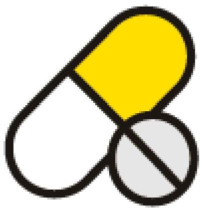
Five stars

A study on the effect of seller's reputation controlled for buyer loyalty on online drug markets



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Abstract

The aim of this paper was to investigate the question what role a seller's reputation plays in the decision of buyers to trust this seller and therefore in facilitating cooperation on online drug cryptomarkets, while controlling for buyer loyalty. Earlier research found that having a high reputation as a seller increased the number of sales (Hardy & Norgaard, 2016; Przepiorka, Norbutas, & Corten, 2017), but also that buyers often buy from the same seller multiple times (Décary-Hétu & Quessy-Doré, 2017; Norbutas, 2018), which could have led to an overestimation of the positive effects of reputation in these studies. This paper therefore re-examined the effect of reputation on the number of sales of a seller, while also looking at the number of unique buyers, to control for buyer loyalty, by conducting linear mixed model regressions on data from a cryptomarket named Abraxas. The results show that a higher weekly average rating of a seller significantly increased the number of sales of a seller and his number of unique buyers. The conclusion of this paper is therefore that reputation plays an important role in the decision of buyers to trust a seller, but that buyer behaviour is a relevant, non-negligible factor in this mechanism, which should be looked into in future studies.

Keywords: cryptomarket, online drug market, reputation system, buyer loyalty, repeated buying, trust problem

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1. Introduction

'A narco-state', that is what the Dutch police union (*Nederlandse Politiebond*) called the Netherlands in a pamphlet published in February 2018 (Vos, 2018). By using the term 'narco-state', which is a state in which the production and trade of illicit drugs happens on a large scale, they particularly meant to point out the growing body of online platforms to trade illegal drugs. The Netherlands play a fair role in these platforms, being the country with the highest revenue per capita of this online drug trafficking (Kruithof et al., 2016). Yet also outside of the Netherlands, these platforms, known as cryptomarkets, have been drawing attention since the opening of the first of those cryptomarkets, named *Silk Road*, in 2011. The Global Drug Survey 2018, a worldwide survey with over 65,000 respondents, reported that 11.2 percent of the drug users has purchased their drugs on cryptomarkets at least once, while 9.3 percent did this during the last twelve months (Winstock, Barrat, Maier, & Ferris, 2018).

A cryptomarket is defined as 'a marketplace that hosts multiple sellers or 'vendors', provides participants with anonymity via its location on the hidden web and use of cryptocurrencies for payment, and aggregates and displays customer feedback ratings and comments' (Barratt & Aldridge, 2016, p. 1). In other words, these are online platforms, resembling legal online marketplaces like eBay, on which buyers and sellers interact and exchange products; in this case, illegal drugs. Because the exchange of these goods is illegal, the cryptomarkets assure that both sellers and buyers remain anonymous. This is possible because the markets are situated on the 'deep web', the part of the Internet that isn't accessible via regular search engines like Google, and can only be used with special browsers, of which the most prominent one is called Tor, that conceal the identity and location of users (Décary-Hétu & Quessy-Doré, 2017). Furthermore, users can pay with cryptocurrencies (Bitcoins), which are not bound to someone's identity (Barratt & Aldridge, 2016). The anonymity ensures that users of cryptomarkets can interact relatively safe, with a minimized threat of law enforcement (Norbutas, 2018).

While the provided anonymity facilitates the trade on cryptomarkets, it also creates new risks for the users, namely regarding trust and cooperation. To reduce these risks, cryptomarkets use reputation systems: buyers inform each other about the trustworthiness of a seller by leaving ratings for each transaction and writing reviews on internal forums (Hardy & Norgaard, 2016). A reasonable share of the previous research on cryptomarkets has particularly been focused on these reputation systems (Décary-Hétu & Quessy-Doré, 2017;

Hardy & Norgaard, 2016; Przepiorka et al., 2017; Tzanetakis, Kamphausen, Werse, & von Laufenberg, 2016). Participating in transactions on cryptomarkets is risky for both users and sellers for a number of reasons. Firstly, since the trade of these drugs is illegal and the identities of users are concealed by encryption technologies, these transactions happen outside of the sphere of control of legal authorities (Przepiorka et al., 2017). This creates a trust problem: possible fraudulent behaviour of sellers will not be sanctioned by law enforcement, which increases the risk for buyers. For example, when the seller doesn't deliver the right product, the buyer will have no contractual guarantee (i.e. regulated outside of the marketplace itself) that his money will be returned.

Secondly, the buyer and seller are anonymous towards each other as well and never meet face to face (Hardy & Norgaard, 2016). This makes it impossible to create a personal trust relationship between a buyer and seller to reduce the risks for the buyer. The same two reasons hold for the sellers, who cannot ensure that the buyer is trustworthy and will complete the payment.

Despite the trust problem, cryptomarkets function and trade is facilitated. Reputation and feedback mechanisms play an important role in this (Hardy & Norgaard, 2016). Przepiorka et al. (2017) found that sellers with high ratings and positive reviews (a good reputation) can charge higher prices and sell their products faster than sellers with bad reputations, indicating that trust is made possible by their reputation. Hardy & Norgaard (2016, p. 1) state that reputation "acts as a sufficient self-enforcement mechanism to allow transactions".

Since the goods that are exchanged on cryptomarkets (i.e. illicit drugs) are consumed quickly and are often highly addictive, it might be reasoned that buyers' activity on cryptomarkets doesn't stop after their first purchase, but that they will return to the market to make new purchases. In that case, buyers do not only have the information on sellers that is provided by the feedback system, they also have their previous experiences with buyers as a source of information. For example, if they had a positive experience with a particular seller, they know this seller is trustworthy and it might be a good choice to buy from this seller again the next time. Previous studies have indeed pointed out that buyers often make multiple transactions with the same seller (Décary-Hétu & Quessy-Doré, 2017; Norbutas, 2018). Décary-Hétu & Quessy-Doré (2017), for example, found that buyers make 60 percent of their purchases from one single seller. Taking this repeated buying pattern into account, the same buyer might repeatedly leave a positive review for a seller, resulting in a higher number of positive reviews than the actual number of content buyers.

Because the studies that found positive reputation effects do not take this into account (Hardy & Norgaard, 2016; Przepiorka et al., 2017), the actual effects of reputation on cooperation on cryptomarkets might be overestimated. For example, the increasing sales of a seller with a good reputation might not be due to new buyers being attracted to him because of this reputation, but due to the return of content buyers that he sold his products to before. This paper will therefore set out to see whether reputation actually facilitates cooperation on cryptomarkets when we control for the possibility that buyers repeatedly interact with the same seller, by trying to answer the following question:

What role does a seller's reputation play in the decision of buyers to trust this seller and therefore in facilitating cooperation on online drug cryptomarkets?

This question will be divided into two sub-questions, namely:

1. How does a seller's reputation influence the attraction of buyers?
2. How does repeated buying from the same seller influence the effect of reputation on attracting new buyers?

This paper aims to contribute to the existing academic literature in two ways. Firstly, this research will contribute to the current understanding of cryptomarkets. This study will use a buyer-centered approach. Previous studies have not yet used such an approach and it might be fruitful to not only understand the macro-level of transactions on cryptomarkets (i.e., cooperation between buyers and sellers), but also how this comes into being on the micro-level (i.e., the decision of buyers to trust or not trust a seller).

Furthermore, this research tries to fill the current 'gap' that was mentioned before: by combining the findings about the positive effects of reputation on cooperation with the findings on the loyalty of buyers to sellers, we can get better insight in the actual role reputation plays in cryptomarkets. Previous studies have used methods that did not take into account the possibility of repeated buying, which is suitable for marketplaces like eBay, while cryptomarkets might be different in this regard, since the products sold on cryptomarkets are quickly consumed and often addictive.

Lastly, on a more fundamental level, this research adds to the sociological understanding of human interaction, especially in situations where trust and cooperation between people is established in the absence of a central authority. Since cryptomarkets are unregulated, this environment is suitable to test theories on the emergence and evolution of cooperation, without a legal framework that influences the behaviour and therefore the research outcomes.

Besides these contributions to the scientific debate, this research is of societal relevance, because it contributes to our understanding of the trafficking of illegal drugs, especially the ways in which drug trafficking has innovated since the coming of the Internet and the opening of the first cryptomarket. By understanding the underlying mechanisms that facilitate the trade of illegal drugs on cryptomarkets, governments will have more information to base their policies on attacking these illegal activities on. Reducing the use and trafficking of drugs is included in the policy goals and strategies of several international institutions. The United Nations, for example, gather this goal under their third Sustainable Development Goal, which is 'to ensure healthy lives and promote well-being for all at all ages' (United Nations, n.d.). The European Union has adopted the EU Drug Strategy for 2013-2020, of which two of the objectives are "to contribute to a disruption of the illicit drugs market […]" and " to contribute to a better dissemination of monitoring, research and evaluation results and a better understanding of all aspects of the drugs phenomenon and of the impact of interventions in order to provide a sound and comprehensive evidence base for policies and actions" (European Council, 2017).

To answer the research question, this paper will use data from a cryptomarket named Abraxas (Branwen et al., 2015) and conduct linear mixed model regressions. The remaining of this paper will first provide a theoretical framework about the topic, from which hypotheses will be derived. Subsequently, the used data and method will be discussed and the results of the analyses will be presented. It ends with a conclusion, in which the research question will be answered and a critical reflection on the study will be set out.

2. Theory

This paper is concerned with the role that a seller's reputation plays in the decision of buyers to trust the seller and therefore in facilitating cooperation on online drug cryptomarkets. This question has several different aspects, that will each be discussed in this section. Firstly, general information will be given about cryptomarkets and the process of cooperation on these marketplaces. Secondly, the trust problem that arises in such a process will be explained. Then, the possible mechanism of solving the trust problem with a reputation system will be set out, after which some previous findings on this topic will be discussed. Next, findings on repeat buying patterns and loyalty of buyers to sellers will be discussed and finally, all of these aspects will be integrated to derive the hypotheses of this paper.

2.1 Cryptomarkets

Cryptomarkets have flourished as online platforms for drug consumers and sellers since the creation of the first cryptomarket, named *Silk Road*, in 2011 (Barratt & Aldridge, 2016). *Silk Road* operated successfully for two and a half years, but was then seized by the FBI on October 2nd, 2013. However, the idea persisted. Within weeks after the seizure, the second version of *Silk Road*, along with new rival cryptomarkets, launched (Aldridge & Decary-Hétu, 2016a). Since then, multiple marketplaces have been flourishing, while being shut down after a certain period of time, either by the administrators, called an 'exit scam', or by law enforcement (Moeller, Munksgaard, & Demant, 2017). This is followed by the opening of new marketplaces. Cryptomarkets form only a small proportion of the overall drug market, compared to offline drug markets and transactions: about 11.2 percent of drug users ever purchased drugs on these online marketplaces (Winstock et al., 2018). However, there has been an upward trend over the past years and cryptomarkets seem to grow steadily (Kruithof et al., 2016).

A key feature of cryptomarkets is the anonymity that is ensured for their users (Barratt & Aldridge, 2016; Hardy & Norgaard, 2016; Martin, 2014b). This anonymity is guaranteed by the combination of two types of technologies: a special browser that hides the identities and activities of users, of which the most known is named Tor, and a digital, anonymous form of money (i.e., cryptocurrencies), for example the Bitcoin (Barratt & Aldridge, 2016). Tor is a form of anonymising computer software: communications on this browser don't travel directly from sender to receiver, as is the case on the normal 'surface web', but bounce between several random nodes in the network (Hardy & Norgaard, 2016). This makes it impossible to trace the message back to the initial sender, ergo the possibility to be completely anonymous. Tor is necessary to access the part of the 'web' on which cryptomarkets are situated, namely the 'hidden web' or 'darknet' (Barratt & Aldridge, 2016). The web, which is 'all of the content accessible through browsers connected to the internet', can be divided into the 'surface web', which contains content that is accessible via search engines, and the 'deep web', of which the content is not (Barratt & Aldridge, 2016). Within the ‘deep web’, there is the ‘hidden web’, which can only be entered anonymously, i.e. via Tor, and that is where cryptomarkets are located.

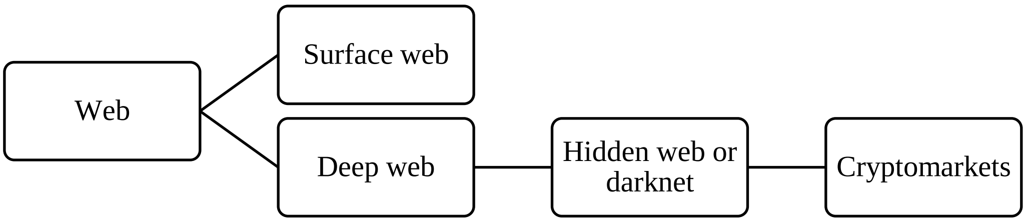

Figure 1. The location of cryptomarkets on the web

Bitcoin is a cryptocurrency, which is not bound to someone’s identity, like traditional currencies (Hardy & Norgaard, 2016). It functions anonymously and electronically, which makes it usable for cryptomarkets.

These technologies thus make it possible to hide the identities of the users of cryptomarkets. Even a buyer and a seller who decide to interact and exchange products, remain anonymous towards each other. This anonymity is essential for the functioning of these marketplaces, since the trade in these markets, in this case the trade in illicit drugs, is illegal. Therefore, being anonymous makes cryptomarkets a relatively safe environment, with a smaller threat of law enforcement (Norbutas, 2018).

On cryptomarkets, individual buyers and sellers can interact and exchange their products (Barratt & Aldridge, 2016; Norbutas, 2018). Such an exchange is usually initiated by a seller, who can introduce an offer on the market independently, including the number of items that he sells and its price (Przepiorka et al., 2017). Subsequently, buyers can buy this product at the price that the seller specified. At most cryptomarkets, the buyer pays before receiving the product, but his money doesn’t travel directly to the seller (Barratt & Aldridge, 2016; Przepiorka et al., 2017). Most cryptomarkets use an escrow service as a third party in the exchange; this service detains the money until the buyer receives the product and only then releases the money to the seller (Barratt & Aldridge, 2016; Przepiorka et al., 2017). If the buyer doesn’t receive the product, he will get a refund. However, using the escrow service is not mandatory and it brings new risks as well (Moeller et al., 2017). There may be a fee (i.e., paying a share of the revenue to the marketplace administrators) to use this service, which makes sellers who don’t use it cheaper and therefore more attractive to buyers. Furthermore, using the escrow service creates the risk that administrators or hackers abscond with the money. Thus, the existence of escrow services does not solve the trust problem that exists on cryptomarkets, which will be explained later on in this section.

The seller sends its product directly to the buyer via the conventional postal network (Martin, 2014a). When the buyer has received the product, he leaves a (numerical) rating, for example one to five stars, and possibly a comment on the transaction, stating for example whether the quality of the product was good, whether the right amount of the product was shipped and how the overall service the seller provided was (Hardy & Norgaard, 2016). These ratings and comments make up the feedback profile of a user and thereby form his reputation on the marketplace. The username of the buyer is not attached to a specific rating or comment, to protect the anonymity and stimulate honest reviews. Only the profiles of sellers are publicly available on the marketplace; information on individual buyers is not (Hardy & Norgaard, 2016).

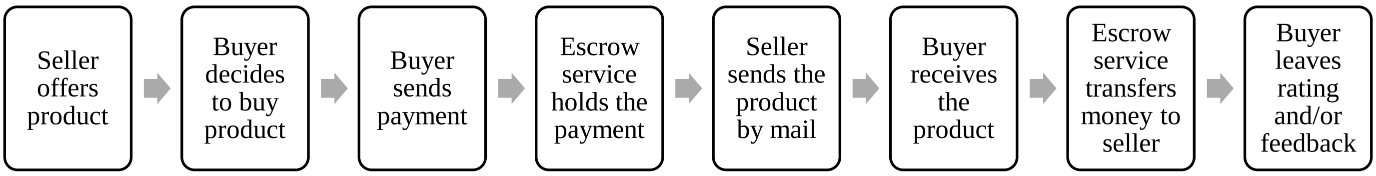

Figure 2. The process of a transaction on cryptomarkets (when escrow service is used).

2.2 The trust problem

Participating in a transaction on cryptomarkets poses risks for both buyers and sellers (Hardy & Norgaard, 2016; Przepiorka et al., 2017; Tzanetakis et al., 2016). As this paper will take a buyer-centered approach, this section will focus specifically on the risks to which the buyer is exposed. The escrow service, that is present on most of the marketplaces, takes away part of the risk for the buyer, namely the risk to pay money and not receive a product (Przepiorka et al., 2017). However, even if the escrow service is used, some risks remain: the quality of the product could be insufficient or the seller could neglect his promises on his service, for example regarding shipping. These risks are not negligible. Problems or misinformation regarding the quality of drugs can be harmful for the health of the user. Furthermore, negligence on the service could expose the buyer to law enforcement, for example when the postal package is stolen, in which case the package, containing illegal drugs, will only be linked to the buyer, whose address is on it.

Buyers and sellers remain anonymous towards each other, meaning that no personal trust relationship between them can be established (Przepiorka et al., 2017). Thus, in the decision to buy or not buy from a specific seller, a buyer cannot rely on his personal relationship with the seller to gain information about his trustworthiness. Furthermore, not only do cryptomarket users want to stay away from legal authorities, since the trade in illicit drugs is illegal, but also it is virtually impossible for these authorities to intervene and enforce the law, due to the anonymising software and cryptocurrencies (Hardy & Norgaard, 2016; Przepiorka et al., 2017). Thus, a buyer can also not rely upon a legal framework to sanction the 'cheating' of sellers.

Clearly, there is a risk for the buyer, that he will have to take in consideration in his cost-benefit analysis to decide whether to buy a product from a specific seller. Dahlman (1979) describes this risk as 'policing and enforcement costs', which are part of the transaction costs an actor has to consider when participating in a market transaction. These are the costs 'of policing and monitoring the other party to see that his obligations are carried out as determined by the terms of the contract, and of enforcing the agreement reached' (Dahlman, 1979, p. 148). When the transaction costs are high, it will be riskier for the buyer to buy a certain product and therefore, the chances that he will decide to do so will be smaller. In this case, the policing and enforcement costs are indeed high: outside of the scope of the escrow service, the buyer cannot enforce the agreement (i.e. in terms of quality and service).

Risk is related to trust: to place trust is to calculate in your cost-benefit analysis that the potential risks will not outweigh the benefits (Tzanetakis et al., 2016). Jordahl (2009, p. 3) describes trust likewise, as 'an actual or potential relation between two persons: one person (the trustor) who trusts another person (the trustee) to cooperate rather than to cheat'. According to Tzanetakis et al. (2016, p. 60) trust is 'a reciprocal, interpersonal element of the relationship between the seller and the buyer of illegal drugs'. Buskens & Weesie (2000) describe such a relationship, or as they call it 'trust situation'. In a trust situation, a buyer, called the trustor, has to decide first whether he trusts a seller, called the trustee. If the trustor decides to trust the trustee, the trustee can either honour this trust or abuse it. Abusing the trust might benefit the trustee, as he will receive the money, but can invest less in the quality of the product. We can apply the trust situation to cryptomarkets: the buyer has to place trust in the seller when he decides to buy the seller's drugs. The seller can then decide to either deliver good quality drugs and stick to his promises, or abuse the trust of the buyer and deliver a bad product, while still receiving the money. This is the ‘trust problem’ that buyers experience on cryptomarkets.

2.3 Reputation systems

Such a trust situation does not happen in isolation, but in a specific context (Buskens & Weesie, 2000). This context can provide the buyer with information to take into account when he decides to buy drugs from a seller or not. This can be via social embeddedness: being embedded in a social network with the seller, for example having acquaintances that know the seller or had past experiences with buying his products, can give the buyer information for his decision to trust (Buskens & Weesie, 2000). However, in cryptomarkets, there is no social embeddedness, as everyone remains anonymous towards each other. This is where the reputation system can form an alternative form of social embeddedness (Diekmann, Jann, Przepiorka, & Wehrli, 2014). The electronic feedback system on legal or illegal online marketplaces (i.e. the ratings and comments) ‘efficiently and systematically disseminates information about traders’ reputations’ (Diekmann et al., 2014). In other words, buyers can use information on the experiences of other buyers with a specific seller to decide whether this seller is trustworthy. The reputation system also incentivizes sellers to cooperate, since every negative experience that a buyer may have with them will hamper their future business, even if they do not trade with that specific buyer anymore, namely in the form of a negative rating for new possible buyers to read (Diekmann et al., 2014). A rational seller will try to avoid such a situation and behave cooperatively.

Previous studies have found positive effects of having a good reputation on cooperation on online marketplaces and on cryptomarkets. Diekmann et al. (2014) found that the number of positive ratings a seller on an online marketplace had, had a positive influence on the number of sales he finalized and the price of their products. Przepiorka et al. (2017) found that sellers on cryptomarkets with better reputations sold more goods and could also ask higher prices for their goods; the researchers concluded that reputation stimulates cooperative behaviour in an environment without law enforcement and among actors that are anonymous towards each other. Finally, Hardy & Norgaard (2016), who specifically researched cryptomarkets as well, found that reputation makes transactions possible, as a self-enforcement mechanism. They even describe the role of reputation as ‘fundamental to the community’s existence’ (Hardy & Norgaard, 2016).

2.4 Loyalty

Users of cryptomarkets are anonymous towards each other and thus are not socially embedded in a conventional way, yet this does not mean that a single buyer and seller never interact more than once. In fact, some studies point out that buyers are loyal to specific sellers and keep returning to them to buy their products (Décary-Hétu & Quessy-Doré, 2017; Norbutas, 2018). While Décary-Hétu & Quessy-Doré (2017) do not find many buyers who only buy their products from one single seller, they do find that buyers make 60 percent of all their purchases from their main seller. This is what they call 'loyalty' from buyer to seller; it means both that the buyer buys from the same seller multiple times, as well as that he has a favourable attitude towards that seller (Décary-Hétu & Quessy-Doré, 2017).

Buyers might return to the cryptomarket for several reasons. In the case of illicit drugs, it might be argued that buyers will return to the market, because drugs are consumed quickly and are often highly addictive. This will lead the buyer to make multiple purchases in a short period of time. When a buyer needs to make multiple purchases, especially when he needs or wants the same drug repeatedly, it might be beneficial to make these purchases from the same seller. After all, when he was satisfied with the product and exchange previous times, the risks (and with that the transaction costs) of a new transaction are diminished when he interacts with that same seller, since he has more information on the trustworthiness of that particular seller. It is therefore likely that the reputation of a seller is especially relevant for new buyers, who want to purchase from the seller for the first time.

Loyalty thus provides a new source of information for buyers. These sources of information and their effect on trust are described by Buskens & Raub (2002). They argue that trust is influenced by the mechanism of 'learning', which is 'the possibility for actors to improve their choices in given interactions using experiences from past interactions' (Buskens & Raub, 2002, p. 170). These experiences can be obtained from third parties, namely other actors that have already interacted with the trustee. In this case, this is the information that can be obtained from the reputation system on the marketplace. However, the experiences for learning can also be obtained from an actor's own past experience with a trustee, which is the case if a buyer buys repeatedly from a specific seller.

The findings on the loyalty of buyer to seller might put the findings on reputation effects in perspective. Since buyers leave a rating for every finalized transaction (Barratt & Aldridge, 2016; Hardy & Norgaard, 2016), loyal customers, who are probably very satisfied with the seller, might account for a big proportion of the positive ratings. The studies that found positive effects of having a good reputation on the amount of sales a seller made (Diekmann et al., 2014; Hardy & Norgaard, 2016; Przepiorka et al., 2017), did not take into account that each individual rating might not be equivalent to an individual buyer. Therefore, the positive effects of reputation might be overestimated: the positive relationship between good ratings and sales might be due to the loyalty of a small group of content buyers, instead of attracting new customers with a good reputation.

2.5 Hypotheses

The integration of the theoretical mechanisms and the findings of previous studies, brings us to the main hypotheses of this paper. As explained above, the reputation system diminishes the trust problem on cryptomarkets, by providing buyers with information on the trustworthiness of sellers and by incentivizing sellers to behave cooperatively. A good reputation of a seller might be vital and crucial to the decision of a buyer to place trust in that seller. This leads to the first hypothesis:

H1: A higher average reputation of a seller increases the number of finalized sales of that seller.

However, as was also explained, buyers might be loyal to specific sellers, from which they buy repeatedly. A fair share of the positive reputation of a specific seller might thus be due to the positive ratings of the same buyers, which is thought to lead to an overestimation of the effects of reputation on attracting new buyers. To find out whether having a positive reputation actually attracts new buyers, the following hypothesis will be tested:

H2: A higher average reputation of a seller increases the number of unique buyers with whom that seller interacted.

3. Data & method

3.1 Data

This study used data from a cryptomarket named Abraxas, which operated worldwide from December 2014 until November 2015. This dataset was collected by Branwen et al. (2015) and covers the period between January 2015 and July 2015.

The data were collected by making mirror copies of the Abraxas website. This method, also called ‘scraping’, creates replicas (i.e., mirrors) of a particular website at a particular point of time. During the period of data collection, a copy was made every two or three days on average. These copies were aggregated to contain only unique, non-repeated information. This method has pitfalls. As the website was not copied continuously, the data is incomplete. After all, sellers, buyers or item listings that became visible after a ‘copy moment’ and disappeared before the next copy was made, are not included. However, the dataset was known to contain about 92.4% of the items listings that were actually present on the Abraxas market during the recorded period (Norbutas, 2018). Thus, while it is important to note this pitfall of the scraping method, the coverage of the data was still high.

The dataset contained information on seller profiles, transactions and item listings. The seller profiles contained the seller’s nicknames, an indication of the number of sales the seller had finalized at the moment of copying, his date of registration, his ‘last seen’ status, the number of days that he has been active on the marketplace and the description that the seller provided of himself. The information on transactions was retrieved from feedback messages that buyers left for sellers, which they can only do if they actually purchased a product from the seller. The feedback data included the identifier of the buyer, the identifier of the item that was purchased and its price in Bitcoins, the buyer’s rating for this transaction on a scale from 0 to 5, textual comments and the date on which the feedback was left. The item listing data included a unique identifier of every item, the nickname of the seller that provided the item, a name and description of the item provided by the seller, the category that the item fell in, the item’s price and weight, the countries that the seller shipped to and from and lastly, the date that the item was first observed.

The dataset was obtained by merging three separate datasets on the Abraxas cryptomarket, namely one containing the seller’s profiles, one containing transactions and left feedback and one containing item listings. The cases in these datasets could be linked to each other by the seller nicknames, which were present in all three datasets and the unique identifiers of items, which were present in the feedback and item listing datasets. The datasets were merged in SPSS, sorting the cases by seller nickname and item identifier. This means that cases that had a missing value for either the seller nickname or item identifier were excluded from the new dataset, as they could not be linked to the other datasets. As the final dataset had the feedback dataset as the basis, this also means that sellers with no sales (and thus, no feedback) were excluded.

The aggregated data contained 10,239 cases, which are 10,239 unique transactions between 466 sellers and 3436 buyers. For the analyses, it was important that every transaction included (1) the date of the feedback, to be able to analyse the effect of reputation over time, (2) the rating that the buyer provided, to determine the reputation of the seller and (3) the identifier of the buyer, to be able to distinguish between unique and "non-unique" buyers. Luckily, the data did not contain any missing values for any of these variables, which left 10,239 cases for the final dataset.

3.2 Variables

3.2.1 Dependent variables

The dependent variable for the first hypothesis was the number of finalized sales of a seller. The seller profiles contained a variable that gave an estimation of the number of sales the seller had finalized, according to the Abraxas cryptomarket. However, this variable was problematic, since it was categorical, not precise (with values like '200~500') and most importantly, there was only one value per seller, instead of the seller's finalized sales at different points in time. Therefore, to operationalize this variable, the number of ratings that the seller received at a specific moment were counted. This is a proxy variable for the number of finalized sales, meaning it is not the exact equivalent of the actual value of the number of finalized sales per seller per week, but it is a relevant indicator of it. Since is a characteristic of the cryptomarket that ratings can only be placed after a finalized transaction, this is a conservative proxy: every seller had at least as many sales as this variable indicated. The number of ratings proved to be a relevant estimation of the number of finalized sales in previous studies, that used this approach as well (Décary-Hétu, Paquet-Clouston, & Aldridge, 2016; Przepiorka et al., 2017; Soska & Christin, 2015). The minimum number of sales per seller per week that was observed was 1. This can be ascribed to the fact that sellers that did not finalize any sales were excluded from the final dataset during the merging of the datasets. The observed maximum number of sales per seller per week was 87 (Table 1). In short, the dependent variable for the first hypothesis gives the number of left ratings (i.e., finalized sales) for a specific seller in a specific week.

The dependent variable for the second hypothesis was the number of unique buyers with whom a seller interacted. This was measured weekly per seller, differentiating by unique buyer identifiers. The minimum number of unique buyers per seller per week that was observed was 1 (Table 1). This was, again, due to the fact that sellers with no sales were excluded. The maximum number of unique buyers per seller per week that was observed was

63 (Table 1). The dependent variable for the second hypothesis thus gives the number of unique buyers that could be observed in the left feedback for the transactions per seller per week. It should be noted that this is also a proxy, since buyers who did not leave feedback were not observed.

3.2.2 Independent variable

The independent variable for both hypotheses is the reputation of a seller. This was operationalized by using the numeric rating that every transaction in the dataset contains. Since these ratings are displayed on the cryptomarkets for future buyers, they give an indication of the reputation that the seller has on the cryptomarket. Moreover, as explained in the theory section, together with the textual comments that previous buyers left for the seller, the ratings are the only indicator for a seller's reputation that buyers can access. This measurement of reputation was also used in previous research (Hardy & Norgaard, 2016; Norbutas, 2018). The rating variable was discrete and had values between 0 and 5. For the independent variable of these analyses, the average of the received ratings was obtained per seller per week. It was assumed that the most recent ratings would have the strongest impact, which is why the analyses used the average rating of the 'current' week. The observed minimum average rating per seller per week was 0; the observed maximum was 5 (Table 1). The mean average rating per seller per week was 4.88, with a standard deviation of 0.477, which indicates that the overall reputation of sellers was very high (Table 1).

3.2.3 Control variables

Several variables were added to the analysis as control variables.

The average rating variable, that was used as the independent variable for the analyses, only took into account the reputation of the seller of a particular week (i.e., the average rating for that week). To control for the reputation that the seller had built before the week for which the dependent variables were measured, a variable was made that controlled for the cumulative number of sales that the seller had finalized before that particular week.

The type of drug that was sold could also have been relevant. As some types of drugs have lower health risks and lower addiction rates than others, the risks for a buyer and therefore the effect of a seller's reputation could differ among drug categories. The types of drugs that were identifiable on the Abraxas marketplace were therefore added to the analysis as dummy variables, namely the categories benzos, cannabis, dissociatives, ecstasy, mixed drugs, opioids, prescription drugs, psychedelics, rc's (research chemicals or 'designer drugs'), steroids and stimulants. These dummies had the value of 1 if the item belonged to that category and the value 0 if it was another type of drug or the type of drug was unspecified. For 8055 out of the 10239 observations, the type of drug was not specified. Therefore, the dummy variable 'unspecified' was added to the analysis, which was used as a reference category.

Table 1. *Descriptive statistics*

	N	**Min**	**Max**	**Mean**	**S.D.**
Independent variable					
Average rating per seller per week	10239	0	5	4.88	.477
Dependent variables					
Number of sales per seller per week	10239	1	87	17.43	18.564
Number of unique buyers per seller per week	10239	1	63	7.08	8.412
Control variables					
Previous sales	10239	0	689	90.02	136.302
Type of drugs (dummies)					
Unspecified	10239	0	1	.79	.410
Benzos	10239	0	1	.01	.105
Cannabis	10239	0	1	.08	.270
Dissociatives	10239	0	1	.01	.055
Ecstasy	10239	0	1	.03	.175
Mixed	10239	0	1	.00	.014
Opioids	10239	0	1	.02	.136
Prescription	10239	0	1	.01	.103
Psychedelics	10239	0	1	.02	.125
RC's	10239	0	1	.00	.031
Steroids	10239	0	1	.00	.039
Stimulants	10239	0	1	.04	.197
Total number of sellers	466	-	-	-	-
Total number of buyers	3436	-	-	-	-

3.3 Method

To estimate the effects of reputation on finalized sales and on unique buyers, this paper used multilevel models; random intercept models in particular. This model is based on a combination of the variance components model and the single level regression model. A single level regression model tries to explain the variance in a dependent variable by the variance in an independent variable, which comes down to the following equation:

$$Y = \beta_0 + \beta_1 X + e_i$$

In this equation, Y is the dependent variable, β_0 is the intercept (i.e., the value of the dependent variable when the independent variable is 0), β_1 is the slope of the independent variable X and e is the error between the predicted value of Y for an individual i and the actual value (i.e., the error). The β_0 and β_1 can be called 'fixed' parameters, meaning that they are the same for the entire population. The e varies per individual, which means that it varies across the population, and can therefore be called a 'random' parameter. This model tries to estimate coefficients that show the connection between two variables. However, the single level regression model assumes the independence of observations, which is not suitable for all kinds of data.

The data for this study was multileveled. This means that it was expected that not every individual observation in the data was independent, but that individual observations were 'nested' in groups and that the observations within such a group were not independent from each other. In this case, there were multiple 'cases' for one seller, namely the values that the seller 'scored' on the dependent and independent variables in different weeks. These cases could be treated as individual cases, independent from any other case. However, it could be expected that the weekly observations for the same seller were related to each other and were more alike than observations from different sellers. Thus, this paper assumed that the weekly observations are 'nested' within sellers. The weekly observations could be called 'Level 1' variables and the sellers, which define the 'groups', could be called 'Level 2' variables (Figure 3).

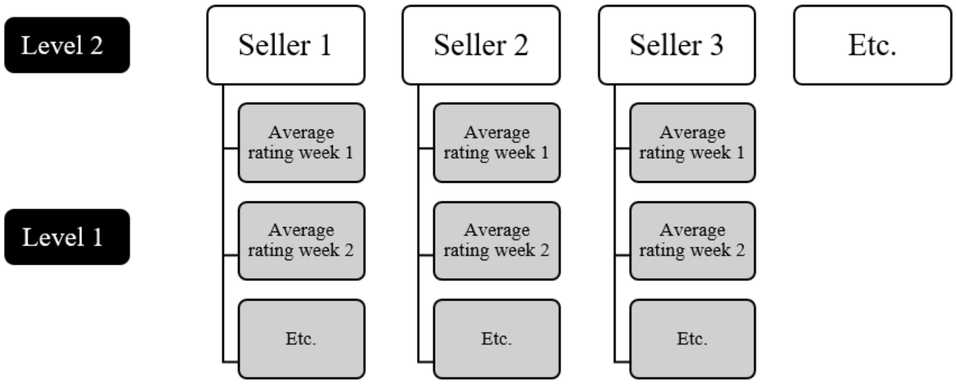

Figure 3. The levels of the model

Multilevel data calls for a different regression model, namely a multilevel model. A multilevel model still focuses on estimating the effects of one variable on another variable, across all observations, yet it takes into account that observations are nested in groups. This study will use a random intercept model, which is defined by the following equation:

$$Y_{ij} = \beta_{0j} + \beta_1 X_i + e_i$$

In this equation, Y is the dependent variable for the individual i in group j. β_0 is the intercept, partly defined by the group j that the observation is in. β_1 is the slope of the independent variable X, of which the value is defined by the individual case i. Lastly, e still determines the individual error. As this is a random intercept model, there is extra variance, namely on the group level, within the intercept. The intercept here is defined by:

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

Here, the ‘random’ coefficient can be seen. γ_{00} is the fixed intercept, which is the estimated average intercept for the entire population. u_{0j} is the variance within the intercept determined by the groups.

This means that this model assumed that the slope, the effect of reputation on either sales or unique buyers, was ‘fixed’ (i.e. the same for every seller), but that the intercept, the number of sales or unique buyers to begin with, was ‘random’ (i.e. varied per seller). For example, a ‘small’ seller might have had a positive effect of reputation when he started with 1 sale and ended up with 5, while a ‘bigger’ seller might have had the same effect, only he started with 10 sales and ended up with 50.

This study conducted two random intercept models. The first model used the average rating per seller per week as the independent variable and the number of sales per seller per week as the dependent variable, while the groups were defined by seller identifier, thus allowing the intercept to vary between sellers. The second model used the average rating per seller per week as the independent variable and the number of unique buyers per seller per week as the dependent variable, while the groups were defined by seller identifier, thus also allowing the intercept to vary between sellers.

4. Results

4.1 Descriptive findings

The Abraxas cryptomarket grew steadily over the observed period, which was from January 15th 2015 until July 3rd 2015 (Figure 4). Especially from March onwards (i.e. 7/8 weeks since the first transaction), the number of transactions in the dataset rose. This could be due to the closing of another major cryptomarket, named Evolution, which was disrupted by an exit scam around March 14th (Norbutas, 2018). It is likely that users of Evolution migrated to alternatives, of which Abraxas was one. The number of transactions reached its peak at the end of May.

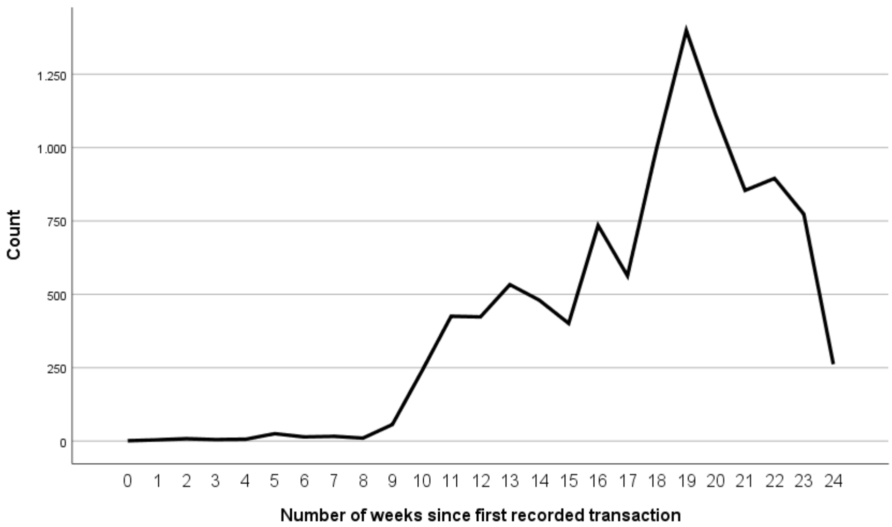

Figure 4. The growth of the Abraxas cryptomarket in number of observed transactions in the dataset, per week since January 15th, 2015.

For 8055 out of the 10239 observed transactions, the category of drugs to which the purchased item belonged was not specified. Out of the transactions for which the type of drug was specified, cannabis was the most common, with 812 purchases. After that, stimulants and ecstasy were observed most often, with 412 and 323 purchases respectively. This pattern is consistent with findings on other cryptomarkets, in which the most popular drugs are often recreational drugs, like cannabis and ecstasy (Aldridge & Décary-Hétu, 2016b; Barratt & Aldridge, 2016; Norbutas, 2018; Van Buskirk, Naicker, Roxburgh, Bruno, & Burns, 2016).

During the observed period, most sellers interacted with only one unique buyer: the mode of the number of unique buyers in total per seller is 1. The median was 24, meaning that half of the observed sellers interacted with 24 or less unique buyers in total. As can be seen in Figure 5, a smaller part of the sellers was very 'big' on Abraxas, even reaching hundreds of unique buyers.

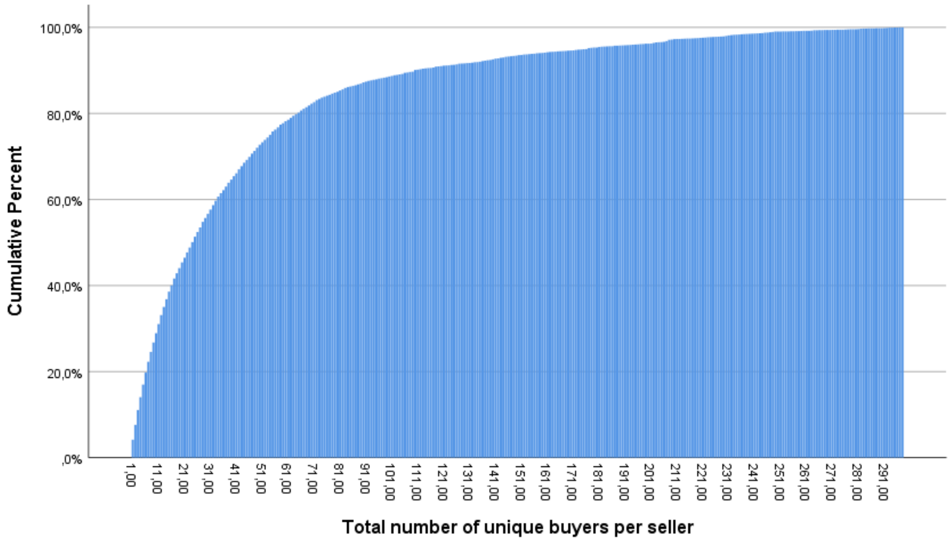

Figure 5. The cumulative percentages frequency distribution for the number of unique buyers per seller.

Note: This graph gives the percentage of buyers (y-axis) who interacted with a certain number of buyers or less (x-axis), i.e. the percentages of sellers are 'stacked' or 'cumulative'. For example, in this plot, it can be seen that the 20% sellers with the lowest number of unique buyers interacted with about 6 buyers or less.

When looking at the number of unique sellers with whom buyers interacted during this period, we can see that most buyers seem to be 'loyal' (Figure 6). The mode of unique sellers per buyer is 1; 53.2% of the buyers only interacted with one seller. To put this into perspective, 14.2% of the buyers only made one transaction in total, which obviously results in being loyal to one seller. The fact that more than half of the buyers only bought from one seller can thus not entirely be explained by the number of transactions that these buyers made. 99.1% of the buyers did not interact with more than 8 sellers. For the remaining group of buyers, the maximum of sellers with whom a buyer interacted was 22. It is interesting to note that the observed maximum number of purchases a buyer has made in the dataset was 51, with 4.1% of the buyers having made more than 22 purchases. These findings point at the fact that there is a discrepancy between the number of purchases buyers make and the number of sellers with whom they interact, which means that buyer loyalty is a relevant factor to take into account in research on cryptomarkets and reputation effects.

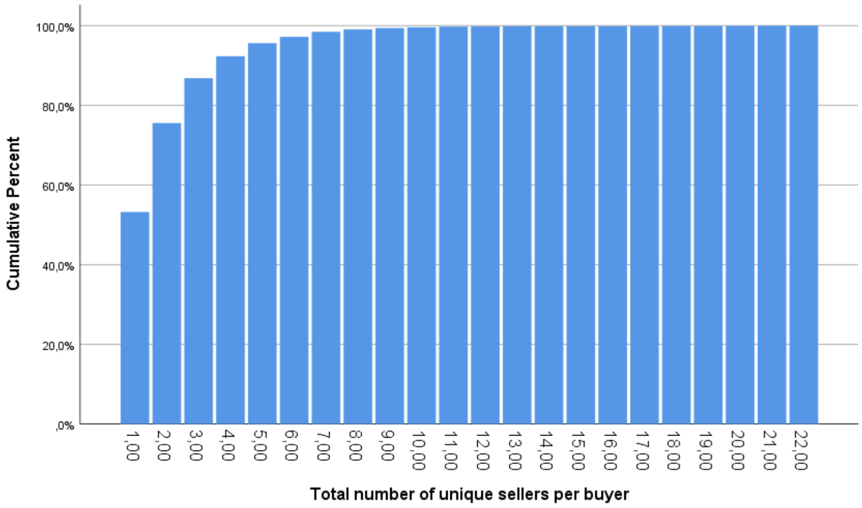

Figure 6. The cumulative percentages frequency distribution for the number of unique sellers per buyer.

Note: This graph gives the percentage of buyers (y-axis) who interacted with a certain number of sellers or less (x-axis), i.e. the percentages of buyers are 'stacked' or 'cumulative'. For example, in this plot, it can be seen that the 75% buyers with the lowest number of unique sellers interacted with 2 sellers or less.

4.2 Analyses

The first hypothesis was:

> *H1: A higher average reputation of a seller increases the number of finalized sales of that seller.*

The results of testing this hypothesis, namely a linear mixed model regression on total transactions per seller per week, are shown in Table 2. The results consist of the estimates of the fixed coefficients, the estimates of the random coefficients and those of the control variables. The fixed part of the intercept (γ_{00}) was significant (B=-3.472, p=.001). The weekly average rating of a seller (β_1) turned out to have a significant effect on the number of transactions for that seller in that week (B=1.928, p<.001), controlled for previous sales and the type of drug. The random part of the intercept, determined by seller, was also significant (B=38.604, p<.001). The residual variance was 72.851 (p<.001). The intra-class correlation coefficient (ICC) is calculated by:

$$ICC = \frac{random\ intercept\ coefficient}{random\ intercept\ coefficient + residual\ variance}$$

The intra-class correlation coefficient for this model was 0.346, meaning that 34.6% of the total variance of the number of total transactions per week was caused by the variance between the sellers.

Table 2. *Linear mixed model regression on total number of transactions per seller per week*

	Coefficient	**S.E.**	**t**	**Wald Z**	**p**
Fixed					
Intercept (γ_{00})	-3.472	1.068	-3.251**		.001
Weekly average rating (β_1; Level 1)	1.928	.205	9.424***		<.001
Random					
Intercept (u_{0j}; Level 2)	38.604	3.456		11.170***	<.001
Residual variance (e)	72.851	1.031		70.684***	<.001
Control					
Previous sales	.026	.001	24.696***		<.001
Type of drug					
Benzos	-1.407	.921	-1.527		.127
Cannabis	-.264	.345	-.766		.444
Dissociatives	-.892	1.606	-.555		.579
Ecstasy	-.366	.523	-.700		.484
Mixed	-1.101	6.067	-.181		.856
Opioids	-.157	.687	-.228		.820
Prescription	-.373	.940	-.396		.692
Psychedelics	-.525	.762	-.690		.490
RC’s	-3.228	2.815	-1.147		.252

Steroids	.701	2.595	.270		.787
Stimulants	-.205	.461	-.445		.656
Intra-class correlation	0.346				

*p<0.05, **p<0.01, ***p<0.001

Note: For the type of drugs control variables, the category 'unspecified' was used as the reference category.

The second hypothesis was:

H2: A higher average reputation of a seller increases the number of unique buyers with whom that seller interacted.

The results for testing this hypothesis are shown in Table 3. A linear mixed model regression was conducted with the number of unique buyers per seller per week as the dependent variable. Like in the first model, the fixed intercept (γ_{00}) was significant for this model (B=1.523, p=.031). In this model too, controlled for previous sales and types of drugs, the weekly average rating of a seller (β_1) had a significant effect on the number of unique buyers with whom that seller interacted during that week (B=.546, p=<.001). The random intercept coefficient, defined by the variance between sellers, was also significant (B=5.502, p<.001). The residual variance was 36.927 (p<.001). The intra-class correlation coefficient was 0.130, which means that 13% of the variance of the number of unique buyers per week was caused by the variance in sellers.

Table 3. *Linear mixed model regression on number of unique buyers per seller per week*

	Coefficient	**S.E.**	**t**	**Wald Z**	**p**
Fixed					
Intercept (γ_{00})	1.523	.705	2.159*		.031
Weekly average rating (β_1; Level 1)	.546	.140	3.898***		<.001
Random					
Intercept (u_{0j}; Level 2)	5.502	.574		9.579***	<.001

Residual variance (e)	36.927	.521		70.883***	<.001
Control					
Previous sales	.010	.001	13.923***		<.001
Type of drug					
Benzos	-2.091	.637	-3.283**		.001
Cannabis	-4.235	.241	-17.598***		<.001
Dissociatives	-3.341	1.127	-2.964**		.003
Ecstasy	-2.532	.367	-6.893***		<.001
Mixed	.680	4.318	.157		.875
Opioids	-2.481	.476	-5.209***		<.001
Prescription	-1.780	.648	-2.747**		.006
Psychedelics	-2.191	.524	-4.179***		<.001
RC's	-2.449	1.983	-1.235		.217
Steroids	-.536	1.757	-.305		.760
Stimulants	-2.502	.323	-7.755***		<.001
Intra-class correlation	0.130				

*p<0.05, **p<0.01, ***p<0.001

Note: For the type of drugs control variables, the category 'unspecified' was used as the reference category.

4.3 Comparison

The reasoning of this paper was that the positive effects of having a high reputation that previous studies found (Hardy & Norgaard, 2016; Przepiorka et al., 2017), for which the number of finalized sales of a seller was used as the dependent variable, could be overestimated, due to the repeated buying from a seller by the same buyer. The descriptive findings already showed that most buyers seem to be loyal to one seller. To find out whether this influences the effect of reputation, we can compare the effects of the weekly average rating on both the number of finalized sales of a seller per week and the number of unique buyers with whom a seller interacted per week and see if this effect differs.

Table 4 shows the estimated coefficients of weekly average rating and its significance for both models again. In both models, having a higher reputation had a significant positive effect, namely on the number of sales (B=1.928, p<.001) and on the number of unique buyers (B=.546, p=<.001). This means that the positive effect of a good reputation holds, even when repeated buying of the same buyer is taken into account. As these models use different dependent variables with different scales, the coefficients are not directly comparable. Separate statistical analyses could be conducted to test the difference in these coefficients, yet 'eyeballing' them already shows that the weekly average rating coefficient for unique buyers is smaller than the weekly average rating coefficient for the number of sales. This could mean that not taking into account repeated buying patterns could lead to an overestimation of the positive effect of a high reputation.

Table 4. *Comparison of the weekly average rating coefficients in both linear mixed model regression analyses*

	Coefficient	**t**	**p**
Model 1			
Effect weekly average rating on total transactions per seller per week	1.928	9.424	<.001
Model 2			
Effect weekly average rating on unique buyers per seller per week	.546	3.898***	<.001

*p<0.05, **p<0.01, ***p<0.001

Note: Complete results of these analyses can be found in Table 2 and Table 3.

4.4 Robustness check

To check whether the measure of the effects was robust, the same type of linear mixed model regression analysis was conducted, but with a different measure of reputation, namely having received zero-star ratings. After all, if it is indeed true that having a higher reputation increases the number of finalized sales and unique buyers for a seller, having a low reputation should decrease these variables. Therefore, in these analyses, the independent variable was the percentage of the total number of sales of a seller that received a rating of zero. This analysis was only conducted with the total unique buyers of a seller as the dependent variable. Using the total number of finalized sales of a seller as the dependent variable was problematic, since the independent variable, the percentage of zero stars ratings, was constructed with the total number of sales as well. The estimated coefficient for the percentage of zero stars ratings for this analysis is shown in Table 5.

The results show that having received a zero-stars rating had indeed a negative effect on the total number of unique buyers with whom a seller interacted (B=-.885). However, this effect was highly insignificant (p=.939).

The insignificance of this coefficient seems to denigrate the robustness of the analyses that were conducted in this paper. However, it should be noted that the number of zero-star ratings was very low; only 151 out of the 10239 transactions received zero stars. The number of sellers with a relatively high percentage of zero stars was therefore also low, which could be the cause of the insignificance for this robustness check. Furthermore, it could be the case that sellers who received zero star ratings had to leave the market (and perhaps come back with another profile), due to their damaged reputation. In that case, a low reputation will still have had a negative influence for the seller, but the coefficient could have appeared falsely positive, since the few transactions that he made (i.e. the ones that received zero stars) will still have been counted as a finalized sale and a buyer. This is also a possible cause of the insignificance.

This robustness check therefore does not imply that we should dismiss all of the previous results, yet it could imply that the measuring of reputation in numerical ratings brings some problems.

Table 5. *Estimates of the coefficients of the percentage of zero-star ratings for a linear mixed model regression on unique buyers per seller in total (Model 3).*

	Coefficient	**t**	**p**
Model 3			
Effect of total percentage of zero-stars ratings on unique buyers per seller in total	-.885	-.077	.939

*p<0.05, **p<0.01, ***p<0.001

Note: Complete results of this analysis can be found in the Appendix, Table A1.

5. Conclusion & discussion

This paper aimed to answer the question what role a seller's reputation plays in the decision of buyers to trust this seller and therefore in facilitating cooperation on online drug cryptomarkets. Previous studies found that having a high reputation on these markets led to more sales for a seller (Przepiorka et al., 2017) and that the reputation system made cooperation and trust on these markets possible, in the absence of law enforcement and among users who are anonymous towards each other (Hardy & Norgaard, 2016; Przepiorka et al., 2017). However, these studies did not take findings on buyer loyalty on these markets into account, which state that buyers often make multiple purchases from the same seller (Décary-Hétu & Quessy-Doré, 2017; Norbutas, 2018). The reasoning of this paper was that buyer loyalty could have led to an overestimation of the positive effects of reputation in earlier research, which is why this paper aimed to find out both the influence of a seller's reputation on the attraction of buyers and how buyer loyalty patterns influence this effect of reputation. It was expected that *'a higher average reputation of a seller increases the number of finalized sales of that seller'* (H1) and that *'a higher average reputation of a seller increases the number of unique buyers with whom that seller interacted'* (H2).

Both of these hypotheses were confirmed by the analyses of this paper, which were linear mixed model regression analyses using data from the cryptomarket Abraxas in 2015 (Branwen et al., 2015). A higher weekly average rating of a seller (i.e., a higher reputation) turned out to significantly increase both the number of finalized sales of that seller and the number of unique buyers with whom he interacted. Thus, not only is this research consistent with the findings on the positive effects of reputation, namely the increasement in sales, it also shows that these effects hold when buying patterns (i.e. buyer loyalty) are taken into account, which was done by also looking at unique buyers instead of finalized sales. However, the estimated coefficient of weekly average rating on unique buyers was smaller than the effect on finalized sales, which could point to the fact that earlier studies indeed overestimated the effect of reputation.

According to this research, the role of a seller's reputation in the decision of a buyer to trust the seller is meaningful. The reputation of a seller seems to give a buyer more information on his trustworthiness, in a 'trust problem' situation, and when the seller's reputation is high, this seems to foster the buyer's decision to trust this seller and buy his product. Thus, this research shows that reputation is an important factor for facilitating trust on cryptomarkets, but moreover this research stresses the importance of buying patterns as a relevant factor in research on reputation systems and cryptomarkets, that should not be neglected.

While this study led to interesting conclusions, there were limitations to the research as well. Most of these were due to the fact that the data were 'scraped' off the web, which makes some of its features less suitable for social science research than data obtained from, for example, a survey. On the other hand, this does assure that the data is 'real' and free from common research biases, like social desirability.

Firstly, the data were not normally distributed. The majority of the transactions received five stars, which resulted in the average weekly rating variable having a mean of 4.88. Very little observations received low ratings. This makes it more difficult to test the actual effect of a high or low reputation. However, this skewed distribution of ratings is a normal phenomenon for cryptomarkets and could also tell us something about reputation, namely that sustaining a high reputation is very important for sellers. The skewness may be caused by the fact that sellers are incentivized to behave cooperatively because of the reputation system or because sellers will be 'forced' to leave the market when they receive bad ratings.

Secondly, there were some limitations to the measurements that were used in the analyses. First of all, the independent variable, weekly average rating, was measured isolated per week; the variable was not a moving average. It could have been the case that the effect of receiving bad or good ratings became more noticeable after the week in which the rating was received, which was not observable in these analyses. However, to account for this possibility, the control variable 'previous sales' was included in the analyses, which will have lessened the impact of this limitation. Furthermore, as mentioned, the dependent variables were proxy variables, but since these were conservative proxy's, the observed effects will not have been overestimated, but underestimated. Besides, the conducted robustness check for the reputation variable did not render significant results and measuring the variables weekly is an arbitrary choice and could have impacted the results.

Lastly, this paper used two different models with two different dependent variables, to look at the effect of repeated buying from the same seller. Therefore, it was difficult to compare the estimated coefficients for the weekly average rating with statistical tests. Future research could give a more in-depth comparison of the effect of reputation by controlling for repeated buying in one model with finalized sales as the dependent variable.

Future research could expand the knowledge on the reputation system on cryptomarkets. These studies could for example look at a broader, more complete image of a seller's reputation, by also including written comments from buyers, the description that sellers provide of themselves and the prices that the sellers ask for their products. Furthermore, the 'evolution' of a seller's reputation and their subsequent successes could be examined more thoroughly, for example by using time series models. This would provide a more complete image of the information on sellers to which buyers have access, which would give more precise insights on the buyer's decisions in the trust problem situation. More importantly, new studies could build on the buyer-centered approach of this study, which has not been researched extensively before and has proven to yield interesting insights for cryptomarket research. These studies could try to obtain more data that specifically describes buyer's behaviour and try to explain the observed patterns. It would also be interesting to look into buyer's decisions with qualitative research, if it would be possible to overcome the anonymity barrier.

Despite the mentioned limitations, this research shed some light on a relatively unexamined topic within cryptomarket research, namely the repeated buying pattern in relation to the effect of a seller's reputation. It has proven that looking into the ways buyers behave, adds important insights to our current understanding of the working of reputation systems on cryptomarkets and the mechanisms by which humans decide to trust each other and cooperate in the absence of a central authority. Hopefully, future research will add to our understanding of this sociologically fascinating phenomenon.

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Appendix

Table A1. *Linear mixed model regression on total number of unique buyers per seller*

	Coefficient	**S.E.**	**t**	**Wald Z**	**p**
Fixed					
Intercept (γ_{00})	21.442	1.257	17.062***		<.001
Percentage zero star ratings (β_1; Level 1)	-.885	11.500	-.077		.939
Random					
Intercept (u_{0j}; Level 2)	287.138	27.031		10.623***	<.001
Residual variance (e)	1190.885	16.807		70.856***	<.001
Control					
Type of drug					
Benzos	-11.627	3.663	-3.173**		.002
Cannabis	-28.988	1.378	-21.042***		<.001
Dissociatives	-17.567	6.440	-2.728**		.006
Ecstasy	-15.746	2.097	-7.506***		<.001
Mixed	3.624	24.526	.148		.883
Opioids	-14.071	2.736	-5.144***		<.001
Prescription	-12.119	3.729	-3.250**		.001
Psychedelics	-13.848	3.019	-4.587***		<.001
RC's	-13.224	11.306	-1.170		.242
Steroids	-2.586	10.201	-.254		.800
Stimulants	-17.699	1.847	-9.585***		<.001

*p<0.05, **p<0.01, ***p<0.001

Note: The control variable 'previous sales' was not included in the analysis, due to redundancy.