On the connection between real-world circumstances and online player behaviour: the case of EVE Online

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Abstract

Games involving virtual worlds are popular in several segments of the population and societies. The online environment facilitates that players from different countries interact in a common virtual world. Virtual worlds involving social and economic interactions are particularly useful to test social and economic theories. Using data from EVE Online, a massive online multi-player game simulating a fantasy galaxy, we analyse the influence of the real-world context in which players live on their in-game behaviour. We found that in-game aggressiveness is positively related to real-world levels of aggressiveness as measured by the Global Peace Index and the Global Terrorist Index at the country level. The ability to make in-game friends is however negatively related to lower levels of real-world aggressiveness. In-game trading behaviour is dependent on the macro-economic environment where players live. The unemployment rate and exchange rate make players trade more efficiently and cautiously in-game. Overall, we found evidence that the real-world environment affects in-game behaviour, suggesting that virtual worlds could be used to experiment and test social and economic theories, and to infer real-world behaviour at the country level.

Introduction

Virtual worlds are computer-simulated games where real-world people or players can create avatars to live, interact and communicate among themselves or with the virtual environment within a particular context or theme \cite{1}. The last two decades has seen the rise of scientific studies of virtual worlds and their potential connection to the real-world \cite{2,6}. Data extracted from virtual worlds allow researchers to test theories on human behaviour in highly controlled environments, for example, sociological behaviour \cite{5,10}, human mobility \cite{7}, international relations \cite{8,9} and economic models \cite{6,11,13}. A major question, however, is whether the data extracted from virtual worlds are representative enough to study real-world socioeconomic phenomena and whether they capture real-world human behaviour.

The World of Warcraft (WoW) is a popular virtual (online) world in a fantasy setting where players can either fight each other or collaborate to meet the game’s preset challenges. Martoncik \cite{14} observed that WoW players were on average more social in the game than in the real-world. Through interactions in the game, players develop different feelings and generally experience less loneliness and social anxiety compared to those feeling in the real-world. The difference is more prominent for
players who prefer to operate in in-game social groups. Zhang and Kaufman [15] studied the social interactions in WoW and the socio-emotional well-being of players. They found that adult players who are part of a club inside WoW can develop meaningful online relationships including friendship with other players. Destiny is also a virtual (online) world in a futuristic setting, where players can play either individually or in groups (with real-world friends or strangers) to complete a number of challenges designed by the game developers. Destiny was used by Perry et al. [16] to analyse the impact of (in- and out-game) relationships between friends and strangers in the in-game behaviour of players. Pardus is another virtual (online) game that can be accessed via an Internet browser. It represents a futuristic universe where players compete for the limited space whilst interacting in various ways (including fighting) with other players. It has been extensively used for scientific research [4,5,7,17,18]. In particular, Szell et al. [17] analysed the population of players and the different interaction channels between them and found that in-game communication, friendship, and animosity interaction networks had non-trivial structural properties. Using both the friendship and enmity networks, they found strong evidence for a generative mechanism known as social balance theory [20,21] that is also found in real-world networks [22–24]. The typical number of social interactions per player in Pardus is similar to Dunbar’s number, in the range 100–250, that is a suggested cognitive limit to the number of people with whom one can maintain stable social relationships in the real-world [25]. Thurner et al. in [18] studied sequences of in-game actions in Pardus and observed a higher probability of “positive” (“negative”) action if the player had received a “positive” (“negative”) action in the preceding time step, suggesting the existence of reciprocal in-game behaviour.

EVE Online is a sandbox massive multi-player on-line game (MMOG) [27] developed by CCP games [27] where over half a million players fight, trade, collaborate, and explore a futuristic galaxy. The players’ actions are recorded with a high level of precision and detail in space and time. Feng et al. [29] have studied the temporal evolution of in-game activity and population for three consecutive years. They found daily cycles and weekly periodicity in the number of social connections of players. EVE Online provides a player-driven complex economy as all items need to be produced from raw materials and traded by players with minimal intervention of the game developers. Hoefman et al. [13] have studied the price of the items in the EVE Online free market and found empirical evidence to support of the theory of hedonic pricing. Hedonic pricing theory proposes that the price of an item in a homogeneous class of goods can be expressed as a function of the prices of the different functional characteristics of that item [30]. Although EVE players have full information about functional characteristics and strong incentives for rational behaviour, they are not only willing to pay for functional characteristics but also for social characteristics of in-game items [13]. Using EVE data, Carter has conducted a study of the use of propaganda during war times as an essential factor for maintaining the morale [28]. Belaza et al. [8,9] have developed a framework based on statistical physics and structural balance to model international relationships. The model was validated against the network of relationships between alliance groups in EVE Online and international relationships between countries during the Cold War era that have similar network structures. The authors provided evidence that a virtual world can be used as a cleaner and a more extensive laboratory than the data from the real-world for evaluating generative mechanisms for networks of relationships observed in the real-world.

In this paper we study the virtual-world Eve Online [27]. We use data on daily social and economic activities of players to study whether the real-world socioeconomic environment in which players live permeates into their in-game behaviour. We first propose a methodology to generate average activity country profiles for in-game behaviour of players and then study the statistical relation between in-game and
real-world behaviour using international indexes at the country level. Our research contributes on identifying the extent, accuracy and flexibility of virtual worlds as effective and reliable proxies to simulate real-world environments for controlled experiments and hypotheses testing.

Materials and methods

In this section, we first introduce EVE Online game, the relevant data of players in-game activities, and the real-world socioeconomic indexes that will be used. Then, we introduce a methodology to aggregate player behaviour and trade activity at the country level.

EVE Online

EVE Online is a sandbox massive multi-player on-line game (MMOG) developed by CCP games. To play EVE Online, a player needs to pay a subscription fee of 15 USD or 15 EUR per month, or spend the equivalent amount by buying an item (called PLEX) inside the game. Once the item is activated and consumed, the subscription extends for another month. There are over half a million players fight, trade, collaborate, and explore a futuristic galaxy. Players can choose to engage in different activities, ranging from mining asteroids to waging war. For example, the distribution of raw materials is pre-defined by the game developers but the extraction, processing and manufacturing of items, and transport and trading of goods are made and controlled by players. The player’s experience is shaped by the activities of the other players. Altogether, this dynamics gives rise to an emergent economy with specialisation of players and intricate economic interactions. Inter-player interactions also play a role at other levels since they create complex social hierarchies used to control territories and exploit their resources. Not least, these structures and frequent inter-player interactions generate a complex world with espionage and game-wide wars as emergent social phenomena. The analysis presented in this work is based on collected EVE Online data from December 2011 to December 2016 (61 months) for the trade activity and the year 2016 for the social and economic activity.

Measures of in-game social and economic activity

We select EVE activities and extract data that are most relevant to study social behaviour, aggressiveness, and production of individual players (Table 1). To capture the in-game social behaviour of a player, we define two variables: (i) “Added As Negative” and (ii) “Added As Positive” encoding whether a particular player gets tagged as friend or enemy, respectively, during inter-player contacts. The difference between these two variables is a measure of in-game pro-social behaviour (“Reputation”). The number of times a player gets involved in virtual combats with other players, both as aggressor or defender, gives the in-game aggressiveness of a player. Aggression is thus the number of “Engaged Attack” minus “Engaged Defense”. In-game aggressiveness is also captured by the number of events involving killing of a Non-Player Character (NPC), which is a ship controlled by the game (“Kill NPC”). To measure in-game production (and recycling) activities of the individual players, we use three variables: the actual production of items (“Production”), the extraction of raw materials from Asteroids (“Mining”) and extraction of material from destroyed ships (“Salvaging”).
Table 1. In-game activities representing the levels of social interaction, of aggressiveness, and of production activity of players.

| Variable | Category                  | Description                                                                 |
|----------|---------------------------|-----------------------------------------------------------------------------|
| Added As Negative social interaction | social interaction | Interacting players can mark the counter-party as friend, enemy or neutral. This mark is visible whenever players meet. |
| Added As Positive social interaction | social interaction | (Added As Positive) - (Added As Negative)                                    |
| Reputation | social interaction | (Added As Positive) - (Added As Negative)                                    |
| Engaged Attack | aggressiveness     | Attack another player.                                                       |
| Engaged Defense | aggressiveness | Being attacked by another player.                                            |
| Aggression   | aggressiveness         | Conflict against others: (Engaged Attack) - (Engaged Defense).                |
| Kill NPC    | aggressiveness         | Destroy ships controlled by the game, usually so-called pirates.            |
| Production | production activity      | Produce an item, using other items as input.                                |
| Mining      | production activity      | Extract materials from asteroids.                                           |
| Industrial | production activity      | Production + Mining                                                          |
| Salvaging   | production activity      | Recover materials from destroyed ships.                                     |

Measures of real-world social and economic activity

To measure aggressiveness in the real-world at the country level, we use the Global Terrorist Index (GTI) and the Global Peace Index (GPI) from the year 2016. The GTI [33] is proposed as a measure of the impact of terrorism in 196 different countries and comes from the Global Terrorist Database curated by the Institute for Economics & Peace. The GPI [34], published by the same institute, combines data on terrorist attacks and other indicators, including for example, criminality rates and military expenses. A low value of GPI indicates a higher level of peace.

To measure real-world socio-economic characteristics of each country, we use the Consumer Price Index (CPI), the Real Effective Exchange Rate (REER), and the Unemployment rate (UNEMP) from the World Bank for the year 2016 [37]. CPI is an inflation index measuring the evolution of a weighted average price level of a fixed basket of basic consumer goods and services like food, ICT, medical care and housing. REER is an exchange rate index describing the strength of the local currency with respect to the rest of the world. It is a weighted average of all exchange rates of the local country currency to the currencies of all the country’s trading partners, weighted by the trade volume. UNEMP is the fraction of the working age population that is unemployed and looking for a job.

In-game country profile

We construct an activity-based in-game profile per country from the selection of key activities listed in Table 1. A country’s profile is based on the average profile of the players that come from that particular country. We first record the number of times that in-game events listed in Table 1 are realised by the players, except for Mining, Salvaging, and Production. The latter three activities result in the generation of an in-game item that we transform into a numeric value using the market prices. Data are aggregated on a weekly basis, creating a specific player profile per week.

There is a large variation in the time scales of different in-game events, for example, marking someone as a friend is an instantaneous event whereas the process of Mining an asteroid can take up to half a minute. The variables Production, Mining and Salvaging are measured through monetary value instead of counting the number of times that the activity has been completed. To deal with different scales and metrics, we define an adimensional “activity coefficient” that combines in-game events and is representative for the activity level of each player during a given week. This is used to re-scale the
measurements of all activities to a common metric. For each activity and week the average over all players is taken. In the analysis, for each player and for all eight independent activities listed in Table 1, we define a measure relative to this average, where zeros are not counted.

The ratio of the action and the normal activity determines the adimensional coefficient. For example, if all players killing NPCs kill on average 200 times per week, and a specific player kills 500 times in a week, the player's activity is recorded as “Kill NPC 500/200 = 2.5” for that particular week. Finally, the player’s profile is normalised by the sum of the eight adimensional measures of the in-game activities. The resulting profile of each player provides information about the way the player spends time in the game. For the country profile, the average of all the profiles of the players belonging to that country is taken and normalised by the standard score of all countries with at least 15 players in EVE online. We have checked that noisy profiles are generated when including countries with only a few players. The required minimum number of players in each country is set to a level to keep a significant sample of countries (106 countries) for analysis. Finally, the country-based measures for the in-game activities are re-scaled to zero mean and unit variance (Z-score).

**Measures of in-game trade activity**

EVE market operates according to a double auction system. Players can set a sell or buy order of a specific item for a certain price. They can also see the full list of active orders and opt to fulfill them. For each country \( c \) and item \( i \), we determine the monthly sell price \( P_{Si}^c \), the monthly buy price \( P_{Bi}^c \), and the monthly volume of sell and buy orders, respectively, \( V_{Si}^c \) and \( V_{Bi}^c \). We collect the data for \( M = 106 \) countries \( c \) with more than 15 players and for 6,882 unique items \( i \). Table 2 shows the in-game measures of trade activity for each player for a specific country. All measures include a sum over all the different items. The mean for each item \( i \) is taken over \( M \) countries, for example, for buy price \( \langle P_{Bi} \rangle_c = \sum_{c=1}^{M} \frac{P_{Bi}^c}{M} \), with equivalent definitions for the other variables.

Table 2. Measures of in-game trade activity of individual players grouped according to country-of-origin.

| Variable        | Definition                                                                 | Description                                                                 |
|-----------------|----------------------------------------------------------------------------|----------------------------------------------------------------------------|
| Buy Price       | \( \sum_i \frac{P_{Bi}^c - \langle P_{Bi} \rangle_c}{\langle P_{Bi} \rangle_c} \) | Buy price in country \( c \) relative to the average over all countries.    |
| Bid Ask         | \( \sum_i \frac{P_{Si}^c - P_{Bi}^c}{P_{Si}^c + P_{Bi}^c} \)                | Bid-ask spread in prices for country \( c \).                               |
| Buy Volume      | \( \sum_i \frac{V_{Bi}^c - \langle V_{Bi} \rangle_c}{\langle V_{Bi} \rangle_c} \) | Volume per transaction of buying orders in country \( c \) relative to the average across countries. |
| Bid Ask Volume  | \( \sum_i \frac{V_{Si}^c - V_{Bi}^c}{V_{Si}^c + V_{Bi}^c} \)                | Bid-ask spread for the traded volume per transaction in country \( c \).    |
| Bid Ask Transactions | \( \sum_i \frac{N_{Si}^c - N_{Bi}^c}{N_{Si}^c + N_{Bi}^c} \) | Bid-ask spread in the number of transactions in country \( c \).            |

\( P_{Bi}^c, V_{Bi}^c, N_{Bi}^c \) stand respectively for price, volume, and number of transactions of buy orders for item \( i \) in country \( c \). \( P_{Si}^c, V_{Si}^c, N_{Si}^c \) are the equivalent for sell orders.

**Results**

In this section, we first present the activity-based in-game country profiles and then perform a regression analysis of the socioeconomic behaviour of players inside the game.
in comparison to their country-of-origin in the real-world.

**In-game country profiles and trade activity**

The in-game country profile is generated by combining a selected number of in-game activities capturing the social interactions, aggressiveness, and production of players. Table 3 shows the country profiles of selected countries and the cosine similarity between pairs of countries for eight in-game activities (See section Materials and Methods for details). The cosine similarity is calculated using the hyper-dimensional vectors that correspond to the country profiles based on all nine in-game activities.

Table 3. Country profiles for selected countries.

| Country      | Russia | Belarus | Ukraine | Canada | France | UK | Germany | Austria |
|--------------|--------|---------|---------|--------|--------|----|---------|---------|
| Added As Negative | 0.177  | 0.357   | 0.325   | -0.024 | 0.133  | 0.209| 0.204   | 0.198   |
| Added As Positive | 0.291  | 0.314   | 0.315   | 0.068  | 0.283  | 0.232| 0.110   | 0.136   |
| Engaged Attack  | 0.384  | 0.444   | 0.439   | 0.355  | 0.389  | 0.413| 0.360   | 0.384   |
| Engaged Defense | 0.560  | 0.684   | 0.670   | 0.512  | 0.542  | 0.570| 0.457   | 0.476   |
| Kill NPC       | 0.849  | 1.207   | 1.556   | -0.230 | -0.095 | -0.169| 0.055   | -0.068  |
| Production     | 0.559  | 1.344   | 1.121   | 0.015  | 0.010  | 0.054| 0.275   | -0.033  |
| Mining         | 0.610  | 0.856   | 0.702   | 0.335  | 0.408  | 0.322| 0.617   | 0.590   |
| Salvaging      | 0.615  | 0.691   | 0.597   | 0.255  | 0.339  | 0.275| 0.389   | 0.310   |
| Cosine similarity* | 0.950  | -0.982  | 0.792   | 0.823  |

*Cosine similarity varies from −1 (low similarity) to +1 (high similarity).

We analysed the similarity between country profiles using the subset of countries with more than 100 players (62 countries). Figure 1 shows the cosine similarity of pairs of countries. The countries are first clustered via an iterative algorithm that at each time step aggregates the two closest clusters (See function hierarchy.linkage in the Python scipy.cluster module and [31,32] for more details of the algorithm) and then ordered in clusters with similar profiles. Figure 1 shows one cluster of countries (upper-left part of the matrix) with highly similar profiles, with Oceanic and Asian countries a bit over-represented, and another cluster of Eastern Europe countries, i.e. Ukraine, Russia, Belarus, Moldova, Bulgaria, Lithuania, among others. Furthermore, France and the United Kingdom have similar profiles, as well as Germany and Austria, suggesting that geography may be relevant. Canada and Ukraine are the countries with highest profile difference (cosine similarity is −0.98). The calculated similarities indicate the robustness of our method.

Using the transaction data from December 2011 to December 2016, we create monthly (61 months) measures of in-game trade activity of individual players grouped according to country-of-origin for the 106 countries with more than 15 players (Table 2). The data is normalised using the average and the standard deviation (Z-score). We also winsorize the data by removing 1.5% of the outliers, i.e. all data points larger than 3 standard deviations. Table 4 shows the summary statistics for each trade activity.

Table 4. Statistics of in-game trade activities at the country level.

| Activity       | count | mean  | std   | min   | 25%   | 50%   | 75%   | max   |
|----------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Buy Price      | 2113  | 0.159 | 0.331 | -0.823| -0.005| 0.099 | 0.235 | 2.946 |
| Bid Ask        | 1614  | -0.088| 0.183 | -0.991| -0.158| -0.079| -0.006| 0.895 |
| Buy Volume     | 2113  | -0.052| 0.426 | -1.000| -0.283| -0.126| 0.065 | 2.981 |
| Bid Ask Volume | 1614  | -0.067| 0.229 | -1.000| -0.155| -0.041| 0.029 | 1.000 |
| Bid Ask Transactions | 1614 | -0.025| 0.209 | -0.967| -0.132| -0.027| 0.056 | 0.976 |
In-game player behaviour and the real-world socioeconomic environment

In this section we study the relation between real-world aggressiveness at country-level and in-game social interactions, aggressiveness, and economic activities of players at the level of their country of origin. Previous studies have suggested that the real-world aggressiveness in a country as defined by the Global Terrorist Index (GTI) correlates with a variety of social, economic, and geographical measures, like the linguistic fractionalisation, the GDP, and the Human Development Index (HDI) [35,36]. As players perform social and economic activities in EVE Online, we hypothesise that the players’ in-game activities and attitudes reflect their real-world socioeconomic environment.

For both the GTI and the GPI, and for all the in-game socioeconomic activities in Table 1 (See Materials and Methods), we propose the following three models:
• Model I: The minimal model that correlates real-world aggressiveness with aggressive in-game behaviour. These models are GTI I and GPI I.

• Model II: An extension of Model I variants that also includes pro-social in-game behaviour (i.e. Reputation). These models are GTI II and GPI II.

• Model III: An extension of Model II variants that adds the measures of productive in-game behaviour (Industrial, Salvaging). These models are GTI III and GPI III.

Table 5. Real-world aggressiveness regression results per country for year 2016.

|             | GTI I  | GTI II | GTI III | GPI I | GPI II | GPI III |
|-------------|--------|--------|---------|-------|--------|---------|
| Intercept   | 2.94*** | 2.95*** | 3.32*** | 1.97*** | 1.97*** | 2.02*** |
|             | (0.29)  | (0.29)  | (0.64)  | (0.05) | (0.05) | (0.11)  |
| Aggression  | -0.71** | -0.70** | -0.98*** | -0.15*** | -0.15*** | -0.22*** |
|             | (0.28)  | (0.28)  | (0.29)  | (0.05) | (0.05) | (0.06)  |
| Kill NPC    | 0.42    | 0.42    | 1.08**   | 0.07   | 0.08   | 0.19*** |
|             | (0.33)  | (0.34)  | (0.41)  | (0.06) | (0.06) | (0.07)  |
| Reputation  | -0.20   | 0.39    | 0.11**   | 0.21*** |
|             | (0.30)  | (0.36)  | (0.05)  | (0.06) |
| Industrial  | -0.31   | -0.04   |          |
|             | (0.56)  | (0.10)  |          |
| Salvaging   | -0.96** | -0.19** |          |
|             | (0.43)  | (0.08)  |          |
| R²          | 0.11    | 0.12    | 0.21    |
| Adjusted R² | 0.09    | 0.08    | 0.14    |
| No. observations | 71 | 71 | 71 |
| Min Eigenval | 5.33e+01 | 5.31e+01 | 7.72e+00 |
| Condition number | 1.22e+00 | 1.23e+00 | 5.04e+00 |
| AIC         | 3.32e+02 | 3.34e+02 | 3.30e+02 |

Ordinary Least Squares (OLS) regressions. Standard errors in parentheses. * p < .1, ** p < .05, ***p < .01.

Table 5 shows the results of Ordinary Least Squares (OLS) regressions for all models. Aggression measures the likelihood that players of a given country are the aggressors in the fights they have with other players. Positive Aggression indicates that players of this country tend to be the first shooter in the game fights they get involved. Industrial is a country-level measure of Production and Mining activities. Salvaging is a country-level measure of extraction of materials from destroyed ships and is thought of as productive (recycling) behaviour in the game. For countries with more than 15 players, there is correlation between the real-world aggressiveness (GTI and GPI) and in-game player behaviour. The linear regression for the Global Terrorist Index (GTI) has a lower R² than for the Global Peace Index (GPI) (Table 5), that takes into account more variables than GTI. GTI only includes intentional acts of violence or threats of violence by a non-state actor (See [33]). On the other hand, GPI includes more indicators as for example the jail population per capita, the size of the armed forces per capita, the number of homicides per capita, as well as the Terrorist index (See [34] for the methodology to construct the indexes).

Based on the AIC (Akaike information criterion), none of the models can be discarded. For all tested models, the coefficient of the in-game aggressiveness against non-player characters (Kill NPC) is positive, though only significantly in models GTI III and GPI III. In-game aggressiveness against NPCs is thus related to higher real-world aggressiveness. The opposite is also true for aggressiveness against fellow players, i.e. Aggression is negatively correlated with both the GTI and the GPI indexes.
in all our models. These results suggest that in-game aggressive behaviour against other players is not a good measure of real-world aggressiveness in the country of origin of these players. Nevertheless, our results indicate that players from safer countries behave on average more aggressively towards other players in the virtual world than players from unsafer countries.

Pro-social behaviour is given by the Reputation that is measured as Added As Positive minus Added As Negative. Positive country’s Reputation indicates that other players mark players from this country more often as friends than enemies. Pro-social behaviour is positively correlated with the GPI, implying that players from less aggressive and more peaceful countries tend to have more friends than enemies in the virtual world.

We have performed robustness checks of the above results. First, we have divided our data into two groups containing respectively 80% and 20% of the data. The linear regression model estimated with the 80% group shows results qualitatively similar to those of the 20%-group. The results from the full data set and the 80%-group are also consistent. In addition, we have tested the imposed minimum number of players per country required for inclusion in the sample (15 players per country above). Imposing a stricter minimum of 25 players per country (and thus adding less countries in the sample) produces results completely in line with those above (Tables 5). On the other hand, relaxing the inclusion constraint to a minimum of 10 players (consequently adding more countries in the sample) produces comparable results to the case of 15 players, however with more noise.

**In-game trading activity and real-world economic outcomes**

In this section we study the relation between real-world economic outcomes at the country level and measures of in-game trade activity (market behaviour) at the level of the country of origin of the player. Since a player can pay the subscription either with real-world money or buy in-game items from other players, those earning enough in-game currency can pay the full subscription without spending any real-world money. Through the subscription cost in the local real-world currency, price variations and unemployed risk in the real-world can all be transmitted to the in-game financial behaviour. We hypothesise that unemployed risk will encourage players to be more cautious in their in-game transactions, as the opportunity cost of real-world money has increased whereas that of spending in game time has decreased. We also hypothesise that exchange rates affect the ratio between the value of in-game currency and real-world currency. Players may react to a real-world depreciation by being more eager to pay for their subscription with money earned in the game, for example by trading more actively or by demanding higher prices for selling in-game goods. Our third hypothesis is based on the fact that inflation creates a connection between real-world money and real-world goods. Therefore, players who experience inflation in the real-world may be inclined to mimic this behaviour in the virtual world by increasing in-game prices (both buy and sell prices). We propose a single regression model for each variable CPI, REER, and UNEMP, taking into account all the in-game trade activities in Table 2 (See Materials and Methods).

Table 6 shows that all three regression analysis have low explanatory power (low \( R^2 \)). Players from countries with higher consumer prices inflation in real-world items (CPI) tend to buy more than sell in-game (higher Bid Ask Volume). This result suggests that real-world inflation experiences in the country-of-origin are transmitted into in-game inflation expectations. The real effective exchange rate is negatively correlated with the in-game Buy Price and Buy Volume, but positively correlated with the bid-ask spread (Bid Ask). That means if a country’s real currency depreciates, in-game money becomes relatively more expensive for the players of this country, urging them to buy smaller
Table 6. Real-world economic outcomes regression results per country for year 2016.

|                    | CPI     | REER    | UNEMP   |
|--------------------|---------|---------|---------|
| Intercept          | 108.90  | 102.27  | 8.17    |
|                    | (2.09)  | (0.56)  | (0.26)  |
| Buy Price          | 0.37    | -2.51   | -1.39   |
|                    | (3.74)  | (1.03)  | (0.47)  |
| Bid Ask            | 2.48    | 3.70    | -2.64   |
|                    | (5.37)  | (1.51)  | (0.68)  |
| Buy Volume         | -1.18   | -1.78   | -0.68   |
|                    | (2.46)  | (0.66)  | (0.32)  |
| Bid Ask Volume     | -15.77  | 0.39    | -0.37   |
|                    | (4.18)  | (1.16)  | (0.53)  |
| Bid Ask Transactions| 3.20   | 1.93    | 1.17    |
|                    | (4.56)  | (1.23)  | (0.58)  |

Ordinary Least Squares (OLS) regressions. Standard errors in parentheses. * p < .1, ** p < .05, ***p < .01.

quantities at lower prices and to trade more efficiently. Finally, the level of unemployment is strongly related to most of the studied in-game trading behaviours. Players from countries with higher levels of unemployment not only buy less (Buy Volume), at cheaper prices (Buy Price) and more efficiently (Bid Ask), but also have more sell transactions relatively to buy transactions (Bid Ask). These findings suggest that players of countries with high unemployment attach a relatively higher opportunity cost to real-world money than to real-world time, increasing their willingness to work in the game to earn in-game money necessary to pay for their subscription, since real-world money is limited or nonexistent.

To check the robustness of our results, here we also randomly divided our data in two sets with 80% and 20% of the original data. The estimations using the 80% sample yields results consistent with those given by the full sample. Estimates using the remaining 20% of the data are also inline to the full data. The root-mean-square error (RMSE) of the estimations on the two samples differ less than 10%.

Discussion

EVE Online is a paid multi-player online game where over half a million players fight, trade, collaborate, and explore a futuristic galaxy. It is not only a social but also an economic game where one of the main activities is trade. In this paper, we propose a series of socioeconomic hypotheses and test them using EVE Online data to find whether in-game player behaviour is connected to real-world human behaviour and to the socioeconomic context in which players live.

We first propose a methodology to combine data from multiple players and to create a representative country profile containing the average player behaviour. This is a fundamental step because individual player data are noisy and difficult to link to individual real-world behaviour in this context. The country-level analysis also helps to understand particular socioeconomic aspects of societies.

Our analysis indicate a negative relation between in-game aggressiveness against
other players and real-world aggressiveness in the players country of residence, as measured by the Global Peace Index and Global Terrorism Index. This result suggests that players experiencing violence in daily life have a tendency to be less aggressive to fellow players in comparison to players who are less exposed to violence and its consequences to society. On the other hand players from more peaceful countries tend to make and maintain more friends than enemies in the game relatively to those living in more violent countries. This result indicates that trust and confidence in the real-world social life are directly reflected on the virtual social experiences. We have observed however a positive relation between in-game aggressiveness against non-player characters and real-world aggressiveness. In this case, players from more violent countries tend to act more violently against non-human characters than those living in peaceful countries.

The analysis of trading patterns indicate a significant, though relatively small, correlation between in-game trading and real-world variables reflecting the macroeconomic context where players live. We find that higher unemployment rates and weaker currencies in the country of residence are associated to more efficient and money-conscious in-game trading behaviour and market dynamics. Not least, the less attractive economic environment of certain countries encourages players from these countries to earn more in-game money. This can be partially explained by the fact that players can use in-game money to pay for their continuous membership on EVE Online.

In this paper, we have found evidence of correlations between social and economic indicators in the real world and the players behaviour in EVE Online, a game simulating a fantasy galaxy with real-world inspired trading and social dynamics. While correlations do not necessarily imply causality, it is intuitive to expect in our study that due to the relative dimensions (i.e. population sizes of both worlds), the country-of-origin of players affect their in-game behaviour and not vice-versa, as in online vs. offline feedback dynamics in specific contexts [38]. Our statistical models could be further improved to better explain the variation of the real-world socioeconomic indicators, their temporal evolution, and the mechanisms driving the influence and inter-relations between players in-game. Future research directions also include similar analysis at the individual player level using online questionnaires. Overall, our study provides evidence on the in-game impact of the real-world socioeconomic environment and socio-cultural norms in which players are immersed and experience daily-life. These results also support previous research encouraging the use of virtual worlds as realistic in-silico environments to perform controlled experiments and test relevant social and economic theories.

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