

# Repeat Buying Behavior of Illegal Drugs on Cryptomarkets

Veringmeier, L. T.

Utrecht University

BSc Sociology

Bachelor Project 13-6-2019

**Abstract:** The goal of this research is to get a better understanding of buyer behavior on cryptomarkets, and to what extent buyers buy repeatedly from sellers. Cryptomarkets are anonymized markets only accessible through encryption software such as Tor. These markets provide opportunity for people to trade in illegal goods such as drugs in relative safety from legal authorities. Trading on cryptomarkets relies on trust and reputation. Theory from The Trust Game is used to explain the relations between buyers and sellers, as well as the actions that the actors can make. Although sellers have high short-term incentives to scam their customers, long-term success relies on trustworthy behavior. Buyers have to make risk assessments to place trust based on available information and experience. Data was gathered from the AlphaBay cryptomarket shortly before it was taken down by U.S. authorities. Logistic regressions were used to analyze the odds of buyers repurchasing after each purchase both on network level as well as on dyad level. 69.4% of the buyers on AlphaBay bought repeatedly, and 32.5% of all dyads were repeated. It was found that positive experiences give better odds of buyers making more purchases on network and dyad level. Using safe payments services such as escrow and experience also increase odds of buyers repeatedly purchasing. Future quantitative research on buyer behavior may want to focus on availability of alternative products and sellers for buyers, qualitative research may be valuable for finding buyer motivations to keep purchasing, stop purchasing or change sellers.

**Index**

<b>Introduction</b>	<b>2</b>
<b>Theory</b>	<b>5</b>
The trust game	5
Reputation	6
Repeated Interactions	7
Hypotheses	9
<b>Methodology &amp; Data</b>	<b>10</b>
Methodology	10
Data collection	10
Dependent Variables	11
Independent Variables	12
Covariates	13
<b>Results</b>	<b>14</b>
Descriptive Statistics	14
Hypothesis 1	15
Hypothesis 2	18
<b>Conclusion &amp; Discussion</b>	<b>20</b>
Findings	20
Limitations	21
Recommendations for Future Research	22
<b>References</b>	<b>23</b>

### **Introduction**

Since 2011 the world has been exposed to a new form of trading in illegal goods on a scale that had never been seen before (Barratt, 2012). 'Silk Road' was a cryptomarket, a website on an hidden part of the internet where identities and other personal information cannot be traced. Only by using encryption software such as Tor can the website be reached. What made Silk Road different and more successful compared to earlier dark net market places was its professional design, diversity in traded goods, and most importantly using Bitcoin as currency, allowing for untraceable transactions (Buxton & Bingham, 2015). As such, criminal activities like trading drugs in particular were one of many practices commonly seen on the website. Silk Road has been taken offline in 2013, but since then many similar websites have emerged and disappeared (Soska & Christin, 2015).

Sales on cryptomarkets average between 300,000\$ and 500,000\$ a day (Soska & Christin, 2015). It is expected that this number will increase, but the harmful effects of cryptomarkets for society can be debated (Aldridge et al., 2018). Trading drugs on cryptomarkets presents both buyers and sellers with several beneficial factors that decrease their risks less street crime. Incentives for buyers to use cryptomarkets are the relative safety (Barratt, Ferris & Winstock, 2016), anonymity, quick transactions and delivery (Van Hout & Bingham, 2013a; Van Hout & Bingham, 2013b). Cryptomarkets also provided users with a forum and community to discuss safe drug use, activism and social support involving stigmatized topics (Maddox, et al., 2016). Sellers can increase their number of clients, although competition is fierce (Aldridge & Décary-Héту, 2016). Sellers also try to build long term relationships with customers (Aldridge & Askew, R, 2016; Aldridge & Décary-Héту, 2016).

Due to the anonymous nature of cryptomarkets Tzanetakis et al. (2016) find that relations between buyers and sellers on cryptomarkets form differently compared to relations in offline drug trading. Offline drug trading requires trust between buyer and seller before doing business, on cryptomarkets trust is promoted by sellers to attract new buyers, and to protect buyers from getting scammed. Cryptomarkets facilitate this in two ways, a reputation score is kept for all sellers created by the feedback from buyers they interacted with previously. This score can be used by buyers to perceive the trustworthiness of a seller. Secondly an escrow payment service can be used. This payment service works as a third party who keeps the money paid by the buyer and only releases

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

it to the seller after the drugs have been delivered (Barratt & Aldridge, 2016). Escrow services are meant to increase trust as they prevent scamming by sellers to a certain extent.

Most quantitative research concerning relations between buyers and seller on cryptomarkets investigate network structures, or have a seller centered approach. Buyer centered information has been reported twice recently. Décary-Héту and Quessy-Doré (2017) found that 91% of the buyers on cryptomarket bought drugs more than once on the same cryptomarket. The main focus was analyzing to what extent buyers interact with more than one seller. They found that of the transactions between buyers who bought more than once and sellers, 60% were repeated interactions between the same pairs. Their results show that most buyers may be considered loyal, since a significant proportion of repeat buyers are interactions with the same seller.

Research on cryptomarket networks (Norbutas, 2018) found that only 50% of the buyers bought more than once. He also found that 60% of all buyers interact with just one seller, and 21,4% interact with two sellers. This percentage quickly decreases as the amount of dyads per buyer increases. A dyad refers to a set of specific buyer and seller who interacted with one another. Cryptomarket networks consist of many dyads, both buyers and sellers can have multiple dyads with other actors on the market. Although the results of both researches are not completely comparable, a few interesting observations can be made.

First of all, both seem to agree on the idea that customers are loyal, since most transactions are with the same seller. However, in case of Norbutas (2018) we need to realize that most buyers who interact with a single seller also only bought once. Meaning that they did not interact with another seller because they did not make a second purchase at all. Second, in the data used by Décary-Héту and Quessy-Doré (2017) the buyers usernames were partially hidden, and an estimation had to be made about the likelihood that two buyers were in fact the same person. This estimation could have influenced the outcome of the results, partially overestimating the outcome of their analysis according to Norbutas (2018). The empirical facts found in both researches (Décary-Héту & Quessy-Doré, 2017; Norbutas, 2018) however are under-theorized. Explanations for the growth of long lasting relations, loyalty and trust are lacking, especially from a buyers perspective. In this research I will use a theoretic approach on building trust to try and explain how buyers may want to get involved in longer lasting relationships with sellers.

According to Diekmann and Przepiorka (2017) economic transactions are an example of trust-problems, and as such this goes for transactions on cryptomarkets as well. Because of their

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

illegal nature however there are no authorities that can legally protect anyone involved. For buyers the dilemma involves around placing trust, whether or not a unknown seller can be expected to actually send the drugs the buyer paid for. For the seller the dilemma revolves around whether or not to send the drugs after the money is received. ‘Trust’ however is difficult to define and can have many meanings. Williamson (1993) explained that placing trust in someone means taking a risk. Someone who places trust expects to be more likely to see others honor this trust rather than abuse it.

In their research Buskens and Raub (2002) go further by saying that people would only place trust if they expect to gain more when compared to not placing trust. In their research on The Trust Game they analyzed how relations between those placing trust and those being trusted can change over time. Coleman (1990) stated that for something to resemble The Trust Game it needs four elements, these are summarized as follows by Buskens and Raub (2002):

*“(1) Placing trust by the trustor allows the trustee to honor or abuse trust. This action would not have been possible without placing trust by the trustor.*

*(2) The trustor regrets placing trust if trust is abused, but benefits from honored trust.*

*(3) The trustor voluntarily places resources in the hands of the trustee without formal safeguards.*

*(4) There is a time-lag between placement of trust and the action of the trustee.”*

As all these criteria are met by trade on cryptomarkets, theory derived from The Trust Game can help clarify the buyers’ decision making on placing trust. With this theory I will try to answer the following two questions: to what extent do people buy drugs on more than one occasion via cryptomarkets?; how loyal are repeat drug buyers on cryptomarkets to sellers?

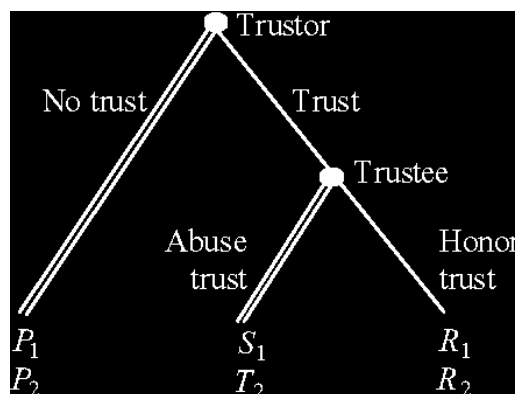
Previous research on cryptomarkets has been primarily seller centered, and the little amount of research on the topic of buyer behavior on cryptomarkets has seemed to produce conflicting results. It is important to get a better understanding of buyer behavior on cryptomarkets as buyers create demand for sellers to sell their drugs. The goal of this paper is to create a clearer picture of buyer behavior on a cryptomarket in general, as well as buyer-seller relations on cryptomarkets in particular. Furthermore by analyzing cryptomarket transaction through the theoretic framework of The Trust Game we get a clearer picture of placing trust and reciprocity among invested actors in an environment without legal repercussions and low socially expected actions.

### Theory

In this section the theoretical framework of this research is presented. First will be discussed how trading via cryptomarkets resembles The Trust Game. Secondly the relevance of reputation on cryptomarkets and how this effects power relations between the actors. Thirdly is explained how power relations may change as buyers and sellers can start interacting repeatedly. Finally I present my hypotheses which I draw from the discussed theories.

#### The Trust Game

The social dilemma's that come with trading on cryptomarkets such as taking risks, trusting strangers, reciprocity and opportunistic behavior resemble The Trust Game. The Trust Game is a game theoretical model which can also be referred to as a 'one-sided prisoners dilemma' (Buskens, 1998). In Figure 1 Buskens and Raub (2013) provide a simple visualization of The Trust Game along with the payoffs for each possible outcome. The game requires two players, the first is the trustor who can either place trust or not place trust. Second player is the seller who takes the role of trustee.



**Figure 1: The Trust Game** ( $S_1 < P_1 < R_1$ ;  $P_2 < R_2 < T_2$ ) (Buskens & Raub, 2013)

Buyers can decide to place trust and purchase from a seller, or not purchase from a seller. The decision to do so is based on incentives a buyer may have, such as what kind of products he requires, how much money he is willing to spend and how much risk he is willing to take with a seller. When no trust is placed a buyer does not purchase anything, and as such does not receive drugs, but neither does he pay any money. Also when no trust is placed the seller does not get to make a choice in the game. When trust is placed a buyer sends money to the seller for the drugs

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

they agree to trade. Now the sellers has a decision to make, either he can honor trust and send the agreed upon products to the buyer, or he can abuse trust by not upholding his end of the deal and just collect the money.

The outcomes of the interaction are different for buyer and seller, as the buyer and seller have different incentives to make their choices. For a buyer it is better to not trade at all with a seller when compared to having his trust abused. As losing money and not receiving drugs is worse than not interacting at all. However if he does receive the drugs for which he paid he will be better off than when not placing trust. The best outcome for the seller is when trust is honored and he receives the drugs he paid for. In Figure 1 the pay-offs of the buyer are represented by the letters with number 1 (Buskens & Raub, 2013). For the buyer the decision to place trust should only be taken if the expected outcome of placing trust is better than the expected outcome of not placing trust (Buskens & Raub, 2002).

The sellers outcomes are represented by number 2 in Figure 1. If trust is not placed the seller does not gain or lose anything. If trust is placed the seller receives the money and thus always be better off compared to no trust situations. However the seller can now decide whether or not to send the drugs to the buyer. The seller has great incentive to abuse trust as he is able to increase his own pay-off considerably, as he gains money and does not lose the drugs which is his best outcome (Buskens & Raub, 2013).

### **Reputation**

As sellers need to attract customers, they will provide information about their products. This information is highly biased as the source of the information is a seller with great incentive to scam. A reputation system is used on the cryptomarket to protect buyers from trust-abusing sellers. A reputation system is a self-regulating form of informal social control (Morselli, et al., 2017). Reputation is based on a score given in reviews by all people who traded with a seller previously. These scores for instance can be on a scale between one to five stars, or a negative, neutral or positive rating. The scores indicate the trustworthiness of a seller as experienced by others who have done business with that seller previously.

Reputation is an important source of information for buyers when deciding to trust a seller with whom they have not dealt with previously, as this is the only way to get information from a more reliable source than the seller himself. It is shown that higher reputation scores improve the

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

business of sellers in two ways (Przepiorka, et al., 2017). More new customers are attracted by sellers with better reputation scores. Since the seller is known as trustworthy, buyers will flock to him, as buying from a trustworthy seller poses less risk to the buyer. Also because the seller is known to deliver his goods he can increase the prices of these goods. The buyers take less risk with a trustworthy seller, and thus they will be more inclined to spend more money since they know they are more likely to get what they paid for.

The reputation score is made up of all reviews given over purchases made from a seller. If abusing trust leads to a bad experience for the buyer, they will give bad reviews to the seller. This will decrease the sellers reputation score and thus discourage others from approaching the seller (Morselli, et al., 2017). New sellers with no reputation at all or sellers with relatively low reputation will have to compensate in their prices to keep attracting customers (Przepiorka, et al., 2017). Lower prices could lure customers as they risk losing less money, and also if they do get their drugs they spent less. Thus reputation systems give sellers incentives to honor trust.

### **Repeated Interactions**

With the reputation system in place sellers have to keep in mind that their choice to abuse or honor trust has consequences for their future business potential (Morselli, et al., 2017). This not only means business from buyers with whom they have not interacted previously, but also opportunities to see buyer return. People buying at cryptomarkets are known to do so more than once and possibly repeatedly from the same sellers (Décary-Héту & Quessy-Doré, 2017; Norbutas, 2018).

In game theory, when games are repeated in succession of one another we speak of repeated interactions. Decisions made in the past can have consequences for the future (Buskens, 1998). If actors want long term successes, their decision-making process may be influenced not only by the payoffs directly at stake, but also by the possibility of future interactions. Axelrod (1984) called this phenomenon “the shadow of the future”, and showed that cooperation becomes a dominant strategy when interactions are repeated. Other research done on this subject shows similar results (Cochard, et al., 2004).

Buskens and Raub (2002) explain how ‘the shadow of the future’ applies to The Trust Game. They name two mechanisms that happen when buyer and seller interact with one another. These mechanisms are called *learning* and *control*, and they work both on a dyad level and a network level. The dyad level refers to the relation between a specific duo of buyer and seller. The



## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

network level refers to all possible interactions between active buyers and sellers active on the cryptomarket.

*Learning* is the mechanism whereby the actor can improve his choices of placing trust based on the information gained from experiences in past interactions (Buskens & Raub, 2002). Positive past experiences can make a trustor place trust again. On a dyad level this can translate to buying repeatedly from the same seller, since the seller proved to be trustworthy. However negative experiences can prevent trustors from placing trust again in the same seller. Possibly moving on to another seller or never using cryptomarkets again, and leaving any seller with one less potential buyer. On a network level this may apply to the buyer approaching other sellers with high reputation in the future, if a low reputation seller abused his or her trust. Or not approaching other sellers since a trustworthy seller has been found already.

*Control* refers to the ability of a buyer to influence the sellers decision to abuse or honor trust (Buskens & Raub, 2002). The seller has short term incentives to abuse trust, but long-term incentives to honor trust. On a dyad level the buyer can prevent the seller from earning more money by not placing trust again if trust was abused previously. Since this is detrimental for the seller, he or she is inclined to cooperate and honor trust when it is placed. On a network level sellers are incentivized to honor trust as trustors will give reputation scores in reviews on their purchases. Buyers control sellers actions by informing others of untrustworthy behavior. Low reputation scores are detrimental for business, since new clients are deterred from doing business with low reputation sellers. Also low reputation is hard to improve again after it drops, since it is impossible to get a perfect reputation which most trustworthy sellers have, and that is what attracts new buyers (Przepiorka et al., 2017).

Furthermore, Bohnet and Huck (2004) find that past experiences are more important for placing trust than general reputation. Meaning that the buyers own experience with a seller is more important for the buyers in terms of placing trust again than the general reputation the seller has. Kollocks research (1994) supports this, and even found that once trust is honored, trustees are more likely to stay with the trustor than move to another with whom they have not had any interaction, even if others proposes a better deal. Although this does not mean that seller reputation has no influence on deciding to place trust in a seller at all, it does show that buyers value their own experiences with sellers highly, supporting the idea of a *learning* mechanism.

## Hypotheses

Within the context of cryptomarkets the *control* mechanism provided by Buskens and Raub (2002) is hardly measurable and also refers to the decision-making process of the seller and not the buyer. In this research I focus on buyer behavior, which according to Buskens and Raub (2002) is explained by the *learning* mechanism in repeated interactions.

The *learning* mechanism explains how buyers can change their decision to place trust based on previous experiences. Positive experiences indicate that trust was honored when placed. As buyers learn that placing trust is rewarded they can become more inclined to do so again. Negative experiences can indicate that trust was abused, and so a buyer may become more reserved to place trust again. On a network level I hypothesize that:

*H1: The higher the reputation-score gives for a drug purchase via a cryptomarket, the more likely the buyer is to purchase again via this cryptomarket.*

The second hypothesis looks more in depth at the dyad level of interactions between buyer and seller. I expect that buyers learn from their previous experiences with specific sellers and want to be at as little risk as possible. Positive experience indicate a trustworthy sellers as he honored trust when it was placed. Repeatedly purchasing with that seller would then pose less risk. My second hypothesis is as follows:

*H2: The higher the reputation-score a buyer gives for a drug purchase from a specific seller, the more likely the buyer is to purchase again from that seller.*

### **Methodology & Data**

In this section I will first explain what methods I will use to test the hypotheses. Then the data collection is discussed, after which I will explain how each variable was created, and how they contribute to the analyses.

#### **Methodology**

To test the hypotheses on whether or not buyers are more likely to return to cryptomarkets and specific sellers based on purchase experience I use regression analyses. SPSS was used to analyze the data. I want to test two things; 1) can we predict whether or not a buyer would return to the cryptomarket based on purchase experience; 2) can we predict whether or not a dyad would be repeated depending on purchase experience. Because the data consists of several non-normally distributed variables and both independent and dependent category variables I will use logistic regressions to test my hypotheses.

As mentioned in the introduction escrow services are meant to improve trust in cryptomarket relations by decreasing sellers the opportunities to scam. Therefore the payment method is used as covariate in the analyses. Also I check for an interaction effect between payment method and rating to see if escrow services resulted both more positive feedback as well as increased odds of buyers repeating purchases.

The number of purchases a buyer had on the cryptomarket in general as well as within a dyad will be taken into account as well. This number indicates the amount of times a buyer placed trust previously, and with it an indication is created for the experience a buyer has on the cryptomarket and with specific sellers. An interaction effect between these indicators and rating may show whether or not more experienced buyers are more likely to experience both positive interactions with sellers and also increase the odds of seeing them return.

#### **Data Collection**

The data used in this research was collected from the AlphaBay cryptomarket. AlphaBay was operational from December 2014 until July 2017, when it was shut down by US authorities in Operation 'Bayonet' (Christin, 2017). The data was collected before the shutdown, by means of

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

'wget' crawling software. Three datasets were made, containing; 1) item listing pages; 2) seller feedback pages; 3) buyer feedback data.

The item listings pages compiled a dataset with all items that were sold, including description of these items, in total 139,773 different items were found. The dataset included many missing's for the item identifiers, due to the items being deleted from the website before running the crawling software. Since all items got a unique identifier we know which items are missing, along with description of these items. The items with identifiers also categorized in types of illicit goods, among which 'drugs and chemicals' was one of the categories. I created a new list of items including only items positively identified as 'drugs and chemicals', which left me with 94,257 items.

The seller feedback data contains over 2.2 million feedback messages linked to seller identifiers. The feedback is given in three categories, positive, neutral and negative. In this dataset 5,989 different sellers could be identified. From this dataset we could also identify buyers who gave this feedback. However only a small portion (6,651 buyers) could be identified where all purchases of the buyer were accounted for. As the buyer nicknames are anonymized on the website, however buyer nicknames mentioned on forum of the AlphaBay website were entered in the website URL addresses. Correct guesses present the page where all feedback on purchases could be found. The information could be matched to sellers by using the feedback pages of identified buyers, creating a third dataset.

The third dataset thus compiles all purchases (36,486) made by buyers who were identifiable, and gave feedback of their purchase on sellers who were also identifiable. This dataset was matched with the item listings dataset which only included drugs and chemicals to obtain a dataset consisting of all drugs purchases by identified buyers from identified sellers (N=16,471 cases). Note that these buyers and sellers might have dealt in other illicit goods that were not drugs, or drugs that were not identifiable.

### **Dependent Variables**

I constructed two dependent variables, each necessary for testing one of the hypotheses. To test the first hypothesis I constructed a variable indicating whether or not a buyer would return for more purchases on the cryptomarket in the future. This was done by sorting the data by buyer and

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

date of feedback. Although the date of feedback is not the actual date of the purchase, it is the closest possible indicator for any order in which the purchases were made.

Out of 16,471 cases 28 cases from a total of 20 buyers had missing values for date of feedback, which meant that for these buyers I could not guarantee the order in which their purchases were made. I made a filter variable which could exclude all purchases from these buyers (123 cases) from the analysis, leaving me with 16,348 cases. From included cases the last purchase of each buyer indicates that the buyer would not return for more purchases to the cryptomarket. Each case was assigned a score on the variable `Buyer_Last_Purchase` of 0 when they would return for more purchases, and 1 for the last purchase made by the buyer.

For the second hypothesis I constructed a variable indicating each last purchase per dyad (`Dyad_Last_Purchase`), by sorting the data per buyer and seller, and then the date of feedback. From the same 28 cases which had missing's on date of feedback 20 different dyads were identified. I constructed a filter variable that excluded all cases (53 cases), from the 20 dyads where the order of purchases could not be guaranteed keeping 16,419 cases. `Dyad_Last_Purchase` was assigned a value of 0 when more purchases would follow, and 1 if the last purchase was identified. Thus creating a dichotomous variable indicating whether a case was the last interaction of a dyad.

The two dependent variables have an overlap. As all scores of 1 for `Buyer_Last_Purchase` per definition also are also 1 for `Dyad_Last_Purchase`. And all scores of 0 for `Dyad_Last_Purchase` also score 0 for `Buyer_Last_Purchase`. Among the scores of 1 for `Dyad_Last_Purchase` there is a group of cases that identify the last purchase within the dyad, however these buyers would go on to keep purchasing from other sellers.

### **Independent variable**

Rating is the only indicator of buyer feedback in this data. Each case is a feedback message with an assigned score on rating. Three categories were present; negative, neutral and positive. From the original string variable within the data a numeric indicator was made called '`Num_Rating`'. These were categorized in one nominal variable for '`Num_Rating`': 1) Positive; 2) Negative; 3) Neutral. Although the scores on this variable are a numeric indicator, this was only done as the analyses could not use string variables which were presented in the data originally. The '`Num_Rating`' variable is used on nominal scale.

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

**Covariates**

Payment method was originally measured in ten categories, which I narrowed down to two categories. Originally there were nine categories for Finalize Early payments between 20% and 100%, and one category escrow payments. I created a new dichotomous variable called 'Payment\_Method' where 0 equals any form of Finalize Early payment, and 1 equals payment by escrow.

To further indicate the order in which purchases were made by a seller I sorted the data again by buyer and date of feedback. Then I used a duplicate count by buyer to create a new variable that indicates in which position a case is among all purchases from each buyer. Buyers with only one purchase in total would score 0 on this duplicate variable. I made a new variable copying the duplicate count, and changing the scores of 0 into 1 for all buyers with only one purchase. The new interval variable indicating the place in a buyers string of purchases is called 'Buyer\_Nth\_Purchase'.

Next I created the 'Dyad\_Nth\_Purchase' count variable, which indicates the position of a purchase from a string purchases per dyad. The same process was followed as for 'Buyer\_Nth\_Purchase' except for two things. First I sorted the data by buyer, then seller and then date. Second I counted the duplicates for each buyer and seller couple. This resulted in a dyad count where all non-repeated dyads would score 0. I made a new variable copying the dyad duplicate count and adjusting all scores from 0 to 1, which I called 'Dyad\_Nth\_Purchase'.

## Results

### Descriptive Statistics

The descriptive statistics of the variables are presented in Table 1. The dependent variables indicate the tendency of buyers to return to cryptomarkets and sellers. We can see that 78.4% of all cases indicate a buyer would come back to the cryptomarket for more purchases. 43.1% of all cases represent repeated interactions within dyads, which is slightly less than the 50% that Norbutas (2018) found.

Furthermore we see that ratings are almost always positive (95.4%). Negative ratings (3.2%) and neutral ratings (1.5%) are much less likely to occur. This is comparable with both licit good markets such as eBay (Dellarocas, 2003) as well as other cryptomarkets such as Silk Road 1.0 (Przepiorka et al., 2017).

The distribution of payment methods is much more equal. Finalize Early payments account for 42.0% of all purchases, while escrow payments were used 58.0% of all cases. Some items may be sold only by either of the methods, and some items only by one of the methods. The data in the table simply shows which method was used, not whether the buyers had a choice.

When looking at 'Buyer\_Nth\_Purchase' we need to keep two things in mind: First I had to exclude all buyers who had at least one missing case on date of feedback, which happened in 28 cases. The order of those buyers' purchases would be incorrectly identified if they were not excluded. This resulted in 3541 buyers accounting for 16348 cases. Secondly this variable does not reflect average number of purchases per buyer. 'Buyer\_Nth\_Purchase' indicates the place of a purchase in a sequence of purchases made by the buyer sorted by date. In the table we read that on average the Nth purchase is the 7.43 purchase made by the buyer. This variable is skewed as the median of this variable is 4, meaning that at least half of the cases are the fourth purchase of a buyer or less. Also, 30.6% of buyers (1,082) only made one purchase at all. This means that 69.4% of all buyers (2,459) made more than one purchase via the same cryptomarket, which is much less than the 90.1% found by Décary-Héту and Quessy-Doré (2017). Nonetheless, a large proportion of buyers active on cryptomarkets are willing to make multiple purchases. The average number of sales per buyer is the total number of cases divided by the total number of buyers in the dataset ( $16,471/3,561=4.63$ ), and is not included in the descriptive table.

For Dyad\_Nth\_Purchase 16,419 cases are used. These cases represent dyads for which all feedback dates are accounted for. We see that each case on average represents the 3.42 transaction

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

within a dyad. This variable is however also heavily skewed, as the median is 1. In total 9,357 cases represent the first interaction of a dyad, meaning 56.9% of all cases are unique buyer seller interactions, and 43.1% of all cases are repeated interactions. 67.5% of all dyads only last a single purchase, 18.6% are repeated once, 5.8% are repeated twice, 8.1% of all dyads lasts four purchases or more.

Table 1: *Descriptive statistics of variables*

Variable	Value	n	%	
<b>Dependent</b>				
<i>Categorical</i>				
Buyer_Last_Purchase	0) No	12910	78.4	
	1) Yes	3561	21.6	
Dyad_Last_Purchase	0) No	7094	43.1	
	1) Yes	9377	56.9	
<b>Independent</b>				
<i>Categorical</i>				
Num_Rating	1) Negative	525	3.2	
	2) Positive	15706	95.4	
	3) Neutral	240	1.5	
Payment_Method	0) FE	6912	42,0	
	1) ESCROW	9559	58,0	
	<b>Mean</b>	<b>Min</b>	<b>Max</b>	<b>SD</b>
<i>Ratio</i>				
Buyer_Nth_Purchase <sup>a</sup>	7.43	1	174	13.01
Dyad_Nth_Purchase <sup>b</sup>	3.42	1	173	10.89

$N=16471$ , Note: <sup>a</sup>  $N=16348$ , <sup>b</sup>  $N=16419$

### Hypothesis 1

In Table 2 we find the logistic regressions on the likelihood of not returning for purchases to the cryptomarket. Model 1 represents the odds of the last purchase being correctly predicted by the rating given for that purchase. The model shows that the rating is a significant predictor for any case being the last purchase by a buyer ( $\chi^2(2)=47.560$ ,  $p<.001$ ). We can see that positive results are 55.8% ( $p<.01$ ) more like to predict the last purchases of a buyer than neutral ratings. Negative ratings however do not significantly predict different odds than neutral ratings. The model itself only predicts .4% (Nagelkerke  $R^2$ ) of the variance within the data.



## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

In Model 2 (Table 2) I added two covariates that could help predicting buyers not returning to the cryptomarket, these covariates are 'Payment' and 'Nth purchase by buyer'. The model is significant ( $\chi^2(4)=498.399$ ,  $p<.001$ ). When controlling for the covariates, positive ratings still significantly predict decreased odds of buyers not returning to cryptomarkets compared to neutral ratings ( $p<.01$ ,  $OR=.669$ ). Negative ratings do not significantly differ from neutral ratings. Payment by escrow seems to be helpful in getting buyers to come back, buyers return 37.9% ( $p<.001$ ) more likely when compared to Finalize Early methods. Also the number of purchases previously made by the buyer at the time of giving feedback is a significant predictor for buyers not returning at the cryptomarket, each purchase increases the odds of returning by 5.9% ( $p<.001$ ). The model shows that even when accounting for payment methods and number of purchases by the buyer positive ratings are still a significant predictor for the chances of buyers not returning to the cryptomarket. Compared to Model 1 the variance explained is increased by tenfold (Nagelkerke  $R^2 = 4.6\%$ ), however the accuracy of Model 2 stays 78,3%.

In Models 3 and 4 (Table 2) I check for interactions between the covariates and the predictor variable 'Num\_Rating'. Model 3 ( $\chi^2(6)=498.951$ ,  $p<.001$ ) and Model 4 ( $\chi^2(6)=500.251$ ,  $p<.001$ ) significantly predict the odds of the buyers returning to the cryptomarket. As the escrow payment method theoretically offers a safer experience for the buyer, this might allow for an interaction between positive ratings and odds of returning. Also as buyers purchase more often they might get better at evaluating risks, leading to more selective interactions with sellers and thus a better experience. However these models shows that no such interaction effect significantly predicts odds of buyers returning to cryptomarkets or not.

Hypothesis 1 is at least partially supported by Model 2. The model shows that user experience measured by 'Num\_Rating' can predict the likelihood of buyers returning for more purchases at least partially. The model shows that positive ratings give better odds of buyers returning to the cryptomarket. Odds of negative ratings do not differ significantly from neutral ratings. The model also shows that using escrow as payment method gives better odds of buyers returning. Furthermore the model shows that as buyers make more purchases on the cryptomarket, they will become increasingly more likely to return for even more purchases. The model substantiates the H1 hypothesis that the high feedback ratings are more likely to result in buyers coming back for more purchases.

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

Table 2: Logistic regressions on Buyer\_Last\_Purchase

Variable	Model 1			Model 2			Model 3			Model 4		
	B	S.E.	OR	B	S.E.	OR	B	S.E.	OR	B	S.E.	OR
Constant	-.872***	.143	.418	-.453**	.147	.636	-.376	.202	.687	-.367	.209	.693
<i>Num_Rating</i> (base = neutral)												
Positive	-.444**	.145	.642	-.402**	.146	.669	-.479*	.202	.620	-.485*	.210	.616
Negative	.182	.171	1.199	.218	.173	1.243	.088	.246	1.092	.037	.241	1.037
<i>Payment_Method</i> (base = FE)												
ESCROW				-	.040	.725	-.480	.290	.619	-.322***	.040	.724
				.322***								
Buyer_Nth_Purchase				-	.004	.944	-	.004	.944	-.078*	.037	.925
				.057***			.057***					
<i>Interaction</i>												
Positive x ESCROW							.156	.293	1.169			
Negative x ESCROW							.254	.347	1.289			
Positive x Buyer_Nth_Purchase										.020	.037	1.020
Negative x Nth Buyer_Nth_Purchase										.042	.041	1.043
N = 16348, * = p<.05, ** = p<.01, *** = p<.001.												
-2LL	17038			16588			16587			16586		
	( $\chi^2=47.560$ , df=2, p<.001)			( $\chi^2=498.399$ , df=4, p<.001)			( $\chi^2=498.951$ , df=6, p<.001)			( $\chi^2=500.251$ , df=6, p<.001)		
Nagelkerke R <sup>2</sup>	.4%			4.6%			4.6%			4.6%		
Classification Accuracy	78.3%			78.3%			78.3%			78.3%		

## Hypothesis 2

Table 3 shows the results for the logistic regression on buyers returning to specific sellers they interacted with previously. I use the models in this table to test Hypothesis 2. Model 5 shows a significant relation between 'Num\_Rating' and buyers repeating purchases at specific sellers ( $\chi^2(2)=57.354$ ,  $p<.001$ ). Positive ratings decrease the odds of buyers not returning to a seller by 81.4% ( $p<.001$ ) compared to neutral. Negative ratings however do not predict significantly different odds than neutral ratings. The model explains only .5% of the variance (Nagelkerke  $R^2$ ), and the classification accuracy is 57.0%.

In Model 6 (Table 3) I added the covariates for 'Payment\_Method' and 'Dyad\_Nth\_Purchase'. Again the model significantly predicts the results ( $\chi^2(4)=1,472.657$ ,  $p<.001$ ). The effect of positive ratings ( $OR=.621$ ,  $p<.01$ ) is slightly lower when compared to Model 5, however still significant. Negative ratings still do not produce significantly different odds. Using escrow as payment method increases the chances of buyers returning to specific sellers by 19.5% ( $p<.001$ ). Every interaction between a buyer and seller increases the chances of a buyer returning to that seller again by 25.0% ( $p<.001$ ). The model itself increases its explained variance to 11.5% (Nagelkerke  $R^2$ ), and its classification accuracy to 64.4%.

In Model 7 and 8 I check for interaction effects between the covariates and rating. The reasons for doing so are again because using escrow as payment method and increased number of interactions within a dyad might influence both the rating and odds of returning. Model 7 ( $\chi^2(6)=1,474.178$ ,  $p<.001$ ) and model 8 ( $\chi^2(6)=1,489.992$ ,  $p<.001$ ) are both significant. However again the models do not produce interaction effects with significantly different odds.

As positive ratings significantly predict higher odds of having buyers repeating an interaction with a seller we find that Model 6 substantiates hypothesis 2. However negative ratings do not predict significantly different odds than neutral ratings. Again we find that using escrow produces higher odds of repeated interactions within dyads. Also we find that the more often an interaction is repeated within a dyad, the more likely the odds become that the interaction will be repeated again in the future.

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

Table 3: Logistic regressions on *Dyad\_Last\_Purchase*

Variable	Model 5			Model 6			Model 7			Model 8		
	B	S.E.	OR	B	S.E.	OR	B	S.E.	OR	B	S.E.	OR
Constant	.851***	.143	2.343	1.340***	.146	3.819	1.397***	.216	4.042	1.352***	.245	3.863
<i>Num_Rating</i> (base = neutral)												
Positive	-.596***	.144	.551	-.476**	.146	.621	-.536*	.216	.585	-.474	.246	.623
Negative	.004	.172	1.004	.071	.175	1.074	1.55	.268	1.168	-.273	.270	.761
<i>Payment_Method</i> (base = FE)												
ESCROW				-.178***	.033	.837	-.283	.291	.753	-.180***	.033	.835
Dyad_Nth_Purchase				-.224***	.009	.800	-.223***	.009	.800	-.230*	.112	.795
<i>Interaction</i>												
Positive x ESCROW							.113	.293	1.120			
Negative x ESCROW							-.130	.356	.878			
Positive x Dyad_Nth_Purchase										.000	.112	1.000
Negative x Dyad_Nth_Purchase										.175	.116	1.192

N = 16419, \* = p<.05, \*\* = p<.01, \*\*\* = p<.001.

-2LL	22382	20967	20966	20950
	( $\chi^2=57.354$ , df=2, p<.001)	( $\chi^2=1472.657$ , df=4, p<.001)	( $\chi^2=1474.178$ , df=6, p<.001)	( $\chi^2=1489.992$ , df=6, p<.001)
Nagelkerke R <sup>2</sup>	.5%	11.5%	11.5%	11.6%
Classification Accuracy	57.0%	64.4%	64.4%	64.4%

### **Conclusion & Discussion**

In this study repeated buyer behavior on cryptomarkets was analyzed. The goals of this research was to answer two questions: to what extent do people buy drugs on more than one occasion via cryptomarkets?; how loyal are repeat drug buyers on cryptomarkets to sellers? Data was collected from the AlphaBay cryptomarket. Logistic regressions were used to calculate the odds of buyers returning to both the cryptomarket in general as well as buyers returning to specific sellers.

### **Findings**

69.4% of the buyers on AlphaBay bought repeatedly, and 43.1% of all cases represent repeated interactions among dyads. Although these percentages are lower than found by Décary-Héту and Quessy-Doré (2017) and Norbutas (2018) they still reflect the same trends in behavior. Buyers on cryptomarkets tend to make multiple purchases, and they seem willing to keep purchasing from the same buyers even in a competitive market with many alternative sellers and products.

As buyers learn from their own experiences with sellers they gather information on sellers trustworthiness. Buyer experiences are represented by feedback ratings that buyers leave with each purchase. Positive feedback was found to predict higher odds of a buyer returning to both the cryptomarket as a whole, as well as sellers they interacted with previously. The odds of seeing buyers return between neutral and negative feedback do not differ significantly. The not significant findings could mean two things; buyers consider neutral and negative experiences not to differ much from one another; or buyers have vastly different neutral and negative experiences. Either way they differ little in their consequences for chances of repeat buying behavior.

Three other factors were also found to have separate effects on the odds of seeing buyers return or not. First the opportunity to pay with escrow services, the relatively safe third-party payment method which releases currency only after confirmation of receiving the drugs has been given by a seller, is meant to create a safer environment for buyers. Escrow services predict better odds of seeing buyers return to both the market as well as the dyad. As such buyers using escrow take less risk with each purchase and are more likely to purchase repeatedly. This effect is seen in both buyers repeatedly buying at the cryptomarket as well as within dyads.

Second the number of previous purchases on the cryptomarket contributed better odds of returning for more purchases to the cryptomarket. This shows that buyers become more committed to buying drugs repeatedly on cryptomarkets with each purchase.

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

Thirdly each purchase taking place within a dyad increases the odds for consecutive purchases within that dyad. Thus buyers tend to establish relationships with sellers, and increasingly choose to do business with those sellers they already know. This could be explained by the notion that buyers want to take as little risk as possible when placing trust, and increasingly choose to do business with sellers that they already know. The three contributing factors however do not interact significantly with the given feedback, showing that these are separate effects with separate mechanisms.

### **Limitations**

This research was limited mainly by three factors. Firstly because of the data collection method where user names were scraped from the discussion forum and placed in the websites URL addresses there may be a selection bias. Buyers active on the discussion forums may show more involvement in the cryptomarket in general compared to those who are not active on the forum. Those active buyers could also have made more purchases, and could be more aware of the risks involved and thus more selective in their choices of placing trust, leading to more positive feedback, longer dyad relations and more activity on the cryptomarket in general.

Secondly the data collection process may have contributed to defining each last purchase for each buyer as well as within a dyad. Buyers may have made more purchases after the data was collected, however this could not be accounted for within the data. This is a problem every cryptomarket research may have to deal with. Intentions of buyers to keep purchasing regardless of the moment of data collection or closing of the market could be gathered through surveys. That however would be thwarted by the anonymity, illegality and secrecy of these markets and communities.

Thirdly there are concerns for the validity of the data since the given feedback measures more than just trustworthy behavior. Sellers may honor trust when it is placed, but even then external factors can influence the experience of the buyers. When shipments that are late or are not delivered at all to can be interpreted as sellers not honoring trust even when sellers are not directly to blame. Or buyers can give positive feedback for receiving the purchase in time, only to find out later that the quality of the drugs was lower than promised. In those cases trust would have been abused but this would not have been reflected in the feedback.

**Recommendations for Future Research**

This research contributed to understanding buyer behavior on cryptomarkets, and presents mechanisms explaining repeated buying behavior and loyalty towards sellers. However the research is hampered by the data collection method, and the anonymity and secrecy of the cryptomarkets. To get a better understanding of buyer intentions that are not measurable in the data I would suggest more surveys and qualitative research to be done among cryptomarket users. Although the process is difficult Van Hout and Bingham (2013a; 2013b) have shown that some cryptomarket users are willing to speak about their experiences. Any information gathered on the subject of intentions to keep purchasing drugs via cryptomarkets, staying loyal to sellers or moving on to other sellers may be invaluable. Future quantitative research on buyer behavior may want to account for availability of alternative products and sellers within the same product categories at the time of purchasing.

## References

- Aldridge, J., & Askew, R. (2016). When drug dealers can advertise: how drug cryptomarkets enable drug dealers to advertise. In *10th Annual Conference of the International Society for the Study of Drug Policy, Sydney*.
- Aldridge, J., & Décary-Héту, D. (2016). Hidden wholesale: The drug diffusing capacity of online drug cryptomarkets. *International Journal of Drug Policy, 35*, 7-15.
- Aldridge, J., Stevens, A., & Barratt, M. J. (2018). Will growth in cryptomarket drug buying increase the harms of illicit drugs?. *Addiction, 113*(5), 789-796.
- Axelrod, R. (1984). *The evolution of cooperation*. New York: Basic Books.
- Barratt, M. J. (2012). SILK ROAD: EBAY FOR DRUGS: The journal publishes both invited and unsolicited letters. *Addiction, 107*(3), 683-683.
- Barratt, M. J., & Aldridge, J. (2016). Everything you always wanted to know about drug cryptomarkets\*( \* but were afraid to ask). *International Journal of Drug Policy, 35*, 1-6.
- Barratt, M. J., Ferris, J. A., & Winstock, A. R. (2016). Safer scoring? Cryptomarkets, social supply and drug market violence. *International Journal of Drug Policy, 35*, 24-31.
- Bohnet, I., & Huck, S. (2004). Realism in Experimental Economics: Integrating the Real World into Experiments-Repetition and Reputation: Implications for Trust and Trustworthiness When Institutions Change. *American Economic Review, 94*(2), 362-366.
- Buskens, V. (1998). The social structure of trust. *Social networks, 20*(3), 265-289.
- Buskens, V., & Raub, W. (2002). Embedded trust: Control and learning. In *Advances in group processes* (pp. 167-202). Emerald Group Publishing Limited.
- Buskens, V., & Raub, W. (2013). Rational choice research on social dilemmas: embeddedness effects on trust. *Handbook of rational choice social research, 113-150*.



## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

- Buxton, J., & Bingham, T. (2015). The rise and challenge of dark net drug markets. *Policy brief*, 7, 1-24.
- Christin, N. (2017). An EU-focused analysis of drug supply on the AlphaBay marketplace. *EMCDDA commissioned paper*. Available on [http://www.emcdda.europa.eu/document-library/eu-focused-analysisdrug-supply-alphabay-marketplace\\_en](http://www.emcdda.europa.eu/document-library/eu-focused-analysisdrug-supply-alphabay-marketplace_en).
- Cochard, F., Van, P. N., & Willinger, M. (2004). Trusting behavior in a repeated investment game. *Journal of Economic Behavior & Organization*, 55(1), 31-44.
- Diekmann, A., & Przepiorka, W. (2017). Trust and reputation in markets. *The Oxford Handbook of Gossip and Reputation*. Oxford: Oxford University Press, nn-nn.
- Décary-Héту, D., & Quessy-Doré, O. (2017). Are repeat buyers in cryptomarkets loyal customers? Repeat business between dyads of cryptomarket vendors and users. *American Behavioral Scientist*, 61(11), 1341-1357.
- Kollock, P. (1994). The emergence of exchange structures: An experimental study of uncertainty, commitment, and trust. *American Journal of sociology*, 100(2), 313-345.
- Maddox, A., Barratt, M. J., Allen, M., & Lenton, S. (2016). Constructive activism in the dark web: cryptomarkets and illicit drugs in the digital 'demimonde'. *Information, Communication & Society*, 19(1), 111-126.
- Morselli, C., Décary-Héту, D., Paquet-Clouston, M., & Aldridge, J. (2017). Conflict management in illicit drug cryptomarkets. *International Criminal Justice Review*, 27(4), 237-254.
- Norbutas, L. (2018). Offline constraints in online drug marketplaces: An exploratory analysis of a cryptomarket trade network. *International Journal of Drug Policy*, 56, 92-100.

## REPEAT BUYING BEHAVIOR OF ILLEGAL DRUGS ON CRYPTOMARKETS

- Przepiorka, W., Norbutas, L., & Corten, R. (2017). Order without law: Reputation promotes cooperation in a cryptomarket for illegal drugs. *European Sociological Review*, 33(6), 752-764.
- Soska, K., & Christin, N. (2015). Measuring the longitudinal evolution of the online anonymous marketplace ecosystem. In *24th {USENIX} Security Symposium ({USENIX} Security 15)* (pp. 33-48).
- Tzanetakis, M., Kamphausen, G., Werse, B., & von Laufenberg, R. (2016). The transparency paradox. Building trust, resolving disputes and optimising logistics on conventional and online drugs markets. *International Journal of Drug Policy*, 35, 58-68.
- Van Hout, M. C., & Bingham, T. (2013a). 'Silk Road', the virtual drug marketplace: a single case study of user experiences. *The International journal on drug policy*, 24(5), 385-391.
- Van Hout, M. C., & Bingham, T. (2013b). 'Surfing the Silk Road': A study of users' experiences. *International Journal of Drug Policy*, 24(6), 524-529.
- Williamson, O. E. (1993). Calculativeness, trust, and economic organization. *The journal of law and economics*, 36(1, Part 2), 453-486.