Reward Prediction Error in Online Game Trades

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Abstract
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 any effect on the post-error trading activity.

JEL Classification: C99, D01, D12, D87

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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 Neuroeconomics 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

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\(^1\)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”
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 2 provides an overview of the literature and constructs the hypothesis. Section 3 describes the data used, and section 4 presents our results. Finally, section 5 concludes.

2 Literature Review and Hypothesises

Olds and Milner (1954) use experiments with rats\(^2\) to show that dopamine levels 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 ex-

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\(^2\)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), 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.
pected 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.

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 (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 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:

\[ \text{An equilibrium process without a Walrasian auctioneer.} \]
**Hypothesis 1:** (DRPE effect) Players trade more frequently after they have exploited a favourable trade error compared to an equal time period before.

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

A more experienced trader should be able to mitigate these effects: Learning effects will improve overall trading performance (Nicolosi et al., 2009).

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

**Hypothesis 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.

### 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

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6In 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.
in the game that needs to be bought via a “donation”\textsuperscript{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\textsuperscript{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\textsuperscript{9} before and a month after this incidence. We standardise the 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

\textsuperscript{7}“Donation” is the term that the game designers use. Economically speaking, one buys a “donation” item for 10$, of course.

\textsuperscript{8}A player is a person. He creates a character (sometimes also called avatar) representing him in the online world.

\textsuperscript{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 were finalised).
compute the intensity of the TE incident by calculating the price difference of the trade mistake to the mean price (intensity). Table 1 describes the data and appendix 6.1 lists and briefly explains all variables used.

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</table>

Table 1: Descriptive statistics for the DRPE dataset

4 Results

Table 2 shows the results of the t-tests comparing the standardised trade occurrences made before\(^\text{10}\) and after a trade mistake. We standardise by using the

\(^{10}\)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.
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.

\[
\begin{array}{cccccc}
\text{N} & \text{mean} & \text{SD} & \text{mean} & \text{SD} & \text{diff} & t\text{-value} \\
\hline
<10\% & & & & & & \\
\text{buyer} & 120 & 1.532 & .346 & 2.246 & .297 & .713^* & 1.705 \\
\text{seller} & 160 & 1.229 & .349 & 1.971 & .355 & .742^* & 1.790 \\
<1\% & & & & & & \\
\text{buyer} & 108 & 1.301 & .376 & 2.173 & .317 & .872^* & 1.972 \\
\text{seller} & 75 & 2.406 & .661 & 1.651 & .569 & -.755 & -1.130 \\
\hline
\end{array}
\]

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 2: Comparing trades a month before and after a TE incident**

To test our second hypothesis, we regress the number of trades made after a TE incident 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 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
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: Regression results: DRPE magnitude

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 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.

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 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.
References


6 Appendix

6.1 Full List of Variables

<table>
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<tr>
<th>Variable</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>tpm</td>
<td>average number of trades per active trading months</td>
</tr>
<tr>
<td>SD_tpm</td>
<td>standard deviation of tpm</td>
</tr>
<tr>
<td>trades_month_before_buy</td>
<td>number of trades made in the month before buying at a TE incident</td>
</tr>
<tr>
<td>trades_month_after_buy</td>
<td>number of trades made in the month after buying at a TE incident</td>
</tr>
<tr>
<td>trades_month_before_sell</td>
<td>number of trades made in the month before selling at a TE incident</td>
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<td>number of trades made in the month after selling at a TE incident</td>
</tr>
<tr>
<td>experience_buy</td>
<td>days active in the market before buying TE incident, scaled by 1/1000</td>
</tr>
<tr>
<td>experience_sell</td>
<td>days active in the market before selling TE incident, scaled by 1/1000</td>
</tr>
<tr>
<td>intensity_buy</td>
<td>mean price minus buying TE incident price, scaled by 1/10000</td>
</tr>
<tr>
<td>intensity_sell</td>
<td>mean price minus selling TE incident price, scaled by 1/10000</td>
</tr>
</tbody>
</table>

Table 4: Variable list and explanation for DRPE dataset

List of Tables

1. Descriptive statistics for the DRPE dataset ........................................ 8
2. Comparing trades a month before and after a TE incident ........................ 9
3. Regression results: DRPE magnitude .................................................. 10
4. Variable list and explanation for DRPE dataset .................................. 16