Three Essays on the Economics of Online Games

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Christoph Safferling
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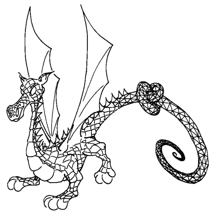
Prüfungskommission:
Prof. Dr. Heinrich Ursprung (Vorsitzender), Universität Konstanz
Prof. Dr. Oliver Fabel (1. Referent), Universität Wien
Prof. Dr. Gerald Eisenkopf (2. Referent), Universität Konstanz



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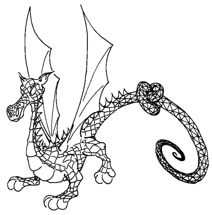

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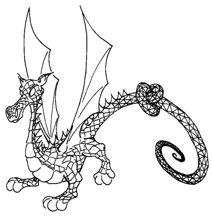

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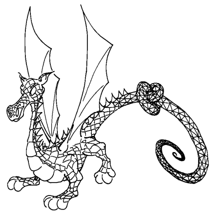

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Summary

This dissertation is a collection of three stand-alone research papers written as part of the *Quantitative Economics and Finance* doctoral program at the University of Konstanz, Germany, during my time as a research assistant there and at the University of Vienna, Austria.

In his article published in *Science*, Bainbridge (2007) argues that virtual worlds and online game worlds offer "great potential as sites for research in the social, behavioral, and economic sciences, as well as in human-centered computer science." This dissertation follows his proposed research agenda into online games. Readily available online data, observable behaviours, and accessible statistics on online goods all result in a wealth of data to be used by scientists. But is this game data a reliable source for economic analysis? Games follow different rules than real life. Thus, can "enjoyment" data be as economically relevant as "business" data? Chesney et al. (2009) validate virtual (non-game) world data. In this dissertation I argue that specifically online *game* data is feasible for use in general economic

research, and provide research results based on this novel type of data.

Chapter 1 is based on the research paper *Economics in the Kingdom of Loathing: Analysis of Virtual Market Data*, joint work with Aaron Lowen of Grand Valley State University. We collect market transaction data from the online game *The Kingdom of Loathing* (KoL) and additional data from external game resource sites. In this chapter, we validate the data for general economic research. We show that actions of agents in the online game marketplace lead to an efficient market outcome: the prices of perfectly substitutable goods are identical. We additionally find a novel way to calculate information diffusion with the help of edits on game-specific wiki sites, a proxy for public knowledge. Finally, we show that human capital endowments of players affect their market decisions in predictable ways.

Chapter 2 builds on the research paper *Social Capital and Online Games*. The concept of social capital, similar to that of human capital, is by now well-entrenched in economics. While human capital represents *what* you know, social capital equates to *whom* you know. An individual's social ties, contacts, and access to friends and colleagues are a factor of production. Thus, rational investment decisions into social capital are profitable, just as for "normal" capital. Durlauf (2002) lists problems with the existing empirical literature and proposes to use experimental data for clean results. Using the quasi-experimental KoL data, this chapter cleanly verifies that social capital exists in online games: players entering a "clan", a voluntary group of players, exhibit increased game performances. Furthermore, an argument from the Peer Effects literature is imported: top performers do not benefit as much as low performers from access to this social capital.

Chapter 3 is founded on the research paper *Dopaminergic Reward Prediction Error and Online Games*. Dopamine is a neurotransmitter. It is set free in the brain and is crucial in driving choice and learning via "reward" levels. In this chapter, KoL trading data is used to test whether revealed behaviour of players follows the

prediction of the Dopamine Reward Prediction Error (DRPE) hypothesis (Caplin et al., 2010). Some of the KoL trades are finalised at prices that are obviously too low. The DRPE hypothesis predicts a high dopaminergic release at these trades. A player will then form an addiction, returning to the marketplace ever trying to repeat such a favourable trade. The data supports this prediction: players finalise significantly more trades in the month after they have exploited such a favourable trade, compared to the month before the incident. However, in contrast to the prediction of DRPE, the magnitude of this favourable trade incident has a negative, rather than a positive influence on the overall effect.

Zusammenfassung

Diese Doktorarbeit ist eine Sammlung von drei eigenständigen Forschungsarbeiten, welche als Teil des Promotionsprogrammes *Quantitative Economics and Finance* der Universität Konstanz während meiner Zeit als wissenschaftlicher Mitarbeiter an den Universitäten Konstanz und Wien entstanden sind.

In seinem Artikel, veröffentlicht in *Science*, argumentiert Bainbridge (2007) dass virtuelle Welten und Onlinespiele "great potential as sites for research in the social, behavioral, and economic sciences, as well as in human-centered computer science" (eigene Übersetzung: grosses Potential als Wirkungsstätte für Sozial-, Verhaltens-, und ökonomischer Forschung haben, wie auch für die Human-Informatik) bieten. Diese Dissertation folgt diesem Forschungsaufruf in die Welt der Onlinespiele. Onlinespiele liefern einfach zugängliche Daten, beobachtbare Verhaltensweisen und zugängliche Statistiken über Onlinegüter, und damit wertvolle Daten zur wissenschaftlichen Analyse. Aber sind diese Spieldaten verwertbar für eine ökonomische Analyse? Spiele folgen anderen Regeln als im realen Leben: Sind "Vergnügungsdaten” ökonomisch genauso relevant wie “Wirtschaftsdaten”? Chesney et al. (2009) validieren Daten einer virtuellen nicht-spiel Welt. In dieser Dissertation vertrete ich den Standpunkt dass im Besonderen Online*spiele*daten zulässig für ökonomische Analysen sind und präsentiere eigene Forschungsarbeiten auf Basis dieser Daten.

Kapitel 1 basiert auf der Forschungsarbeit *Economics in the Kingdom of Loathing: Analysis of Virtual Market Data*, welche zusammen mit Aaron Lowen von der Grand Valley State University verfasst wurde. Wir generieren einen Datensatz mit allen Markttransaktionen des Onlinespiels *The Kingdom of Loathing* (KoL) und zusätzliche Daten von externen Informationsseiten über das Spiel. In diesen Kapitel validieren wir die Daten für weitere generelle ökonomische Analysen. Wir zeigen, dass das Verhalten der Akteure in einem Onlinespielmarkt zu einem effizienten Marktergebnis führt: Diese Preise für vollständige Substitute sind identisch. Des Weiteren präsentieren wir eine neue Methode Informationsdiffusion zu messen, mithilfe der Anzahl der Bearbeitungen von Artikeln auf einer spiel-spezifischen Wikiseite als Proxy für öffentliches Wissen. Abschließend stellen wir dar, wie die Humankapitalausstattungen der Spieler sich auf ihre Marketentscheidungen in vorhersagbarer Weise auswirken.

Kapitel 2 beruht auf der Forschungsarbeit *Social Capital and Online Games*. Das Konzept des Sozialkapitals ist, ähnlich wie das des Humankapitals, bereits in der ökonomischen Theorie verankert. Während Humankapital verkörpert *was* man weiß, entspricht Sozialkapital *wen* man kennt. Es ist die Vorstellung, dass die sozialen Bekanntschaften, Kontakte und Beziehungen ein Produktionsfaktor sind. Daher sind rationale Investitionen in Sozialkapital profitabel, wie auch in “normales” Kapital. Durlauf (2002) identifiziert die Probleme der existierenden empirischen Sozialkapitalliteratur und schlägt vor Experimentaldaten zu nutzen, um den statistischen Problemen ausweichen zu können. Unter Nutzung solcher quasi-Experimentaldaten aus KoL verifiziert dieses Kapitel, dass Sozialkapital in Onlinespielen existiert: Mitgliedschaft in einem "clan", einem freiwilligen Zusammenschluss von Spielern, wirkt sich positiv auf das Spielergebnis der Spieler aus. Des Weiteren wird ein Ergebnis aus der Peer Effects Literatur übernommen und bestätigt: Spitzenspieler profitieren nicht im selben Maße von ihrem Sozialkapital wie schlechtere Spieler.

Kapital 3 entstand aus der Forschungsarbeit *Dopamine Reward Prediction Error and Online Games*. Dopamine ist ein Neurotransmitter, der im Gehirn freigesetzt wird und ausschlaggebend ist für Verhalten und Lerneffekte durch das Freisetzen von "Glück", Belohnung ("reward"). In diesem Kapitel werden KoL Handelstransaktionsdaten verwendet, um die Vorhersagen der Dopamine Reward Error Prediction (DRPE) Hypothese (Caplin et al., 2010) bezüglich des beobachtbaren Verhaltens der Spieler zu untersuchen. Einige der Handelstransaktionen über den KoL Marktplatz werden eindeutig zu niedrigen Preisen abgeschlossen. Nach der DRPE Hypothese führen diese Transaktionen zu einer hohen Dopaminausschüttung beim Spieler. Dieser entwickelt dann eine Abhängigkeit, eine Sucht nach der Dopaminausschüttung, und wird verstärkt am Markt handeln, beständig auf der Suche nach einer vergleichbaren Transaktion. Die Ergebnisse unterstützen diese Hypothese: Spieler, die eine solch vorteilhafte Transaktion abgeschlossen haben, handeln im folgenden Monat signifikant häufiger als im Monat davor. Entgegen der Vorhersagen der DRPE Hypothese jedoch hat die Größenordnung dieser vorteilhaften Handelstransaktion einen negativen, keinen positiven Effekt insgesamt.

1 Economics in the Kingdom of Loathing: Analysis of Virtual Market Data

1.1 Introduction

We use data from an online game economy to examine trade and other market behaviours, and to analyse different impacts on information diffusion as well as trading decisions. Online game markets provide feasible economic data on virtual game goods and therefore lead to new and interesting ways to analyse old economic questions. In particular, we provide a new way to compute information diffusion and moderators thereof by using game-wiki data, and show that players substitute game-specific human capital with more general human capital ("market-savvyness"), to pursue their goals.

Our motivating question is whether players in online economies behave as they would in real-world economies. In other words, does online game market behaviour follow the same rules as real market behaviour? Real-world economic activities are undertaken to create more, and more enjoyable, leisure time (Oswald, 1997). Thus, agents pursue economic activities to be able to play[1]: to be able to ignore real-world economics. We examine whether an online game environment, with users entering to *not* apply real-world economics, still provides valid economic data to test real-world behaviours.

Bainbridge (2007) argues that online worlds offer many new venues for research. Castronova et al. (2009) and Williams et al. (2011) created online games specifically to conduct field experiments. Others use existing online (non-game) worlds as means of communication and have found valid responses (Chesney et al., 2009).

Online games are no niche market. There are 46 million players of online games,

[1]Happiness economics sees economic activities only as a means to an end: ultimately, an individual wants to become "happier" (maximise utility). For recent literature, see for example Tella et al. (2003), Frey and Stutzer (2008), and Konow and Earley (2008).

with a revenue of 3.8 billion US$ in 2009 for the United States alone.[2] *World of Warcraft*, the most well-known online game, has over 11 million subscribers[3], each contributing between 12.99$ and 14.99$ per month, for total revenues of over 1.5 billion US$. Social games specialist Zynga (creator of *Farmville* on Facebook) has reported[4] a revenue for 2010 of 597 million US$ to the SEC.

Online games provide economies, marketplaces, trades, and currencies just like the real world, and face the same fundamental challenges. For example, the Korean supreme court has ruled[5] that virtual and real money are legally exchangeable. Crime (e.g. theft) in online worlds and cyberspace is prosecuted just like in traditional legal settings. The German police in the city of Bochum[6] are searching for stolen "Phoenix boots" and seven million "yang" that were reported stolen from a citizen's online game character. A Dutch court has convicted[7] two teenagers of stealing virtual items in an online game and sentenced them to community service.

McGonigal (2011) suggests that online games provide insight to the real world, and vice-versa. Easy access to online non-game data has inspired its use as valid quasi-experimental data in many cases already: McCarthy (2010) follows up online search keywords to monitor suicide risks of the US population, and Ginsberg et al. (2009) to follow influenza epidemics. Markey and Markey (2010) use internet pornography traffic intensity to predict testosterone levels in users. Askitas and Zimmermann (2009) use google search trends to predict unemployment rates – a

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

[3] http://us.blizzard.com/en-us/company/press/pressreleases.html?081121, accessed March 15, 2010

[4] http://www.sec.gov/Archives/edgar/data/1439404/000119312511180285/ds1.htm, accessed August 5, 2010

[5] http://www.massively.com/2010/01/13/korea-rules-that-virtual-currencies-can-be-exchanged-for-real-mo/, accessed March 15, 2010

[6] http://www.polizei-nrw.de/presseportal/behoerden/bochum/article/meldung-090128-131735-55-117.html (official press release, in German), accessed March 15, 2010

[7] http://www.theregister.co.uk/2008/10/22/teens_sentenced_for_runescape_item_theft/, accessed March 15, 2010

faster and less expensive method than the well-established labour market surveys. Hitsch et al. (2010) use data from online dating agencies to test matching theories and equilibria.

Using game data is thus an extension of this trend. It has already been used in the natural sciences: Cooper et al. (2010) created a multiplayer "shooter" game, where players would walk in a world full of protein strings while shooting/killing anomalies (bad proteins). The best players are actually better at finding these anomalies than the algorithms used by the scientists.

The remainder of this chapter is organised as follows: section 1.2 provides an overview of the relevant literature and constructs the hypothesis. Section 1.3 describes the data used, with section 1.4 presenting our results. Finally, section 1.5 concludes.

1.2 Related Literature and Hypothesises

1.2.1 Related Literature

We do not examine interactions between real and virtual worlds. Rather, we show that online game markets follow predictions from standard economic theory, and can thus be interpreted and exploited as quasi-field experiment data.

Online games are just that; games. There is no inherent (real-world) risk to in-game actions, and an individual's income will not usually depend on his in-game choices. Games are generally played by users for recreation, enjoyment, and fun. Nevertheless, economic research has begun to see games as a valid tool in an economist's toolbox. We argue that games can be used as a controlled field experiment, if done correctly. Harrison and List (2004) classify six areas in which field experiments can provide insights: the subject pool, the information subjects bring with them to the experiment, the commodities used in the experiment, the task or the rules applied in the experiment, the stakes, and the environment used. For our dataset and analysis, we can contribute at least partly to any of these six fields, with the first two (subject pool and information these bring with them) and fourth (task and rules of the experiment) field being those with the highest real-world relevance.

A number of researchers have already used the internet and virtual worlds as settings for experiments. For example, Drehmann et al. (2005) set up experiments to test the theory of informational cascades in financial markets. Setting up a (closed) online game environment specifically as a field experiment is fairly new: two examples are Castronova et al. (2009) and Williams et al. (2011). Castronova et al. (2009) set up two versions of an online game, identical but for a price difference for a single good. Players have a marginal rate of substitution for in-game goods, and the authors were able to compute an elasticity of demand. Williams et al. (2011) set up a game world with the explicit goal to use it as an experiment. They report the structure of the experiment, and the data. Their results suggest that games can be used as a controlled experiment by examining the effects of specific, controlled changes in the game world.

The social sciences have been studying virtual worlds for some time. Legal concerns were among the first addressed: Lee (2005) examines the legal boundaries of online worlds. Psychological and sociological papers mainly focused on the *player* behind the online games (see Cole and Griffiths (2007), Hendaoui et al. (2006), Whang and Chang (2004), and Williams et al. (2009)). Medical papers are often concerned with the addiction effects of online gaming (for an overview see Kuss and Griffiths (2011)). Economic research has been conducted by Castronova (2006b) and Castronova and Falk (2009) who consider the value of games as field experiments, Castronova (2006a) analysing the effects of real-money trades in online games, and

Lehdonvirta (2005) examining how economic modelling can explain online game behaviour. For an overview of research on online worlds, see Messinger et al. (2009).

1.2.2 Online Game Markets

Some research finds behaviour in online worlds follows real-world patterns. Burt (2011) argues that virtual worlds have "enormous potential" as a research venue, especially for social capital research. He raises the concern of validity, and confirms that virtual worlds provide valid results for two aspects of social capital: higher achievement of network brokers, and higher trust between members of the same network. Chesney et al. (2009) conducted a series of standard economic experiments in the online world *Second Life* to test whether virtual worlds can be used in experimental settings, generally validating the use of online environments as an experimental tool. For instance, playing Ultimatum Games (Güth et al., 1982) via an online world, Chesney et al. do not find significant differences from the usual experimental results.

Other research using *Second Life* for experimental data finds online players behaving differently from their real-world counterparts: trust levels and investments are lower than in comparable real-world experiments (Fiedler et al., 2011; Füllbrunn et al., 2011), individuals invest on poorly-informed decisions and stock markets are not efficient (Bloomfield and Cho, 2011), more experienced traders follow less fundamental value investment strategies (Fiedler, 2011), and communication over virtual world channels increases transferred assets relative to real-world experiments (Fiedler and Haruvy, 2009).

Previous empiric findings are thus mixed, even on the same experimental population (users of the online world *Second Life*). We nevertheless believe that *game* data in particular can provide valuable insights on economic aspects that are otherwise difficult or impossible to observe. *Second Life* is not a game, no particularly competitive environment. Its users are thus not induced to behave "optimally". Before using our game data for any empirical research, we must first validate it for economic analysis: are online game markets (as opposed to online world markets) *efficient*?

Hypothesis 1.1: *(Efficiency of online game markets) Perfectly substitutable goods show identical price patterns.*

1.2.3 Goods in Online Games

Next we move into the markets themselves. Markets trade on information (French and Roll, 1986; Cutler et al., 1989), with the quality of the information affecting the price finding mechanism (Veronesi, 2000). If hypothesis 1 holds, game markets should possess the same feature.

Any relevant information must reach the players to be of use. Online game data is the closest one can get to informationally efficient markets (Grossman and Stieglitz, 1980), as the players are a closely-knit community with low costs of communicating online. Diffusion theory has been analysed by many fields, be they social or natural sciences. For an overview see Chatman (1986). In economics, marketing research has analysed the effects of new product diffusion (Mahajan et al., 1990). Abrahamson and Rosenkopf (1997) analyse the effects of (social) networks creating a "bandwagon effect" (multiplicator) of diffusion. De Valck et al. (2009) show "word of mouse" (the online analogy to word of mouth) having a large effect on information diffusion in online interactions: Social networks allow a faster diffusion of information. Bolton et al. (2004) analyse this in online markets: a higher buyer's or seller's reputation[8] leads to higher transaction efficiency. Gruhl et al. (2004) applies the concept of diffusion to online blogs, while Prince and Simon (2009) analyse the effect the internet has had on diffusion times of new products. Pástor and Veronesi (2009)

[8] Dellarocas and Wood (2008) provide estimates for this using eBay buyer/seller reputations.

have tied asset prices to technological diffusion. We follow Ghossoub and Beladi (2011), who argue that the stock prices represent the differences and severity of information diffusion for each stock.

New items introduced differ regarding their "strategic complexity"; their actual use is not always immediately obvious. Typically, virtual world mechanics are not fully explained initially, so informed decisions are not possible immediately. A crucial advantage of online game goods is that their qualities and complexity can (ex post) be known with certainty: computer game goods are represented in numbers.

Specifically, we analyse data from a specialised game-wiki. We compute the number of edits, and the days it took to get a finalised version for each game-good article.[9] The longer it takes for an article on the wiki to be updated, and the more updates are needed, the more difficult it was for the community to "grasp" the quality of the respective item. The higher the number of edits made on a wiki article, the more complex the good, with many attempts needed to incorporate all information and finalise the article. In contrast, a high number of relatively early edits indicates a well-researched game good. The uncertainty regarding the good was addressed early in its lifetime and has since then entered the public knowledge domain.

Hypothesis 1.2: *(Goods in online game markets) Complex goods take longer to be understood by agents and affect the game market.*

1.2.4 Agents in Online Games

Given that different goods have different complexities, differing beliefs on these complexities will lead to imperfect information, and thus arbitrage possibilities. A trader believes he has an informational advantage and will buy an item he thinks

[9]Like the more well-known Wikipedia, a wiki site allows all users to edit all articles. Each edit is logged publicly, exposing the entire "creation history" of the article.

will be profitable. Jensen (1982) is the seminal paper on adoption of innovations.[10] Wozniak (1987) shows that human capital drives this adoption of innovations. In our case, an "innovation" is a new game good, forcing players to adapt playing and trading strategies.

Broadly speaking, there are two types of players. *Content players*, with the goal of "beating" the in-game content. They value acquiring in-game skill to become faster, "better", players. The second type, *market players* are more interested in the game market.

Content players have more game-specific human capital and do not need to enter the market to buy an in-game advantage through in-game goods. In contrast, players endowed with relatively less game-specific human capital, and those that are relatively more interested in the game markets, use the general human capital "market savvyness" to purchase in-game advantages. In effect, market players substitute their lack of game-specific human capital with more a general human capital. This leads us to our third hypothesis, analysing the participants of online game markets:

> **Hypothesis 1.3:** *(Agents in game world markets) (Game-specific) human capital will determine whether a player will act (trade) on an innovation.*

1.3 The Data

Our data is derived from the online game called *The Kingdom of Loathing* (henceforth referred to as KoL). KoL is an internet, browser-based, multiplayer[11], game. Fig-

[10] The adoption of technology is similar to the adoption of innovations. Griliches (1957) is an early example, discussing the adoption of hybrid corn in several US states. A whole literature on the Technology Adaption Model (TAM) has evolved; for an introduction and critical analysis see Legris et al. (2003) while King and He (2006) provide a meta-analysis of over 70 TAM studies.

[11] Massively Multiplayer Online games, or MMO games

- the player creates a character
- the nominal purpose of the game is completing quests
- after completing the primary storyline, players have earned the accomplishment of "ascension", allowing them to restart the game with a more powerful character
- each ascension can be done in one of eight difficulty modes: normal, or difficult (called "hardcore"), each with three (optional) restrictions
- in-game accomplishments are publicly displayed on "leaderboards", the most prominent being the speed of the ascension

Figure 1.1: *The Kingdom at a glance*

ure 1.1 provides the game basics, with a more detailed description in appendix 1.A.1.

To follow our analysis, only two aspects of the game need to be known: *ascension* and *donation items*. First, the concept of *ascension*: a player who has nominally finished the game can choose to re-start at any time. One of the goals of the game is to finish an ascension in the shortest time possible, and leaderboards computed by the game automatically list players who have accomplished these feats.

The second aspect is a *donation item*: the game itself is free to use, but donating[12] 10 US$ will generate an item[13] called a "Mr. Accessory" (henceforth "Mr. A") that is given to the donator's character. A Mr. A is a fairly powerful item and can be bought or sold in the in-game marketplace. Additionally, a Mr. A can be swapped for a limited-time to obtain the "item of the month" (henceforth "iotm") on a one-to-one basis. These iotm are powerful items in their own right, but also valued investments due to their limited window of purchase of only one month. Every month, a new

[12] "Donation" is the term used by the game designers. Economically speaking, it is of course *buying* a Mr. A for $10.

[13] Goods in online games, and in KoL specifically, are commonly called "items".

iotm is introduced, and a Mr. A can only be swapped for a specific iotm in its active month. Once a new iotm appears, the total supply of the previous iotm is fixed – no more iotm of that type can be generated by players.

Each iotm's purpose or "power" is only hinted at initially, leaving players to speculate, hypothesise and test to uncover the details. With a new iotm entering the game world every month, the players are forced to formulate new, or adapt existing, playing strategies. Some items have a higher "strategic complexity" than others; Some iotm substitute for, or complement, existing iotm, while others introduce entirely new game effects.

KoL includes an in-game marketplace in which nearly all of the in-game items can be traded. Our data comprises all transactions made in this marketplace from April 2006 to October 2008. We can identify individual buyers and sellers over time. The KoL community increased from roughly 850,000[14] in April 2006 to nearly 1.8 million in October 2008. The total number of stores (players can own a "store" and sell items in the game) more than doubled from 48,000 in April 2006 to 115,000 in October 2008.

While we have data on the *characters*[15] in the game, we know little about the specific *player* behind each character. The demographics of other MMOs are surveyed by Hursthouse (2005), Yee (2006), and Meredith et al. (2009). The KoL community conducted a survey of the players in 2006, with the results presented in Fnord7 et al. (2006). Randomly selecting 3,000 active players (those logged into the game in the past 14 days) and achieving a response rate of roughly one third, the results are close to being representative of the playerbase. 76% reported to be male, compared to 85.4% reported by Yee. The players are young, 35% are younger than 18, 48% between 18 and 29 years of age, and 17% are aged 30 or older. This is roughly in line

[14] Own data. Numbers collected on April 4th, 2006: 857,723 total players and 48,046 total mall stores. Numbers for October 1st, 2008: 1,797,178 total players and 115,506 total mall stores.

[15] *avatar* is the word commonly used in the literature

with the average age of 26.57 years stated by Yee. 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 consumes a large part of the players' leisure time, 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 smaller than in other games: Hursthouse and Yee report more than 20 and 22 hours played per week, respectively. One third of the players stated that they had donated for a Mr. A at least once, while two thirds said they had not yet donated.

We chose to limit our analysis to donation items: Mr. A and iotm. These are the most prominent "investment items", and have relatively liquid markets. Any player trading these items signals a commitment to play the game (it is otherwise free to play). Thus, restricting the sample to trades in donation items eliminates players that never actively engaged in the game. Also, if a character has owned a donation item once, the character will be flagged as *non-delete*. This character will not be deleted from the game servers for inactivity. Limiting the dataset to trades (and thus traders) of donation items guarantees that we can use all publicly available information on the respective characters, as they are not deleted.

From this basic marketplace data, we derive three datasets (one for each hypothesis to test) by combining them with external data from game community sites.

	count	mean	sd	min	max
mra	937	4482303	313737.9	3995966	5830000
activeiotm	937	4475119	344549.7	2656562	6094343
N	937				

Table 1.1: *Descriptive statistics for dataset 1: Donation items*

The first hypothesis concerns the prices of fully substitutable items. During the active month, a Mr. A can be traded on a one-to-one basis for an iotm. Hence, for the respective active month, an iotm and a Mr. A are perfect substitutes – a player can either buy a Mr. A and trade that for the current iotm, or buy the iotm directly off the marketplace. We therefore compute two time series out of our data: a time series of Mr. A prices, and a time series of active iotm prices. Table 1.1 summarises the dataset. To construct equi-distant prices for time series analysis, we aggregate our intraday data at the daily level. The results presented below are based on the mean of the intraday prices. The complete dataset was trimmed: we drop the top and bottom 1% of each price timeseries to exclude outliers.[16] Missing dates in our trade data were added from the "Items of Loathing"[17] database, where available.

	count	mean	sd	min	max
editsday1	27	16.22222	10.88165	1	38
edit_mth_minus	27	9.333333	10.55025	0	46
edits	27	40.81481	24.8287	11	95
delay	27	.4074074	.9306433	-1	3
meandiff	27	787148.8	920305.6	-397427	3154461
sddiff	27	272194.6	386079.6	-123140.1	1587914
iotm_nobs_dif	27	45.81481	114.5496	-228	276
mra_mean_t	27	4456555	303512.6	4037180	5506366
iotm_sd_t	27	363309.9	292256.7	109677.5	1408041
iotm_sd_t1	27	560239.2	404127.3	110360.1	1860447
familiar	27	.4814815	.5091751	0	1
skill	27	.1111111	.3202563	0	1
famequip	27	.0740741	.2668803	0	1
mydate	27	17370.7	255.9788	16922	17776
N	27				

Table 1.2: *Descriptive statistics for dataset 2: Item data*

For the second hypothesis, which examines information diffusion and goods in

[16]We have also used medians as means of aggregation, and winsorised rather than trimmed the data. The resulting four datasets were used as robustness checks: aggregated by means and by medians, each set trimmed or winsorised. The results did not change qualitatively.

[17]`http://www.itemsofloathing.com` (accessed March 15, 2010), a player-run, non-official (daily) price database.

online worlds, we use all data on each individual iotm from our intraday marketplace data. We combine this data with information on each individual iotm collected from the KoLwiki.[18] Table 1.2 presents the descriptive statistics of the items data.

The KoLwiki is the leading community-made game reference site: There are nearly 19,000 registered users on the wiki, and a total of over 300 million page views[19], making the KoLwiki the largest known reference site for KoL. Just like the more well-known Wikipedia, the KoLwiki is a wiki site. All users can edit pages on the wiki, so (economically speaking) the articles contain the accumulated public knowledge on the game mechanisms.

We use three different proxies for informational complexity of an iotm. The first is the *difference in means*: we calculate the mean price of the iotm in the active month, and its mean price in the first month following – the first month the marketprice "floated" (when it is no longer possible to arbitrage between Mr. A and the iotm). More valuable items (items with less uncertainty regarding its functions) should show a larger increase in price difference. Our second proxy is the *difference in standard deviations*, again between the active month of the iotm and the first floating month. If the item is sufficiently complex to understand, the market price should be more volatile in adjusting to the free-floating regime, and the difference in standard deviations should be larger. Our third proxy is the *difference in actual trade occurrences*, again between the active iotm month, and the first floating month. If the item is more complex, a risk-averse and uninformed player might not have swapped the iotm in the active month, and will need to fall back to buying from the market in the next month. A more complex item should have a larger difference in the number of trades.

The third hypothesis concerns traders. From the marketplace data we obtain a

[18] `http://kol.coldfront.net/thekolwiki/index.php/Main_Page`, accessed March 15, 2010

[19] Numbers from March 2010; see `http://kol.coldfront.net/thekolwiki/index.php/Special:Statistics`, accessed March 15, 2010

listing of all *traders* of donation items, and the amount of trades each made of every item. We combine this data with collected data on the characters from two other sources: the Kingdom of Loathing Database (koldb)[20], a database that presents the ascension history of each character of the game, and the Display Case Database (DCdb)[21], a site presenting the publicly displayed possessions of players. Table 1.3 shows the descriptive statistics of this third dataset.

	count	mean	sd	min	max
perc_speed_sc	28534	.4818089	.3472065	0	1
perc_speed_hc	26874	.2610364	.3502595	0	1
perc_speed_hco	26224	.1649265	.2962689	0	1
perc_dedic_sc	28534	.3732749	.2829526	0	.7757
perc_dedic_hc	26874	.2152113	.2878147	0	.7926
perc_dedic_hco	26224	.1231036	.2251806	0	.6519
mra_buy	29472	7.220107	49.74611	0	4233
iotm_buy	29472	2.477911	11.1951	0	685
mra_sell	29472	7.220107	57.77676	0	4229
iotm_sell	29472	2.477911	16.20814	0	1634
playerid	29472	825911.3	442041.1	13	1792712
clan_dummy	29472	.5137758	.4998187	0	1
sc_asc	28534	8.391112	17.30919	0	447
hc_asc	26874	5.941802	13.88718	0	249
fastest_sc	9728	5265.214	9613.392	346	180320
fastest_hc	8105	2937.581	3317.145	658	90161
av_lvl_at_asc	12873	17.30677	4.055816	12.9697	50
wealth	29472	8.284141	7.760635	0	25.47765
exploited_trade_error	29472	.0134365	.1151364	0	1
made_trade_error	29472	.0128936	.1128175	0	1
total_exploited_errors	29472	.0247014	.339659	0	19
total_made_errors	29472	.0247014	.8555947	0	128
mra_trader	29472	.2515608	.4339175	0	1
iotm_trader	29472	.2507125	.4334307	0	1
N	29472				

Table 1.3: *Descriptive statistics for dataset 3: Player data*

[20] `http://www.koldb.com`, accessed March 15, 2010
[21] `http://www.jickenwings.org/collections/index.cgi`, accessed March 15, 2010

Koldb provides information on the playing habits of each player. Once a player has finished all "quests" (essentially sub-chapters of the complete game), he can ascend and start the game over, keeping one in-game skill from his current ascension. Thus, his next ascension should be faster and/or easier. There is a large community dedicated to finishing an ascension as fast as possible – trying to find the "optimal" way to finish the game. A player with more ascensions should be able to judge item values faster and more easily. Koldb reports the number and the type of ascensions of each player, and also how fast the player is relative to the others. A percentile speed value ranks the players from slowest to fastest: 0.99 means that 99% of all players are slower than the character in question. In the same way, the percentile dedication ranks players from those with the least ascensions of a difficulty type to those with the most. All rankings are computed for the three main difficulty modes of the game, as players self-select into playing these difficulty modes. Also from koldb, we construct a dummy variable if the player is a member of an in-game "clan", a voluntary association of players.

There are a number of variables that indicate a player putting more value on market activities than game-content itself. One is playerid as proxy for character age. "Older" characters have a lower id number. Younger characters entered the game later. They were not focal when first marketing the game: gameplay (ascension) does not have such a large appeal to them relative to the players that entered the game in its early stages. A second variable is the dummy variable of having exploited a trade mistake. This points to a player spending considerable time in the market, "hawking" to quickly grab an opportunity before others do so. Lastly, game time spent not actually playing the main game. The average level at ascension is our proxy for this: the higher this level, the more the character will have done outside of the main game before he ascends and re-starts the game. This indicates a player who spends more time in the game after their earliest possible ascension date to participate in the marketplace.

We do not have direct information on the wealth of a character, as this information is not public. However, the DCdb allows us to compute a proxy of a character's wealth. Players can (and most do) create a display case to exhibit any number of items. We compute the market value of this display case as a proxy for character wealth. Appendix 1.A.2 lists and briefly explains all variables of our three datasets used in our regressions.

1.4 Results

1.4.1 Hypothesis 1: Online Game Markets

The first hypothesis concerns the efficiency of the in-game market. The Kingdom of Loathing introduces a new iotm every month. In each month, the data indicates a Mr. A and the currently active iotm are perfect substitutes.

To illustrate this relationship, figure 1.2 shows the prices of a Mr. A (blue) and the June 2008 iotm (red). They match nearly perfectly, until the end of the month, when the new iotm for July 2008 arrives (green). The price for the June iotm spikes[22] as the supply is now fixed and the market adjusts the price. The Mr. A price now follows the July iotm price, again nearly perfectly.

Figure 1.3 shows the price for Mr. A and the price of the current active iotm over the course of our dataset. They appear to follow the same pattern. To be sure, we test for co-integration: an underlying equation that drives the two time series. Not only should the two prices be identical, but they should simultaneously move in identical directions as well.

[22] For a real-world analogy, Ursprung and Wiermann (2011) provide evidence that the price for art pieces spikes on the day of the artist's death – an artist's supply of art is then credibly fixed.

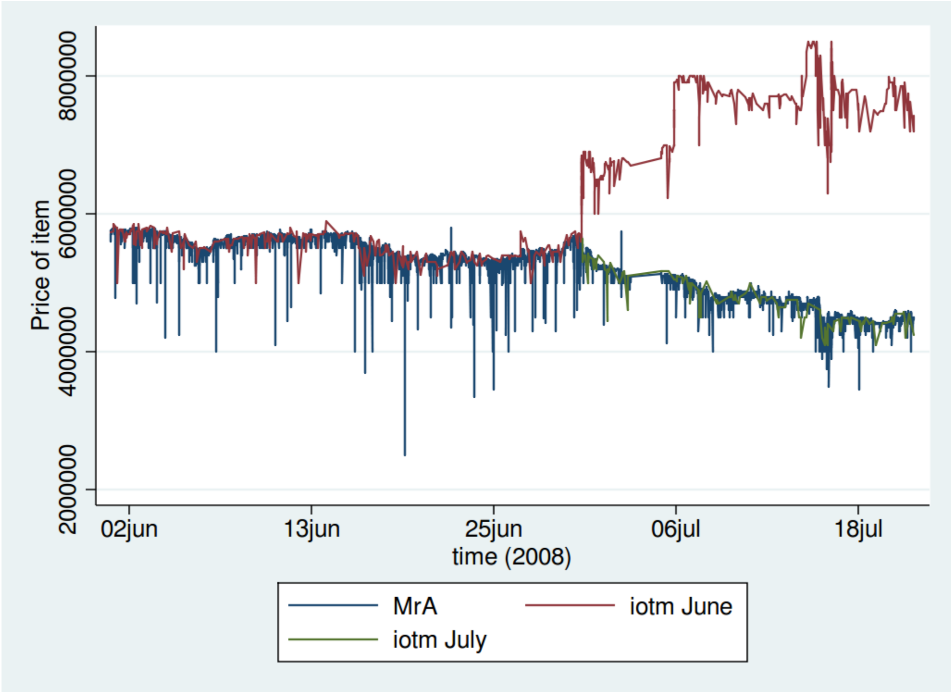

Figure 1.2: *MrA and iotm prices, June/July 2008*

A prerequisite of the co-integration test is a unit root in at least one of the time series. Our unit root test results[23] are presented in table 1.4. The results cannot reject the possibility of a unit root for the Mr. A and iotm time series with an advanced Dickey-Fuller (DF) test, at the 5% level. The Phillips-Perron (PP) test always rejects the null of a unit root for the iotm time series, and yields mixed results for the Mr. A series. While we are concerned with the results of the iotm time series, we do not place too much weight on them. We construct this iotm series by merging the trades of all iotm in their respective first months; hence it actually lines up 27 different time series. As months change, data problems may occur[24], potentially skewing the unit

[23]The lag length was taken from the usual lag-order selection statistics; For the Mr. A, the Likelihood-Ratio (LR), Hannan and Quinn information criterion (HQIC), and Schwarz's Bayesian information criterion (SBIC) test return one lag, the final prediction error (FPE) and Akaike's information criterion (AIC) eight. For the iotm, SBIC returns 5 lags, HQIC and LR 6 lags, FPE and AIC return 7 lags.

[24]For instance, some iotm may appear on the market a few days late, see our analysis for the second hypothesis.

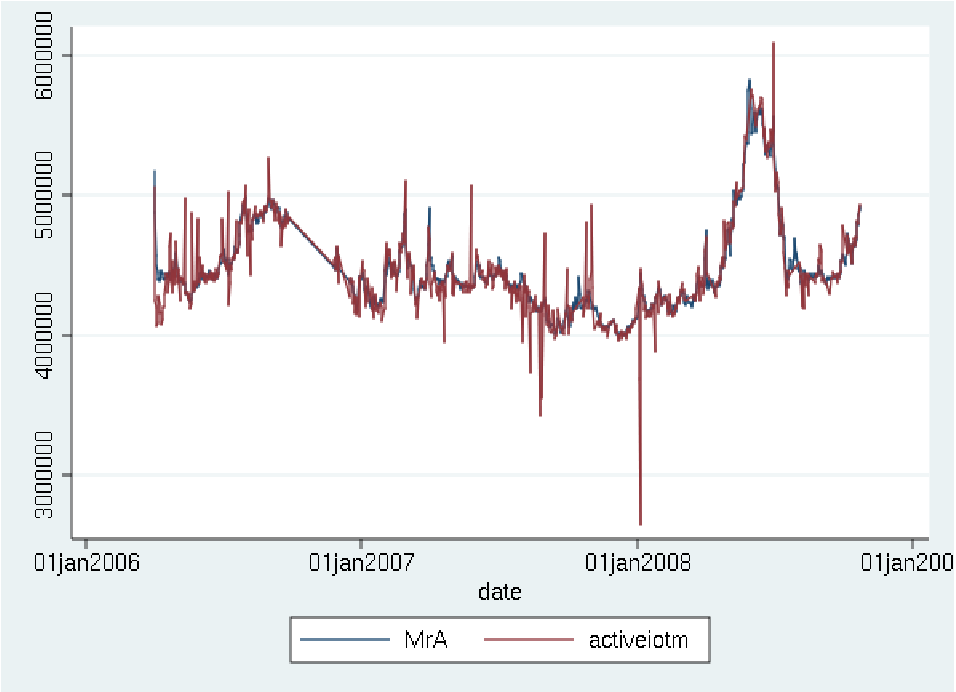

Figure 1.3: *MrA and current active iotm prices*

root test results. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is a third unit root test. It differs from the usual DF and PP tests by setting the null hypothesis as stationarity: *absence* of a unit root. All KPSS tests clearly reject the null of stationarity at the 1% level. Jointly, all three tests indicate a unit root in both time series, more strongly for the Mr. A time series. This allows us to continue with the co-integration tests.

We use the Johansen test for co-integration (Johansen, 1988, 1991), which reveals a rank of one, and thus a single co-integrating equation. The trace statistic[25] at the first rank is 4.945, with a 5% critical value of 9.42.

To further illustrate the single co-integrating equation property, we fit a bivariate vector-error-correction-model (VECM). From the two time series we generate a

[25] We use one lag and specify a restricted constant for the Johanson test, thus allowing for a constant in the co-integrating equations. Results with specifying a restricted trend, and with differing lag values, all stay under the 5% and 1% critical value.

adv. Dickey-Fuller				**Phillips-Perron**			
MrA		iotm		MrA		iotm	
lags=1		lags=5					
-2.637†	(0.085)	-2.484	(0.119)	-2.894*	(0.046)	-5.643**	(0.00)
-2.655	(0.254)	-2.490	(0.332)	-2.916	(0.157)	-5.669**	(0.00)
lags=8		lags=6		**KPSS**			
-2.130	(0.232)	-2.329	(0.162)	MrA		iotm	
-2.137	(0.525)	-2.336	(0.413)	1.108**	(Schw.)	1.084**	(Schw.)
		lags=7		0.391**	(N-W)	0.387**	(N-W)
		-2.272	(0.180)				
		-2.278	(0.445)				
Significance levels: †: 10%, $*$: 5%, $**$: 1%							

Unit root tests; The null of the DF and PP tests is the time series contains a unit root, the null of KPSS is stationarity (no unit root). MacKinnon's approximated p-values in parenthesis. The first line is the value for the test with no trend specified, the second line specifies a trend. For the KPSS tests, the first line uses lags derived from the Schwert criterion, the second line Newey-West optimal bandwidth lags. The critical values for the KPSS tests are 0.216 at the 1% level, for all our tests.

Table 1.4: *Unit Root test results*

predicted co-integrating equation. If the two time series are indeed equal, the VECM equation should revert back to zero. The predicted co-integrating equation in figure 1.4 shows no trend: large shocks are apparent (and especially in the early dates of the dataset there are deviations from the zero), but the equation quickly reverts to zero every time.

We conclude that the two time series follow an identical pattern: if the price for a Mr. A increases, so does the price for the current iotm, and vice-versa. Thus, we conclude: the in-game market is *efficient*.

1.4.2 Hypothesis 2: Goods in Online Games

Next, our second hypothesis. Compared to conventional market data, our dataset possesses the advantage that all goods characteristics are represented by numbers

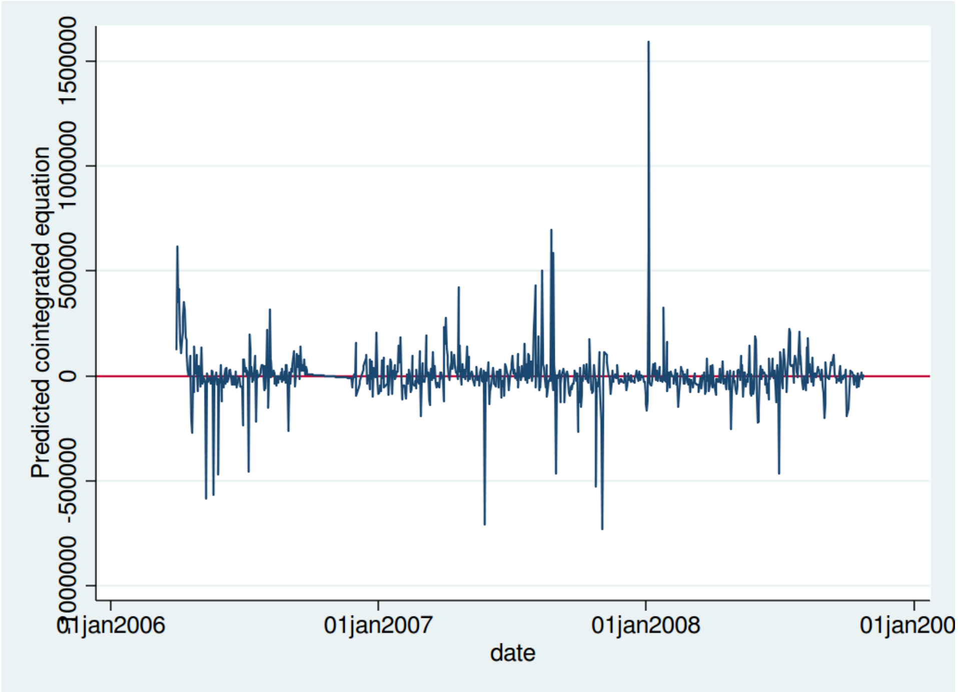

Figure 1.4: *Predicted cointegration of a bivariate VECM of Mr. A and active iotm prices*

– as computer game items are essentially just that: a collection of statistics. Each iotm is connected to an article on the KoLwiki, from which we can take further information on the respective item. The information being published on a wiki is public and the wiki structure allows measuring of how quickly this information generated (i.e., how fast it enters public knowledge).

Table 1.5 shows the results of our regressions (with robust standard errors) using each of our three proxies for information diffusion. Our results show that number of edits on the wiki article of an iotm influences all three proxies for information diffusion, while sometimes only significant at the 10% level. Nevertheless, with only 27 observations, the clarity of these findings is rather surprising.

For the difference in means, a larger difference implies that the iotm is seen as more valuable by the market. Our variable of interest, edits, shows a positive effect: the price difference increases with more wiki edits. Simply put, a more researched item fetches a better price. The two largest control variable effects are the price of a Mr. A in the active month of an iotm, and "skill", a dummy that denotes an iotm that can be used in all difficulty modes. These effects are not surprising, as a perceived-valuable iotm will already drive up the Mr. A prices in the active month, as the supply of Mr. A is drained to be swapped for the iotm.

The difference in standard deviations is less clear-cut. It is interesting that the total number of edits has no effect. Rather, only the number of edits that were made in the first month (net of the first day) matter. The edits made in the first month of the iotm (the active month) have a negative effect on the difference in standard deviations: more edits on the first day reflect more uncertainty of the item, but more edits in the first month point to a well-researched item. Many updates in the first month mean that the item receive thorough testing by the community. Control variable analysis shows a larger difference in means leading to a larger difference in standard deviations: higher prices also lead to more uncertainty in the marketplace if the evaluation was indeed correct. Also not surprising, "skill" type iotm, those valuable to all players regardless of difficulty mode of the game, leads to a lower difference. These items are generally seen as a safe bet, so there is little risk associated with them.

Finally, we focus on the difference in the number of trades. Effects of the edit variables are significantly positive for the total edits, and significantly negative for the edits in the first month and first day. This suggests that total edits reflect an item being more complex, so players do not buy until more details are discovered: Relatively more trades are made in the second month. Edits in the first month, and especially on the first day, on the other hand represent a dedication of the community to discover precisely these details: more edits during the first month reassure the market that the information is disclosed and allow it relatively more trades in the first compared to the second month.

Examining control variables, skill is no longer is significant. It drives the number of trades in *both* individual months, but taking differences this cancels out. Skill-type items are universally seen as very valuable. There are more trades in the active *and* more trades in the floating month. Thus there is no reason for agents to buy more of these items in the second compared to the first month; they buy in both months. As expected, a higher standard deviation in the floating month leads to a higher difference in trades. More volatility in the floating month means that a complex item is not well understood in the first month. Players are buying the iotm later, when its usefulness is uncovered.

Summarising, we use wiki data to measure different setups of information diffusion in a market. Early wiki edits point to a less complex, better-researched item, reducing uncertainty in the market. Relatively more late edits indicate a complex, not well-understood item, with correspondingly higher uncertainty in the market.

1.4.3 Hypothesis 3: Agents in Online Games

For the third hypothesis, we examine the *agents* in these game markets: the players themselves. Specifically, we use Heckman selection regressions (Heckman, 1976) to analyse which players decide to enter the market for donation items. The results are shown in tables 1.6 (Heckman selection) and 1.7 (Heckman regression). We discuss two different markets: the market for Mr. A and the market for iotm.

First, we examine the selection equations. Character wealth does not influence the decision to enter the Mr. A market. However, it increases the probability of entering the iotm market. Buying an iotm will benefit the character immediately, and richer players can afford to buy this in-game advantage with in-game currency. They do not, however, need to enter the Mr. A market, as an iotm can be bought directly.

The percentiles of speed and dedication at varying game difficulty modes are particularly interesting. All speed percentiles show a negative effect on entering the iotm market (second column). All dedication percentiles exhibit a positive effect on this decision. Content players (those who complete ascensions quickly) with more game-specific human capital are less likely, while more dedicated players (those who complete many ascensions) are more likely to enter the iotm market.

At the same time, there are no corresponding effects in the Mr. A market. However, variables corresponding to the different type of player are significant: a player who puts weight on market activities rather than ascension. From our discussion in section 1.3, these are playerid as a proxy for younger characters, exploiting a trade mistake, and the average level at ascension as proxy for time spent not playing the main game. Thus, more market-driven players enter the Mr. A market.

The differences between the factors that influence the decision to enter either of the two markets reflect the differing properties of the items. An iotm is immediately beneficial to a character wanting to play the game's non-market content. Yet, only a maximum of one of each iotm is needed. Players that primarily play the game content, and the market only casually, are the prime drivers of this market. A Mr. A, rather, is a stock item. It can be swapped for later iotm; rational investment decisions are profitable. Players who primarily trade and secondarily play the game content enter this market.

Heckman regressions results in table 1.7 reconfirm our reasoning. For the iotm market, the most important variable that pushes the number of iotm bought (apart from participation in Mr. A market) is clan membership. A clan is a voluntary grouping of like-minded individuals that can share information and strategies.[26] Clan membership is a co-ordination device: members notice that they are missing a certain iotm for a particular game strategy, and buy it on the market. Character wealth and the number of exploited mistakes do not have any effect on the amount of iotm bought: demand is set by need rather than by arbitrage. Regarding the

[26]This points to some social capital effects in addition to our human capital arguments.

number of Mr. A bought, clan membership has no effect. Rather, wealth and our arbitrage proxy are highly significant.

A Mr. A is a normal good in the classic economic sense: the richer the character, the higher their demand for Mr. A. Speculators also drive a large portion of trades, market activity increases with more exploited trade mistakes. In contrast, activity in the iotm does not influence the demand for Mr. A. This finding reinforces that a Mr. A is used for investment and hedging purposes.

1.5 Conclusion

We investigate the validity of data from an online computer game market economy for use in general economic research. We have three primary results. First, in-game markets are efficient. Second, more complex goods have higher uncertainty, and longer time, in the price-finding mechanism of the market. Finally, how human capital endowment affects the market decisions of the agents in predictable ways.

Our work is of interest to firms that use a similar "donation"-based[27] business model, potential designers of virtual worlds, and designers of quasi-field experiments such as those by Castronova et al. (2009), Williams et al. (2011), and designers of economic experiments using online worlds as the locales for their experiments such as Fiedler et al. (2011). Online games offers a novel market environment that offer new insights on the subject pool, the information and capital subjects bring with them, and tasks and rules of the markets themselves. Using online game worlds is not dissimilar to early attempts at laboratory experiments and the "cigarette economies" of POW camps (Radford, 1945), and will lead to new perspective and results in the field of economics.

[27]The established term in the profession is "F2P": free to play

	differences in:		
OLS	**means**	**std deviations**	**trades**
editsday1	-51592.5	989.2	-10.70**
	(36794.4)	(19170.5)	(3.107)
edits1stmth_lessday1	-50530.0	-28250.9†	-6.647†
	(32238.9)	(14472.4)	(3.639)
edits	55899.9*	10638.8	6.027*
	(24209.8)	(12985.2)	(2.069)
delay	-11925.8	-80130.7	-29.39**
	(201381.0)	(72488.5)	(9.852)
mra_mean_activemonth	0.915*	-0.297	-0.00000687
	(0.377)	(0.177)	(0.0000310)
iotm_sd_activemonth	-0.915	—	
	(0.535)		
diff_mean	—	0.297*	—
		(0.119)	
iotm_sd_floatingmonth	—	—	0.000137*
			(0.0000481)
familiar	388242.9	83246.1	-24.69
	(572699.5)	(152973.3)	(38.16)
skill	1293596.2*	-525238.8**	36.27
	(513680.7)	(166793.4)	(36.73)
famequip	-85773.0	-159517.4	106.2†
	(486249.0)	(197571.4)	(57.61)
timetrend	436.8	383.6	-0.0480
	(782.9)	(231.2)	(0.0545)
Intercept	-11837380.1	-5426528.6	834.3
	(13158810.7)	(4539117.4)	(974.7)
N	27	27	27
R^2	0.444	0.620	0.652
Adjusted R^2	0.096	0.383	0.434
$F_{(10,16)}$	5.298	5.165	17.24
Significance levels: †: 10%, ∗: 5%, ∗∗: 1%			

Regressing the three different proxies for information diffusion on number of edits for the respective wiki articles. Robust standard errors in parenthesis.

Table 1.5: *Explaining information diffusion*

Heckman selection	**mra_buy**	**iotm_buy**
perc_speed_sc	0.070	-0.749**
	(0.087)	(0.141)
perc_speed_hc	-0.224	-0.603**
	(0.186)	(0.175)
perc_speed_hco	0.054	-0.424**
	(0.103)	(0.148)
perc_dedic_sc	-0.127	0.354*
	(0.113)	(0.166)
perc_dedic_hc	0.262	0.710**
	(0.209)	(0.200)
perc_dedic_hco	-0.095	0.679**
	(0.118)	(0.179)
playerid	0.000**	0.000
	(0.000)	(0.000)
fastest_sc	0.000	0.000
	(0.000)	(0.000)
fastest_hc	0.000	0.000**
	(0.000)	(0.000)
clan	0.109†	-0.142
	(0.066)	(0.125)
av_lvl_at_ascension	0.025**	0.010
	(0.008)	(0.009)
sc_asc	0.003**	0.001
	(0.001)	(0.001)
hc_asc	0.013*	0.003
	(0.006)	(0.002)
exploited_trade_mistake	1.761**	0.549*
	(0.560)	(0.238)
made_trade_mistake	0.542	0.126
	(1.060)	(0.175)
iotm_trader	0.354**	–
	(0.121)	
mra_trader	–	0.652**
		(0.046)
wealth	0.004	0.020**
	(0.003)	(0.003)
Intercept	-0.585**	0.166
	(0.147)	(0.203)

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

Heckman Selection Equations with robust standard errors in parenthesis.

Table 1.6: *Heckman selection output*

Heckman regression	**mra_buy**	**iotm_buy**
iotm_buy	-0.072	–
	(0.170)	
mra_buy	–	0.101^{**}
		(0.030)
iotm_sell	$0.891^{\dagger}$	–
	(0.460)	
mra_sell	–	0.049^{*}
		(0.019)
playerid	0.000^{**}	0.000
	(0.000)	(0.000)
clan	4.756	1.255^{**}
	(2.899)	(0.428)
fastest_sc	0.000	0.000
	(0.000)	(0.000)
fastest_hc	0.000	0.000
	(0.000)	(0.000)
sc_asc	0.157^{**}	0.023^{*}
	(0.039)	(0.011)
hc_asc	-0.085	0.013
	(0.052)	(0.014)
av_lvl_at_ascension	1.090^{**}	$0.125^{\dagger}$
	(0.336)	(0.064)
total_made_mistake	1.577	0.780
	(2.258)	(0.857)
total_exploited_mistake	40.180^{**}	4.095
	(14.038)	(3.739)
wealth	0.268^{*}	-0.004
	(0.105)	(0.037)
Intercept	-27.240^{**}	1.121
	(6.491)	(1.237)
N	4767	4767
Log-likelihood	-18421.445	-14273.324
$\chi^2_{(12)}$	1301.739	117.446
athrho	4.162^{**}	-0.230^{**}
	(0.938)	(0.037)
lnsigma	3.820^{**}	2.373^{**}
	(0.138)	(0.138)

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

Heckman Regression results with robust standard errors in parenthesis.

Table 1.7: *Heckman regression output*

References of Chapter 1

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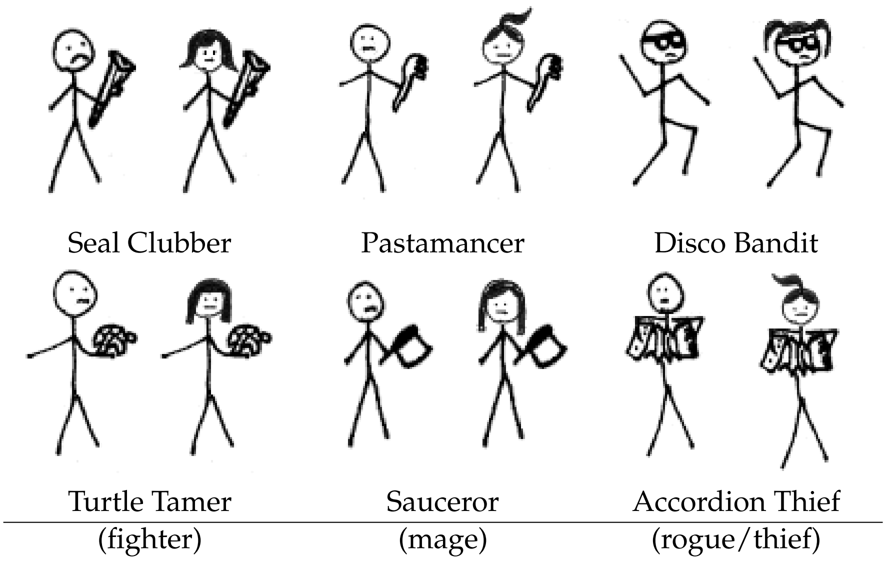

Figure 1.5: *Classes in the Kingdom of Loathing*

1.A Appendix

1.A.1 The Kingdom in Detail

The Kingdom of Loathing is an online, browser-based game that spoofs traditional MMORPGs such as Everquest or World of Warcraft. A player generates a character (avatar) by choosing from one of six character classes (the classes are visualised in figure 1.5). The character can then complete a series of quests and puzzles until the final quest – defeating the *Naughty Sorceress* – is finished. At that point he can opt to stay in the game to accomplish high-level feats or more effectively earn in-game currency and tradeable items, or *ascend*, essentially restarting the in-game content. Upon ascension, the player may choose a new character class (or the same again), and choses one class-specific skill he can permanently keep. So, in general, a character with more ascensions will have more skills to use and will be able to complete an “ascension” (a full game of the main quest) faster than a character with fewer ascensions (and thus fewer skills).

1.A.2 Full List of Variables

First dataset: Donation items	
mra	time series of Mr. A prices
activeiotm	time series of each currently active iotm prices

Table 1.8: *Variable list and explanation for dataset 1: Donation items*

Second dataset: Item data	
editsday1	iotm wiki article edits on the first day of the item
edit_mth_minus	iotm wiki article edits on the first month (net of first day) of the item
edits	iotm wiki article total edits
delay	delay in days of the iotm release (0 = released on time on the first day of a month)
mra_mean_t	mean price of a Mr. A in the active month of an iotm
iotm_sd_t	standard deviation of the price of an iotm in its active month
iotm_sd_t1	standard deviation of the price of an iotm in its first floating month
meandiff	difference in means between the first floating and the active month of an iotm
sddiff	(iotm_sd_t - iotm_sd_t1)
iotm_nobs_dif	difference in trade occurances between the first floating and the active month of an iotm
familiar	dummy variable = 1 if the item is a "familiar"
skill	dummy variable = 1 if the item is a "skill" (usable in all difficulty modes)
famequip	dummy variable = 1 if the item is a "familiar equipment"
mydate	time variable to catch bias due to increasing players of KoL

Table 1.9: *Variable list and explanation for dataset 2: Item data*

Third dataset: Player data	
perc_speed_sc	percentile ranking of speed over all KoL players (not only the dataset). 0.99 means 99% of all players are slower than this character; normal difficulty mode
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 means 99% of all players have 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
fastest_sc	turns of the fastest game (normal, "softcore" difficulty mode)
fastest_hc	turns of the fastest game ("hardcore" difficulty mode)
mra_buy	total number of Mr. A bought
iotm_buy	total number of iotm bought
mra_sell	total number of Mr. A sold
iotm_sell	total number of iotm sold
playerid	unique player ID (smaller = created earlier)
clan	dummy variable = 1 if character is member of a clan
sc_asc	total number of normal ("softcore") ascensions made
hc_asc	total number of hardcore ascensions made
av_lvl_at_asc	average character level at ascension (higher if character did not ascend immediately)
wealth	log of (market value of a character's display case +1)

Table 1.10 – continued on next page

Table 1.10 – continued from previous page

exploited_trade_error	dummy variable = 1 if player bought an item at less than 10% of the mean market value
made_trade_error	dummy variable = 1 if player sold an item at less than 10% of the mean market value
total_exploited_errors	total number of trades bought at less than 10% market value
total_made_errors	total number of trades sold at less than 10% market value
mra_trader	dummy variable = 1 if bought and sold at least one Mr. A
iotm_trader	dummy variable = 1 if bought and sold at least one iotm

Table 1.10: *Variable list and explanation for dataset 3: Player data*

2 Social Capital in Online Games

2.1 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

[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

of "virtual" social capital that enhances individual performance.

The remainder of this chapter is structured as follows: Section 2.2 gives an overview of relevant literature and constructs the hypothesis. Section 2.3 presents the data and methology, and section 2.4 the results. Finally, section 2.5 concludes.

2.2 On Social Capital and Online Worlds

2.2.1 Related Literature

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.

[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).

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.

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.

2.2.2 Hypothesis 1: Social Capital

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

2.2.3 Hypothesis 2: Peer Effects

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

[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).

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

2.3 Data and Methodology

2.3.1 Dataset

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

[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.

	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 2.A.2.

Table 2.1: *Descriptive statistics for the social capital dataset*

number of characteristics and achievements of all KoL characters. Table 2.1 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 `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 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 2.A.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

[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.

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.

2.3.2 Methodology

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

[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 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.

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 estimation; 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

[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.

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 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.

2.4 Results

All regression models[16] provide clear-cut results supporting our first hypothesis. The results for clan membership are listed in Table 2.2. 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

[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).

[16] Full regression tables are in appendix 2.A.3.

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.

	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 2.A.3 for the full regression outputs.

Table 2.2: *Clan membership benefits*

Subsequently we focus on the second hypothesis. We examine individuals within different tiers of achievement. Table 2.3 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

	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 2.A.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 χ^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 2.3: *Clan membership benefits by tiers*

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).

2.5 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-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.

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2.A Appendix

2.A.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

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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
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 2.4: *Explanation of variables: social capital dataset*

2.A.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

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	count	mean	sd	min	max
sco	29472	.1050828	.8759268	0	81
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 2.5: *Full descriptive statistics: social capital dataset*

2.A.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**

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	(0.001)	(0.001)	(0.001)
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 2.6: *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

Table 2.7 – continued on next page

Table 2.7 – continued from previous page

	(0.002)	(0.003)	(0.002)
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 2.7: *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†	.3550535
perc_speed_hco	.2592761	.3730311	.348874	.3677189
perc_dedic_sc	-.1855526	.2499896	-.2438112	.2376803
perc_dedic_hc	.5910778	.3902732	.741332†	.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†	.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 2.8: *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†	.0179762	.0239838	.0150358
blackcat_runs	.1745574†	.1040524	.1806088†	.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†	.0015838
wealth	.0186882**	.0045829	.0187212**	.0044023
_cons	1.070296**	.2848485	.6673916**	.2490205

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

Table 2.9: *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)

Table 2.10 – continued on next page

Table 2.10 – continued from previous page

expl err	-0.063†	-0.174†	-0.150	-0.015	-0.124	-0.575**
	(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 2.10: *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 χ^2) is again highly significant at less than the 1% level. The results for all regressions with bootstrapped standard error did not change qualitatively.

3 Dopaminergic Reward Prediction Error in Online Games

3.1 Introduction

We use trade data from an online game economy to test the *dopaminergic reward prediction error* (DRPE) hypothesis: upon buying a game item at a price which is obviously too low, a player should become more active in the trading market. We find that players are more willing to buy goods in the in-game market after such a trade incident. Hence, the effect predicted by the DRPE model is visible. Yet, contrary to the prediction of DRPE, the magnitude of the prediction error does not have a positive effect on the post-error trading activity. Propositions from behavioural economics, anchor pricing and disappointment aversion, can explain the magnitudes of the trading activities.

Neuroscience transfers psychological constructs such as motivation or emotions into the laboratory for experimental tests. Such constructs are themselves unobservable. Thus, the goal is to find (observable) neurological effects that drive these constructs to arrive at a better understanding of human behaviour. The new field of Neuro*economics* explores the potential neuroscience has for the economics profession. Apart from providing new data for empirical research by scanning brain functionality, a neuroscientist can also pin decisions, actions, or preferences to specific brain areas that are known to form part of specific emotions or behaviours. This allows for a more precise formulation of theories of economic behaviour. For an overview of the field of Neuroeconomics, see Rustichini (2005), Camerer et al. (2005), and Glimcher et al. (2009). Not all agree that Neuroeconomics is a worth-while addition to an economist's toolbox. Bernheim (2009) gives a critical review of "guarded optimism", and Gul and Pesendorfer (2008) are highly sceptical.

Dopamine is a neurotransmitter. It is set free in the brain and is crucial in driving choice and learning via "reward" levels. The main[1] model used in neuroscience is the dopaminergic reward prediction error (DRPE) model. This model postulates that a dopaminergic release in the brain correlates with the difference of predicted and actually experienced "reward".

From an economic perspective, Caplin and Dean (2008, 2009) and Caplin et al. (2010) formulate the DRPE model on an axiomatic utility theory which is empirically testable. The decisive argument is that DRPE leads to (revealed) behaviour of individuals that can be tested.

We test the DRPE model using data from an online game as a quasi-experiment. Video games are well-suited for this task, as they stimulate the reward centres of the brain (Johnson, 2005). By their very nature, such games are full of (expected and unexpected) rewards of differing intensity. As all game transactions are made online, game action data is readily available for testing purposes.

The remainder of this chapter is organised as follows: section 3.2 provides an overview of the literature and constructs the hypothesis. Section 3.3 describes the data used, and section 3.4 presents our results. Finally, section 3.5 concludes.

3.2 Literature Review and Hypothesises

3.2.1 Related Literature

Olds and Milner (1954) use experiments with rats[2] to show that dopamine levels

[1]Not all neuroscientists agree. Caplin and Dean (2009) lists three competing theories are that dopamine drives either "incentive salience" ("wanting" to have something, rather than "liking" what you have) (Berridge and Robinson, 1998), or "salience" (distinctiveness) regardless of reward level (Zink et al., 2003), or that dopamine does not govern reward, but rather guides attention (Redgrave and Gurney, 2006).

[2]Experiments on animals have often been used to explain human behaviour, especially in decision theory. There have been experiments with e.g. bees (Real, 1981), locusts (Pompilio et al., 2006),

drive behaviour of individuals by affecting "rewards" computed by the brain. Animals (including humans) make choices to maximise this reward[3] (Gardner and David, 1999). The dopamine reward model was refined to *expected* reward driving dopamine levels by Rescorla and Wagner (1972) and Montague et al. (1996). Schultz et al. (1993) trained monkeys to press a button when thirsty. A bell sound and simultaneous release of juice leads to an increase in dopamine levels. Once the monkey learns that a bell sound implies a certain amount of juice to quench their thirst, the dopaminergic response is also measurable when the bell sounded and juice is released with delay. Hence, it is the *expectation* of juice that leads to the dopaminergic reaction, not the actual juice reward itself. An unexpected deviation from the "normal" juice levels then leads to high dopaminergic reactions.

3.2.2 Hypothesis 1: DRPE Effect

In our online game world, in-game goods (called "items") can be traded via an in-game marketplace. Some trades clearly occur at too low prices, by an order of magnitude or more. We call these trades "trade error incidents" (TE incidents). Such a TE incident could be the result of an actual player error (the player mis-typing the price when selling, or mis-clicking the offer). An alternative explanation is that these trades occur at off-equilibrium "false prices" (Leijonhufvud (1968, 1973), or Laidler (2006) for a recent application), or by a "non-tâtonnement" equilibrium process[4] (Negishi (1961), or Nakatsuka et al. (2000) for a recent application).

Players will participate in the in-game markets, and "normal" trades will return a "normal" expected reward. Then, DRPE predicts that upon buying at one of the TE incidents, the player will receive a large, unexpected, dopaminergic release. An

monkeys (Lakshminarayanan et al., 2011), pigeons (Battalio et al., 1981), rats (Battalio et al., 1985), and starlings (Kacelnik and Marsh, 2002).

[3]Economists know this behaviour as utility-maximising.

[4]An equilibrium process without a Walrasian auctioneer.

addiction is then triggered by seeking similar, repeated dopaminergic reactions (Bernheim and Rangel, 2004; Redish, 2004). A player will spend more time in the in-game marketplace, ever seeking the reward from the TE.

Thus, we formulate our first hypothesis for testing the DRPE *effect* by revealed actions of online game traders:

> **Hypothesis 3.1:** *(DRPE effect) Players trade more frequently after they have exploited a favourable trade error compared to an equal time period before.*

3.2.3 Hypothesis 2: DRPE Magnitude

Focusing on in-game transactions has a crucial advantage: we can calculate the price difference of the trade mistake that triggered the DRPE effect of hypothesis 1. A trade at lower prices should trigger the dopaminergic effect, and the price difference of the trade to the mean price is a proxy for the *magnitude*. Larger differences should be associated with higher unexpected reward, and thus a higher dopaminergic release. This results in relatively more trades being finalised in the period after the TE incident.

A competing explanation is based on behavioural economics, specifically anchor theory (Tversky and Kahneman (1974), Ariely et al. (2003)). Anchor theory predicts that an individual will "anchor" expected outcomes to reference points. Differing reference points will induce different behaviours. In our online game market, a larger price difference of a favourable TE will lead to a lower reference point, and the player actually being "spoilt". He will only buy at prices he perceives as a good deal, and his perception of a good deal has been skewed downwards after the lucky buy. This will lead to relatively less trades being finalised in the period after the TE incident.

Thus, we obtain our second hypothesis examining two competing explanations of a TE magnitude:

> **Hypothesis 3.2:** *(DRPE magnitude) Larger magnitudes of favourable trade errors will affect trades in the following time period.*

3.2.4 Hypothesis 3: Effect of Experience

A more experienced trader should be able to mitigate these effects: Learning effects will improve[5] overall trading performance (Nicolosi et al., 2009). Mizrach and Weerts (2009) study a group of real-world stock traders from an internet chat room. They replicate the learning effect on trades for this online (but non-game) group of traders.

Behavioural economics again provides a competing explanation. Recently, Gill and Prowse (forthcoming) have proposed "disappointment aversion" (Bell (1985), Loomes and Sugden (1986)) as an additional facet of loss aversion. In our game setting, the more experienced a player, the less likely a TE selling incident made in ignorance. An experienced player will then chide himself for the "stupid" error made, and returns to the market with increased[6] zeal.

> **Hypothesis 3.3:** *(Experience) Experience is a moderator on the effects of DRPE-induced trading.*

Caplin et al. (2010) find support for a separation of positive and negative reward prediction errors. Consequently, we examine the positive prediction errors of *buying* at a TE incident and the negative prediction errors of *selling* at a TE incident separately for all hypothesis.

[5] Kaniel et al. (2008) find that (aggregated) traders generate positive profits the month after high respective trading occurrences, also suggesting learning effects as an explanation.

[6] In the direct effort competition experiments of Gill and Prowse (forthcoming), the "second mover" reduces his efforts if he sees the "first mover" exerting a high effort. In our case, we have no direct effort competition, so the disappointment aversion effect is more in line with the loss aversion effect. In Gill and Prowse, a player reduces his effort to mitigate the (ex-ante expected) disappointment. In our online game, a player *increases* his effort to combat the ex-post disappointment.

3.3 The Data

We use data from an online roleplaying game called *The Kingdom of Loathing*, henceforth referred to as KoL. Our data covers all in-game item (goods) transactions via the in-game market from April 2004 to October 2006, uniquely identifying buyers and sellers. From these transactions we select players that buy or sell at least one donation item. A so-called donation item is a valuable item in the game that needs to be bought via a "donation"[7] of 10 US$. Apart from the (voluntary) "donation", there are no (direct) costs associated with playing the game. It follows that donation items are powerful and valuable. This value is directly tied to a monetary scale. Trades in these donation items should trigger the highest dopaminergic reaction. Selecting only traders with donation items is necessary, because every character[8] who possesses a donation item at least once is flagged as *no delete* on the game servers. This character will not be deleted for inactivity. Hence, we can ensure that all data on all characters that is used in our study is still available in all databases.

From these trades in donation items, we compute incidents of "trade errors": trades occurring at prices that are too low. We use two different measures for a TE incident: trades at a price less than 10% of the mean price of the respective good, and trades at less than 1% of the mean price. We identify buyers and sellers involved in TE incidents and compute the amount of (donation item) buying trades for each a month[9] before and a month after this incidence. We standardise the

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

[8]A *player* is a person. He creates a *character* (sometimes also called avatar) representing him in the online world.

[9]Using weeks rather than months does not change the results qualitatively. Focusing only on the day of the TE incident, players trade more than their daily average, but do not trade more than their *active* trading days daily average (only counting days where actual transactions in donation items

trades by calculating the average trades per month (`tpm`) and the respective standard deviations. The average trades are calculated over the active trading months of an individual, not over the entire time period. This procedure eliminates the possible bias associated with individuals only entering the game late, and for this reason exhibiting a relatively too low average trades rate.

To obtain a measure of experience, we count the days that a player was active in the market before the TE incident occurred (`experience`). Finally, we compute the intensity of the TE incident by calculating the price difference of the trade mistake to the mean price (`intensity`). Table 3.1 describes the data and appendix 3.A.1 lists and briefly explains all variables used.

3.4 Results

Table 3.2 shows the results of the *t*-tests comparing the standardised trade occurrences made before[10] and after a trade mistake. We standardise by using the average trades per month and respective standard deviation to obtain equal distributions for all individuals. For a TE incident defined as a trade at less than 10% of the mean price, both the buyer and the seller of the mistake buy significantly more donation items in the month after the incident than before. If we use the stricter definition (trades at less than 1% of the mean price), only the buyer becomes significantly more active in the market after the incident. Hence, we find clear support for the first hypothesis in our data.

To test our second hypothesis, we regress the number of trades made after a TE in-

were finalised)

[10]The *t*-tests were restricted to individuals that have a full month of market activities prior to the TE incident. Hence, we only analyse individuals with a full month of trading before the TE incident. This is to not bias the results from trades after a TE incident always being larger if the TE incident actually was the first trading occurrence of a player.

	count	mean	sd	min	max
trades at <10%					
tpm	670	6.111	16.255	.0952	217
SD_tpm	818	1.681	1.8574	0	16.951
trades_month_before_buy	164	15.04	37.500	1	374
trades_month_after_buy	409	9.274	25.412	1	317
trades_month_before_sell	225	16.378	46.616	1	516
trades_month_after_sell	282	14.652	33.659	1	317
experience_buy	409	.1498	.19899	0	.839
experience_sell	334	.1344	.18637	0	.794
intensity_buy	409	568.409	20.078	522.396	580.39
intensity_sell	503	550.833	22.007	522.396	580.39
trades at <1%					
tpm	411	7.372	17.942	.0952	217
SD_tpm	490	1.797	1.9996	0	16.951
trades_month_before_buy	152	13.99	37.425	1	374
trades_month_after_buy	339	9.457	27.019	1	317
trades_month_before_sell	97	29.845	68.722	1	516
trades_month_after_sell	109	21.486	43.648	1	317
experience_buy	339	.156	.199	0	.818
experience_sell	125	.154	.198	0	.794
intensity_buy	339	580.171	.822	575.396	580.39
intensity_sell	183	579.822	1.252	575.396	580.39

Table 3.1: *Descriptive statistics for the DRPE dataset*

cident on the respective intensity. The independent variable is a non-negative count variable. Hence, simple OLS regressions would lead to biased results. Therefore, we use negative binomial regressions. Table 3.3 shows the results of these regressions.

First, focus on the buyers of favourable TE incidents. The magnitude of the mistake does have a significant effect, but the sign is opposite of what the DRPE hypothesis predicts: a higher price difference (higher intensity trade mistake) leads to less items being bought, not more. In contrast to the buyers at TE incidents, the severity of the error made has no significant effect on the amount of trades for sellers. This indicates that the behavioural economics explanation of anchor pricing theories

		month before		month after			
	N	mean	SD	mean	SD	diff	t-value
<10%							
buyer	120	1.532	.346	2.246	.297	.713*	1.705
seller	160	1.229	.349	1.971	.355	.742*	1.790
<1%							
buyer	108	1.301	.376	2.173	.317	.872*	1.972
seller	75	2.406	.661	1.651	.569	-.755	-1.130
Significance levels: †: 10%, ∗: 5%, ∗∗: 1%							

t-tests comparing the trades in the month before and the month after a TE incident. The values are standardised using the individual's mean and standard deviation of trades per month to be comparable. A TE incident is defined to be a trade occurring at less than 10% or less than 1% of the mean price.

Table 3.2: *Comparing trades a month before and after a TE incident*

plays a relatively more important role in this online trading environment.

Our third hypothesis is concerned with the learning effect from trading experience. For buyers of TE incidents, the experience (days spent in the in-game marketplace before the TE incident is exploited) has no influence on the amount of trades after the TE incident. Contrast this with the surprising results for the sellers at TE incidents. Experience here exhibits a significant effect, though again of an opposite sign than predicted by DRPE. With more experience, a seller will finalise more trades in the month after the mistake, not less. Again, the explanation offered by behavioural economics (loss and disappointment aversion) offers a better fit for our data.

3.5 Conclusion

We have used online game data to test if the DRPE model holds in online game worlds. We show that the effect conjectured by the DRPE exists, but we cannot find

	buy mistake		sell mistake	
	$< 10\%$	$< 1\%$	$< 10\%$	$< 1\%$
tpm	0.073**	0.074**	0.042**	0.030**
	(0.021)	(0.021)	(0.009)	(0.007)
experience	0.477	0.597	1.680**	1.858**
	(0.369)	(0.422)	(0.454)	(0.541)
intensity	-0.008*	-0.255**	0.005	0.073
	(0.004)	(0.089)	(0.004)	(0.075)
constant	6.020**	148.935**	-1.294	-40.591
	(2.273)	(51.411)	(2.040)	(43.743)
lnalpha	0.024	-0.039	0.013	-0.171
	(0.108)	(0.120)	(0.081)	(0.107)
N	336	279	249	102
χ^2	21.421	29.334	44.720	38.021

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

Negative Binomial regressions on the amount of trades made in the month after a trade error. Robust standard errors in parenthesis. First two columns on those that bought the trade mistake, last two columns on those that sold the trade mistake. The trade mistake was set at a trade at less than 10% of the mean price ((1), (3)), or less than 1% of the mean price ((2), (4)).

Table 3.3: *Regression results: DRPE magnitude*

any support for the magnitude effect predicted.

The contrary results to those expected from the DRPE theory of our second and third hypothesis are surprising. The explanations offered by behavioural economics suggest fruitful spill-over effects between neuroeconomics and behavioural economics.

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3.A Appendix

3.A.1 Full List of Variables

tpm	average number of trades per active trading months
SD_tpm	standard deviation of tpm
trades_month_before_buy	number of trades made in the month before buying at a TE incident
trades_month_after_buy	number of trades made in the month after buying at a TE incident
trades_month_before_sell	number of trades made in the month before selling at a TE incident
trades_month_after_sell	number of trades made in the month after selling at a TE incident
experience_buy	days active in the market before buying TE incident, scaled by 1/1000
experience_sell	days active int he market before selling TE incident, scaled by 1/1000
intensity_buy	mean price minus buying TE incident price, scaled by 1/10000
intensity_sell	mean price minus selling TE incident price, scaled by 1/10000

Table 3.4: *Variable list and explanation for DRPE dataset*

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ERKLÄRUNG

Ich versichere hiermit, dass ich die vorliegende Arbeit mit dem Thema

Three Essays on the Economics of Online Games

ohne unzulässige Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus anderen Quellen direkt oder indirekt übernommenen Daten und Konzepte sind unter Angabe der Quelle gekennzeichnet. Weitere Personen, insbesondere Promotionsberater, waren an der inhaltlich materiellen Erstellung dieser Arbeit nicht beteiligt.* Die Arbeit wurde bisher weder im In- noch im Ausland in gleicher oder ähnlicher Form einer anderen Prüfungsbehörde vorgelegt.

Konstanz, den 1. September 2011

(Christoph Safferling)

*Siehe hierzu die Abgrenzung auf der folgenden Seite.

Abgrenzung

Kapitel 1 entstammt einer gemeinsamen Arbeit mit Professor Aaron Lowen (Grand Valley State University, Grand Rapids, MI, USA). Die individuelle Leistung im Rahmen dieser Arbeit gliedert sich wie folgt:

i) Introduction: 70% Safferling / 30% Lowen

ii) Literature and Hypotheses: 60% Safferling / 40% Lowen

iii) Data: 40% Safferling / 60% Lowen

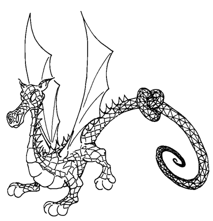
iv) Results: 70% Safferling / 30% Lowen

v) Conclusion: 30% Safferling / 70% Lowen

Ich versichere hiermit, dass ich Kapitel 2 und 3 der vorliegenden Arbeit ohne Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe.

Konstanz, den 1. September 2011

(Christoph Safferling)


Drawing of Poli-co the dragon by Clara Löh.