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

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Abstract

We analyze a unique data set from a massively-multiplayer online video game economy called *The Kingdom of Loathing*[1] to assess the viability of these markets in conducting economic research. The data consist of every transaction in a market with over one million players over three years of real time. We find that 1) the game markets are efficient, 2) the complexity of the product determines information diffusion times, and 3) we can classify which and how players participate in trade.

JEL Classification: C81, C99, D12, D84, G14

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[1]We would like to thank Jick, the creator of KoL, for giving us access to the (private) market data. We would also like to thank Fnord7, Elarrina, and Derek Peterson for their work and willingness to share their market data. Chris Maloof's help in collecting and giving us access to his koldb website for the player data was invaluable. Fryguy was similarly indispensable for helping us collect the display case data. We would like to thank Oliver Fabel and Christian Hopp for helpful comments. Finally, our thanks go to the KoL community for their tireless game analysis and optimising behaviour.

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[2]: 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, with a revenue of 3.8 billion US$ in 2009 for the United States alone.[3]

[2]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).

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

World of Warcraft, the most well-known online game, has over 11 million subscribers[4], each contributing between 12.99$ and 14.99$ per month, for total revenues of over 1.5 billion US$. Social games specialist Zynga (creator of *Farmville* on Facebook) has reported[5] a revenue for 2010 of 597 million US$ 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[6] 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[7] 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[8] 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 faster and less expensive method than the well-established labour market surveys. Hitsch et al. (2010) use data from online

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

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

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

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

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

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 2 provides an overview of the relevant literature and constructs the hypothesis. Section 3 describes the data used, with section 4 presenting our results. Finally, section 5 concludes.

2 Related Literature and Hypothesises

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).

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

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[9] 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) 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 me-

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

chanics 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.[10] 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 2:** *(Goods in online game markets) Complex goods take longer to be understood by agents and affect the game market.*

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 will be profitable. Jensen (1982) is the seminal paper on adoption of innovations.[11] 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.

[10] 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.

[11] 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.

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

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[12], game. Figure 1 provides the game basics, with a more detailed description in appendix 6.1.

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

[12] 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: *The Kingdom at a glance*

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[13] 10 US$ will generate an item[14] 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 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.

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

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

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[15] 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*[16] 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 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

[15]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.

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

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: *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 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.[17] Missing dates in our trade data were added from the "Items of Loathing"[18] 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 2: *Descriptive statistics for dataset 2: Item data*

For the second hypothesis, which examines information diffusion and goods in online worlds, we use all data on each individual iotm from our intraday marketplace data. We combine this data with information on each individual

[17] 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.

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

iotm collected from the KoLwiki.[19] Table 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[20], 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 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 charac-

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

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

ters from two other sources: the Kingdom of Loathing Database (koldb)[21], a database that presents the ascension history of each character of the game, and the Display Case Database (DCdb)[22], a site presenting the publicly displayed possessions of players. Table 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 3: *Descriptive statistics for dataset 3: Player data*

Koldb provides information on the playing habits of each player. Once a player has finished all "quests" (essentially sub-chapters of the complete

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

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 6.2 lists and briefly explains all variables of our three datasets used in our regressions.

4 Results

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.

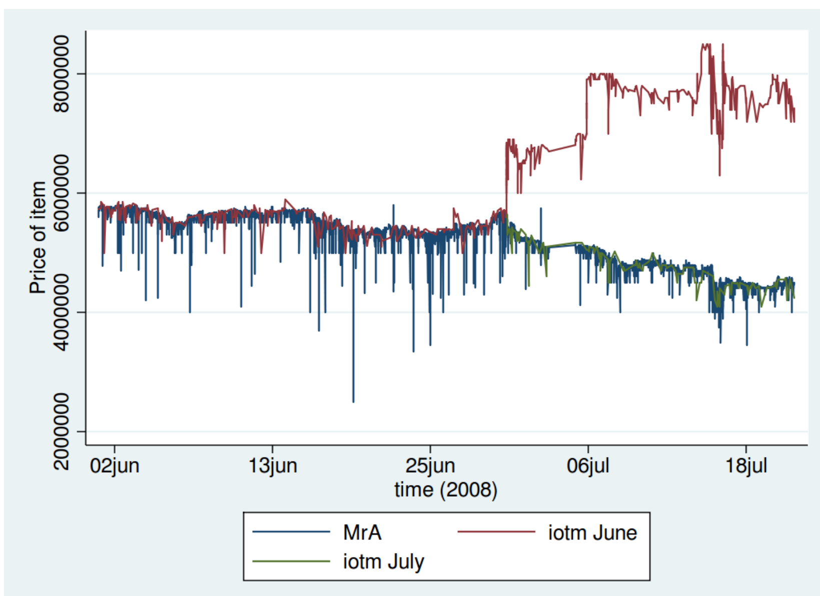

Figure 2: *MrA and iotm prices, June/July 2008*

To illustrate this relationship, figure 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[23] 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.

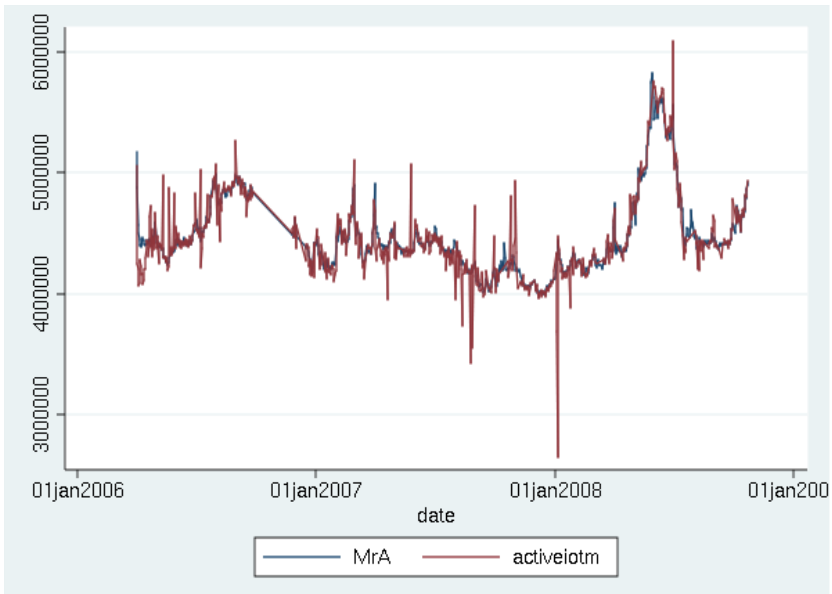

Figure 3: *MrA and current active iotm prices*

Figure 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.

A prerequisite of the co-integration test is a unit root in at least one of the time series. Our unit root test results[24] are presented in table 4. The results can-

[23]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.

[24]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 infor-

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 4: *Unit Root test results*

not 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[25], potentially skewing the unit 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.

mation criterion (AIC) eight. For the iotm, SBIC returns 5 lags, HQIC and LR 6 lags, FPE and AIC return 7 lags.

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

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[26] at the first rank is 4.945, with a 5% critical value of 9.42.

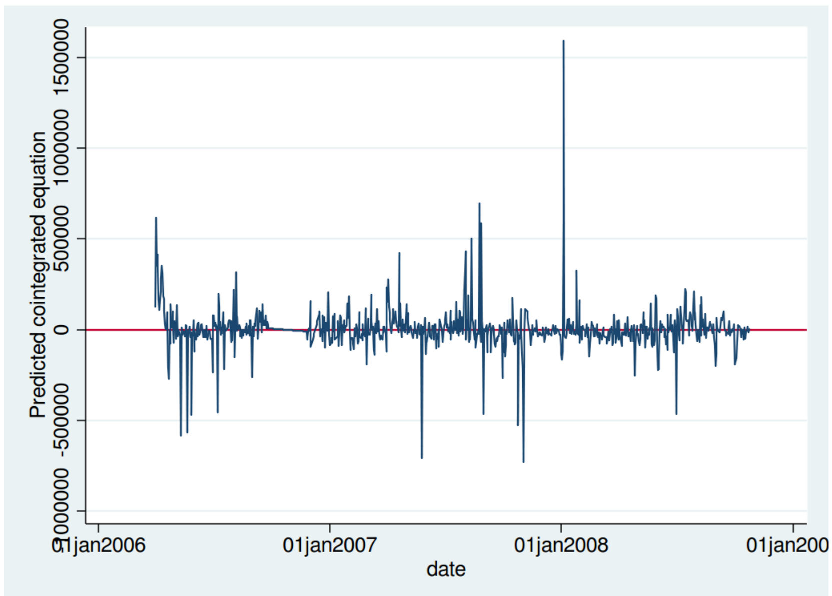

Figure 4: *Predicted cointegration of a bivariate VECM of Mr. A and active iotm prices*

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 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 4 shows no trend: large shocks are apparent (and especially in the early dates of the dataset there are deviations from the

[26]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.

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*.

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

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 6 (Heckman selection) and 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 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 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.[27] 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 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

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

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.

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[28] 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.

[28]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 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 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†	–
	(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†
	(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 7: *Heckman regression output*

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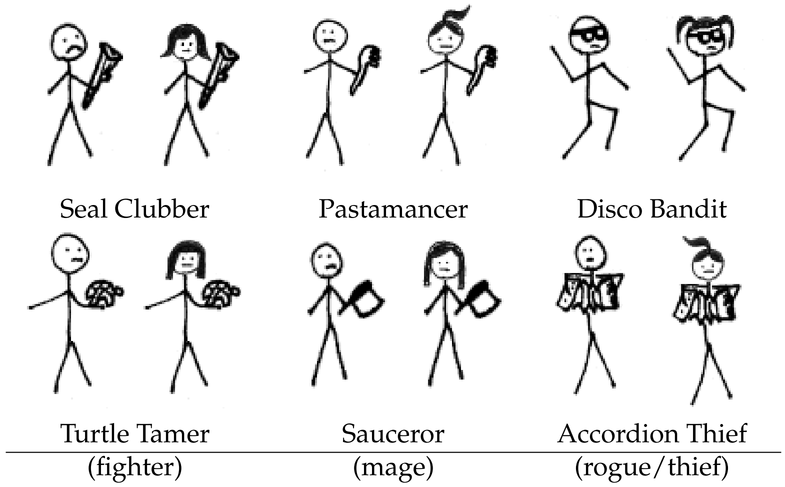

Figure 5: *Classes in the Kingdom of Loathing*

6 Appendix

6.1 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 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).

6.2 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 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 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)
exploited_trade_error	dummy variable = 1 if player bought an item at less than 10% of the mean market value

Table 10 – continued on next page

Table 10 – continued from previous page

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 10: *Variable list and explanation for dataset 3: Player data*

List of Tables