social capital and knowledge creation: Diminishing returns of the number and strength of exchange. The Academy of Management Journal 47 (5), pp. 735–746.

Nahapiet, J., Ghoshal, S., 1998. Social capital, intellectual capital, and the organizational advantage. The Academy of Management Review 23 (2), pp. 242–266.

Ogilvie, S., 2004. Guilds, efficiency, and social capital: evidence from German proto-industry. The Economic History Review 57 (2), 286–333.

Papargyris, A., Poulymenakou, A., January 2005. Learning to fly in persistent digital worlds: the case of massively multiplayer online role playing games. SIGGROUP Bull. 25, 41–49.

Robison, L. J., Schmid, A. A., Siles, M. E., 2002. Is social capital really capital? Review of Social Economy 60 (1), 1–21.

Rodrigues, L. C., Mustaro, P. N., 2008. Desenvolvimento de coleta de dados automatizada para análise de redes sociais de comunidades de jogos on-line. In: Workshop on Information Visualization and Analysis in Social Networks – WIVA 2008. pp. 31–40, `http://www.lbd.dcc.ufmg.br/bdbcomp/servlet/Trabalho?id=7598`.

Rosenbaum, P. R., Rubin, D. B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70 (1), pp. 41–55.

Sobel, J., 2002. Can we trust social capital? Journal of Economic Literature 40 (1), 139–154.

Stam, W., Elfring, T., 2008. Entrepreneurial orientation and the performance of high-technology ventures: The moderating role of intra- and extraindustry social capital. Academy of Management Journal 51, 97–111.

Yee, N., 2006. The demographics, motivations and derived experiences of users of massively-multiuser online graphical environments. PRESENCE: Teleoperators and Virtual Environments 15 (3), 309–329.

# 6 Appendix

## 6.1 Full List of Variables

| **Social capital dataset** | |
|---|---|
| lnfastestSC | Logarithm of the time (in turns) of the fastest ascension (normal, "softcore" difficulty mode). Lower is better. |
| lnfastestHC | Same, but "hardcore" difficulty mode. |
| clan | dummy variable; =1 if player is member of a clan |
| playerid | PlayerID/10,000. "Younger" characters have a higher ID. |
| scnp | Total number of ascensions of the difficulty mode normal ("softcore"). |
| scb | Same, but softcore boozetafarian difficulty mode. |
| sct | Same, but softcore teetotaler difficulty mode. |
| sco | Same, but softcore oxygenarian difficulty mode. |
| hcnp | Total number of ascensions of the difficulty mode "hardcore". |
| hcb | Same, but for hardcore boozetafarian difficulty mode. |
| hct | Same, but for hardcore teetotaler difficulty mode. |
| hco | Same, but for hardcore oxygenarian difficulty mode. |
| av_lvl_at_asc | Average character level at ascension. Higher if the character did not ascend immediately. |
| iotm_buy | total number of iotm bought |
| iotm_sell | total number of iotm sold |
| mra_buy | total number of Mr. A bought |
| mra_sell | total number of Mr. A sold |
| wealth | log of (marketvalue of a character's display case +1) |
| expl_error | total number of trades bought at less than 1% of the mean price |
| make_error | total number of trade sold at less than 1% of the mean price |
| perc_speed_sc | percentile ranking of speed over all KoL players (not only the dataset). 0.99 translates to 99% of all players being slower than the character; normal difficulty mode |

*Table 4 – continued on next page*

*Table 4 – continued from previous page*

| | |
|---|---|
| perc_speed_hc | same, but for hardcore difficulty mode |
| perc_speed_hco | same, but for hardcore oxygenarian difficulty mode |
| perc_dedic_sc | percentile ranking of dedication (number of ascensions made). 0.99 translates into 99% of all characters having less ascensions than this character; normal difficulty mode |
| perc_dedic_hc | same, but for hardcore difficulty mode |
| perc_dedic_hco | same, but for hardcore oxygenarian difficulty mode |
| fam_100_runs | total number of ascensions made without switching "familiars", an in-game restiction |
| fam_99_runs | total number of ascensions made with 99% of all turns made with just one "familiar" (a failed 100% familiar run) |
| blackcat_runs | total number of "blackcat" ascensions (a specific familiar) |
| total_bm_runs | total number of "bad moon" ascensions (a specific in-game restriction) |

**Table 4:** *Explanation of variables: social capital dataset*

## 6.2 Full Descriptive Statistics

| | count | mean | sd | min | max |
|---|---|---|---|---|---|
| lnfastestSC | 9728 | 7.971839 | .9446542 | 5.846439 | 12.10249 |
| lnfastestHC | 8105 | 7.773895 | .5646562 | 6.489205 | 11.40935 |
| clan | 29472 | .5137758 | .4998187 | 0 | 1 |
| playerid | 29472 | 8.259113 | 4.420411 | .00013 | 17.92712 |
| scnp | 29472 | 8.12405 | 17.09508 | 0 | 447 |
| scb | 29472 | .2011401 | 1.803461 | 0 | 125 |
| sct | 29472 | .6106474 | 3.241259 | 0 | 173 |
| sco | 29472 | .1050828 | .8759268 | 0 | 81 |

*Table 5 – continued on next page*

*Table 5 – continued from previous page*

| | count | mean | sd | min | max |
|---|---|---|---|---|---|
| hcnp | 29472 | 5.418024 | 13.36753 | 0 | 249 |
| hcb | 29472 | .2707655 | 1.621064 | 0 | 62 |
| hct | 29472 | 1.01442 | 4.577189 | 0 | 107 |
| hco | 29472 | .9235206 | 2.6273 | 0 | 73 |
| av_lvl_at_asc | 12873 | 17.30677 | 4.055816 | 12.9697 | 50 |
| iotm_buy | 29472 | 2.477911 | 11.1951 | 0 | 685 |
| iotm_sell | 29472 | 2.477911 | 16.20814 | 0 | 1634 |
| mra_buy | 29472 | 7.220107 | 49.74611 | 0 | 4233 |
| mra_sell | 29472 | 7.220107 | 57.77676 | 0 | 4229 |
| wealth | 29472 | 8.284141 | 7.760635 | 0 | 25.47765 |
| expl_error | 29472 | .0247014 | .339659 | 0 | 19 |
| make_error | 29472 | .0247014 | .8555947 | 0 | 128 |
| perc_speed_sc | 29472 | .4664745 | .35195 | 0 | 1 |
| perc_speed_hc | 29472 | .2380256 | .3425552 | 0 | 1 |
| perc_speed_hco | 29472 | .1467505 | .2841988 | 0 | 1 |
| perc_dedic_sc | 29472 | .3613947 | .2860202 | 0 | .7757 |
| perc_dedic_hc | 29472 | .1962401 | .2815277 | 0 | .7926 |
| perc_dedic_hco | 29472 | .1095368 | .2158797 | 0 | .6519 |
| fam_100_runs | 25188 | 1.2793 | 5.539057 | 0 | 216 |
| fam_99_runs | 25188 | .8087581 | 2.9575 | 0 | 155 |
| blackcat_runs | 25188 | .0830157 | .2914467 | 0 | 8 |
| total_bm_runs | 25665 | .5971946 | 1.81621 | 0 | 63 |
| *N* | 29472 | | | | |

**Table 5:** *Full descriptive statistics: social capital dataset*

## 6.3 Full Regression Outputs

| | OLS | CEM(1) | CEM(2) |
|---|---|---|---|
| clan | -0.170** | -0.130** | -0.115** |
| | (0.030) | (0.038) | (0.039) |
| playerid | -0.009** | -0.023** | -0.010** |
| | (0.002) | (0.002) | (0.002) |
| scnp | -0.009** | -0.028** | -0.011** |
| | (0.001) | (0.001) | (0.000) |
| scb | -0.004 | -0.003 | 0.002 |
| | (0.003) | (0.007) | (0.003) |
| sct | 0.001 | 0.007† | 0.001 |
| | (0.003) | (0.004) | (0.002) |
| sco | 0.004 | 0.006 | 0.009 |
| | (0.006) | (0.012) | (0.006) |
| hcnp | -0.005** | -0.007** | -0.005** |
| | (0.001) | (0.002) | (0.001) |
| hcb | -0.008 | -0.015 | -0.004 |
| | (0.006) | (0.015) | (0.006) |
| hct | 0.004 | -0.002 | 0.004 |
| | (0.003) | (0.007) | (0.002) |
| hco | -0.025** | -0.022** | -0.024** |
| | (0.004) | (0.007) | (0.006) |
| av_lvl_at_asc | 0.129** | 0.128** | 0.130** |
| | (0.002) | (0.002) | (0.002) |
| iotm_buy | -0.009** | -0.012** | -0.011** |
| | (0.002) | (0.002) | (0.002) |
| iotm_sell | 0.004** | 0.003* | 0.004** |
| | (0.002) | (0.001) | (0.001) |
| mra_buy | 0.000 | 0.001 | 0.000 |
| | (0.001) | (0.001) | (0.001) |
| mra_sell | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) |
| wealth | -0.013** | -0.010** | -0.013** |
| | (0.001) | (0.001) | (0.001) |

*Table 6 – continued on next page*

*Table 6 – continued from previous page*

| | | | |
|---|---|---|---|
| expl_error | -0.010 | 0.042 | -0.023 |
| | (0.055) | (0.052) | (0.051) |
| make_error | 0.003 | 0.036 | 0.004 |
| | (0.021) | (0.027) | (0.028) |
| _cons | 6.311** | 6.581** | 6.264** |
| | (0.050) | (0.058) | (0.057) |
| $N$ | 9728 | 7611 | 7966 |
| adj. $R^2$ | 0.423 | 0.451 | 0.444 |
| F | 324.160 | 348.064 | 354.747 |

Robust (OLS) and weighted (CEM) standard errors in parentheses

Significance levels: †: 10%, ∗: 5%, ∗∗: 1%

**Table 6:** *Full matching results – SC*

| | OLS | CEM(1) | CEM(2) |
|---|---|---|---|
| clan | -0.107** | -0.127** | -0.145** |
| | (0.023) | (0.027) | (0.027) |
| playerid_scaled | -0.027** | -0.030** | -0.027** |
| | (0.001) | (0.001) | (0.001) |
| scnp | -0.002** | -0.003** | -0.002** |
| | (0.000) | (0.001) | (0.000) |
| scb | -0.003† | 0.018† | -0.004 |
| | (0.002) | (0.010) | (0.002) |
| sct | 0.000 | 0.004 | 0.000 |
| | (0.001) | (0.004) | (0.002) |
| sco | -0.004 | 0.001 | -0.006 |
| | (0.004) | (0.012) | (0.006) |
| hcnp | -0.012** | -0.022** | -0.012** |
| | (0.001) | (0.001) | (0.000) |
| hcb | 0.000 | 0.004 | 0.001 |
| | (0.002) | (0.003) | (0.002) |

*Table 7 – continued on next page*

*Table 7 – continued from previous page*

| | | | |
|---|---|---|---|
| hct | 0.002* | 0.008** | 0.001† |
| | (0.001) | (0.002) | (0.001) |
| hco | -0.012** | -0.005* | -0.012** |
| | (0.001) | (0.002) | (0.001) |
| av_lvl_at_asc | 0.068** | 0.069** | 0.070** |
| | (0.003) | (0.002) | (0.002) |
| iotm_buy | -0.005** | -0.006** | -0.004** |
| | (0.001) | (0.001) | (0.001) |
| iotm_sell | 0.001† | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) |
| mra_buy | 0.000 | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) |
| mra_sell | -0.000 | 0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) |
| wealth | -0.008** | -0.008** | -0.008** |
| | (0.001) | (0.001) | (0.001) |
| expl_error | -0.067* | -0.064 | -0.073† |
| | (0.033) | (0.045) | (0.039) |
| make_error | 0.001 | -0.007 | 0.002 |
| | (0.010) | (0.035) | (0.018) |
| _cons | 7.313** | 7.437** | 7.334** |
| | (0.047) | (0.044) | (0.041) |
| $N$ | 8105 | 5957 | 7094 |
| adj. $R^2$ | 0.391 | 0.391 | 0.404 |
| F | 162.678 | 213.116 | 267.908 |

Robust (OLS) and weighted (CEM) standard errors in parentheses

Significance levels: †: 10%, ∗: 5%, ∗∗: 1%

**Table 7:** *Full matching results – HC*

| | PSM(1) | | PSM(2) | |
|---|---|---|---|---|
| Probit | Coef. | Std. Err. | Coef. | Std. Err. |
| playerid | -.0106179 | .0084309 | -.0042825 | .0081022 |
| perc_speed_sc | -.0136034 | .2054286 | .0932932 | .2006953 |
| perc_speed_hc | -.3336597 | .3453695 | -.6214494$^{\dagger}$ | .3550535 |
| perc_speed_hco | .2592761 | .3730311 | .348874 | .3677189 |
| perc_dedic_sc | -.1855526 | .2499896 | -.2438112 | .2376803 |
| perc_dedic_hc | .5910778 | .3902732 | .741332$^{\dagger}$ | .4020526 |
| perc_dedic_hco | -.5350588 | .4289758 | -.6150255 | .4308055 |
| fam_100_runs | .0089293 | .0098673 | .010658 | .0085484 |
| fam_99_runs | .008951 | .0161748 | .0081442 | .0133395 |
| blackcat_runs | .2671068$^{*}$ | .1415088 | .2856545$^{*}$ | .1388029 |
| total_bm_runs | .0316246 | .0282015 | -.0088598 | .0256295 |
| scnp | -.0116946$^{**}$ | .0042498 | -.0003509 | .0027905 |
| scb | .0253718 | .0359444 | -.0085273 | .0080395 |
| sct | -.0055159 | .0114501 | -.0042582 | .0087108 |
| sco | .007707 | .0427417 | .0239054 | .0373043 |
| hcnp | -.0361515$^{**}$ | .0081993 | -.0036792 | .0041949 |
| hcb | -.0468176 | .0411337 | -.0032118 | .0235995 |
| hct | .0149173 | .0209887 | .0107331 | .0119325 |
| hco | .0560491$^{\dagger}$ | .0328293 | .0228571 | .0275545 |
| av_lvl_at_asc | .0287342$^{**}$ | .0082621 | .0348144$^{**}$ | .0082166 |
| iotm_buy | .0164384 | .0103517 | .0129841 | .0099005 |
| iotm_sell | -.008124 | .007245 | -.0071633 | .0078792 |
| mra_buy | .0011533 | .0034582 | .0018191 | .0034922 |
| mra_sell | .000839 | .0027327 | .0008258 | .0026645 |
| wealth | .0247786$^{**}$ | .0041432 | .0235579$^{**}$ | .0040702 |
| _cons | 1.271916$^{**}$ | .2140999 | .9700662$^{**}$ | .1972589 |

Significance levels: †: 10%, $*$: 5%, $**$: 1%

**Table 8:** *Binary probit estimation results for selection into a clan – SC*

| | PSM(1) | | PSM(2) | |
|---|---|---|---|---|
| Probit | Coef. | Std. Err. | Coef. | Std. Err. |
| playerid | -.0072628 | .0094303 | -.0003654 | .0088637 |
| perc_speed_sc | -.1496262 | .2310245 | -.0783274 | .2198329 |
| perc_speed_hc | -.1211604 | .274399 | -.2000719 | .2698747 |
| perc_speed_hco | .1333147 | .2491472 | .1679245 | .240284 |
| perc_dedic_sc | -.2539446 | .298187 | -.1781519 | .2596588 |
| perc_dedic_hc | .0814826 | .3343824 | .2397798 | .3237825 |
| perc_dedic_hco | -.1313882 | .3060429 | -.2602211 | .2932379 |
| fam_100_runs | .0062038 | .0107359 | .0110183 | .0092206 |
| fam_99_runs | .032208$^{\dagger}$ | .0179762 | .0239838 | .0150358 |
| blackcat_runs | .1745574$^{\dagger}$ | .1040524 | .1806088$^{\dagger}$ | .0991239 |
| total_bm_runs | .0499998$^{**}$ | .019988 | .0381264$^{*}$ | .0183356 |
| scnp | -.0244876$^{**}$ | .0061643 | -.0030959 | .0025681 |
| scb | -.0210561 | .0491076 | -.0100428 | .0086359 |
| sct | .0117992 | .0211624 | .0040927 | .0124239 |
| sco | -.0292393 | .0343698 | -.0270994 | .0267573 |
| hcnp | -.0151043$^{**}$ | .0044187 | -.0014544 | .0032164 |
| hcb | .0059599 | .0155779 | .0037563 | .0148089 |
| hct | -.0034344 | .0068231 | -.0014776 | .005222 |
| hco | -.0005331 | .0104347 | -.0026513 | .0088566 |
| av_lvl_at_asc | .0534958$^{**}$ | .0128651 | .0559079$^{**}$ | .0123541 |
| iotm_buy | .0179058 | .0155435 | .0227087 | .0143479 |
| iotm_sell | .0162897 | .0168613 | .0109213 | .0137911 |
| mra_buy | .0066063 | .0066871 | .0079513 | .0056175 |
| mra_sell | -.0006889 | .002902 | -.0029242$^{\dagger}$ | .0015838 |
| wealth | .0186882$^{**}$ | .0045829 | .0187212$^{**}$ | .0044023 |
| _cons | 1.070296$^{**}$ | .2848485 | .6673916$^{**}$ | .2490205 |

Significance levels: †: 10%, $*$: 5%, $**$: 1%

**Table 9:** *Binary probit estimation results for selection into a clan – HC*

| | hardcore game mode | | | softcore game mode | | |
|---|---|---|---|---|---|---|
| | low 90% | top 10% | top 5% | low 90% | top 10% | top 5% |
| clan | -0.117** | -0.062 | -0.068 | -0.161** | -0.245* | 0.179 |
| | (0.000) | (0.255) | (0.513) | (0.000) | (0.020) | (0.349) |
| playerid | -0.025** | -0.019** | -0.007 | -0.012** | 0.024** | 0.024† |
| | (0.000) | (0.000) | (0.330) | (0.000) | (0.004) | (0.077) |
| scnp | -0.002** | -0.002 | 0.004 | -0.008** | -0.001 | -0.141 |
| | (0.000) | (0.233) | (0.362) | (0.000) | (0.974) | (0.246) |
| scb | -0.003* | -0.016 | -0.040 | -0.004 | 0.114 | 0.849** |
| | (0.044) | (0.517) | (0.480) | (0.247) | (0.383) | (0.000) |
| sct | -0.000 | -0.003 | -0.002 | 0.001 | -0.077 | -0.200 |
| | (0.867) | (0.729) | (0.795) | (0.823) | (0.469) | (0.367) |
| sco | -0.004 | -0.034 | -0.033 | 0.004 | 0.256 | 2.254** |
| | (0.365) | (0.137) | (0.491) | (0.537) | (0.265) | (0.000) |
| hcnp | -0.011** | -0.023 | -0.020 | -0.005** | 0.003 | -0.007 |
| | (0.000) | (0.189) | (0.645) | (0.000) | (0.805) | (0.688) |
| hcb | -0.000 | 0.071 | 0.098 | -0.008 | -0.045 | -0.030 |
| | (0.968) | (0.219) | (0.481) | (0.195) | (0.128) | (0.370) |
| hct | 0.001† | 0.007 | 0.033 | 0.004 | -0.002 | 0.003 |
| | (0.065) | (0.834) | (0.680) | (0.160) | (0.855) | (0.912) |
| hco | -0.011** | -0.041* | -0.035 | -0.026** | -0.017 | -0.009 |
| | (0.000) | (0.018) | (0.340) | (0.000) | (0.544) | (0.744) |
| avg asc lvl | 0.066** | 0.060** | 0.059** | 0.124** | 0.110** | 0.126** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| iotm_buy | -0.004** | -0.003 | 0.003 | -0.009** | -0.010 | 0.001 |
| | (0.000) | (0.264) | (0.751) | (0.000) | (0.333) | (0.918) |
| iotm_sell | 0.001† | -0.005 | -0.013 | 0.004** | -0.006 | -0.000 |
| | (0.058) | (0.427) | (0.158) | (0.006) | (0.391) | (0.984) |
| mra_buy | 0.000 | 0.002 | 0.007 | 0.000 | 0.009† | 0.005 |
| | (0.568) | (0.357) | (0.365) | (0.560) | (0.079) | (0.493) |
| mra_sell | -0.000 | -0.000 | 0.002 | 0.000 | -0.004 | -0.004 |
| | (0.468) | (0.760) | (0.292) | (0.949) | (0.322) | (0.356) |
| wealth | -0.008** | -0.007** | -0.006† | -0.013** | -0.011* | -0.024** |
| | (0.000) | (0.004) | (0.096) | (0.000) | (0.013) | (0.002) |
| expl err | -0.063† | -0.174† | -0.150 | -0.015 | -0.124 | -0.575** |

*Table 10 – continued on next page*

*Table 10 – continued from previous page*

| | | | | | | |
|---|---|---|---|---|---|---|
| | (0.062) | (0.078) | (0.101) | (0.785) | (0.614) | (0.000) |
| make err | 0.005 | -0.089 | -0.028 | 0.007 | -0.079 | -0.200 |
| | (0.580) | (0.498) | (0.802) | (0.744) | (0.644) | (0.348) |
| Constant | 7.276** | 7.722** | 7.649** | 6.367** | 6.779** | 6.331** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| $N$ | 7250 | 855 | 427 | 8987 | 741 | 291 |
| Adj. $R^2$ | 0.374 | 0.200 | 0.164 | 0.398 | 0.353 | 0.423 |
| F | 133.167 | 9.550 | 4.177 | 234.713 | 38.094 | . |

Significance levels: †: 10%, ∗: 5%, ∗∗: 1%

**Table 10:** *Clan membership benefits by tiers – full output*

Regressions with robust standard errors, $p$-values in parenthesis. The $F$-value for the top 5% softcore regression is missing due to a singularity of the outer-products-of-gradients matrix for this regression. Bootstrapped standard errors do not have this limitation, and the $F$-test (actually $\chi^2$) is again highly significant at less than the 1% level. The results for all regressions with bootstrapped standard error did not change qualitatively.