



Believe it when you see it: Dyadic embeddedness and reputation effects on trust in cryptomarkets for illegal drugs



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ABSTRACT

Large-scale online marketplace data have been repeatedly used to test sociological theories on trust between strangers. Most studies focus on sellers' aggregate reputation scores, rather than on buyers' individual decisions to trust. Theoretical predictions on how repeated exchanges affect trust within dyads and how buyers weigh individual experience against reputation feedback from other actors have not been tested directly in detail. What do buyers do when they are warned not to trust someone they have trusted many times before? We analyze reputation effects on trust at the dyadic and network levels using data from an illegal online drug marketplace. We find that buyers' trust decisions are primarily explained by dyadic embeddedness - cooperative sellers get awarded by repeated exchanges. Although buyers take third-party information into account, this effect is weaker and more important for first-time buyers. Buyers tend to choose market exit instead of retaliation against sellers after negative experiences.

1. Introduction

Reputation is key for establishing trust between individuals in social interactions and market exchanges in which information about partner's trustworthiness or true quality of goods and services is hard to obtain (Akerlof, 1978; Axelrod, 1984; Granovetter, 1985; Coleman, 1990; Dellarocas, 2003; Diekmann et al., 2014). When uncertainty is high, people can rely on their social networks to exchange with someone they already know (DiMaggio and Louch, 1998). Social ties can also be used to get information about trustworthiness of potential partners, or sanction them after opportunistic behavior (Buskens, 2002; Buskens and Raub, 2002).

When economic exchanges take place between many anonymous actors, such as in large online marketplaces, social network effects are often substituted by reputation systems (Resnick and Zeckhauser, 2002; Dellarocas, 2003). These systems allow buyers to rate sellers' trustworthiness and product quality after exchanges. The information is then disseminated to all market actors. Reputation information allows buyers to select cooperative sellers without having individual experience with any one of them. While opportunistic sellers have no incentive to cooperate in one-shot exchanges, buyers can use the reputation system to sanction uncooperative behavior by informing others, which introduces a shadow of the future (Axelrod, 1984). Previous studies of online marketplaces found that reputation systems

incentivize cooperative behavior by increasing sales and selling price of highly-reputed sellers, and simultaneously driving those with poor reputation out of the market (Dellarocas, 2003; Diekmann et al., 2014; Kollock, 1999; Przepiorka, 2013).

Trustors' decisions on whom (or whether) to trust can also be based on their own experience with particular trustees when exchanges are repeated over time; reputation can work at both, the dyadic and network levels (Buskens and Raub, 2002). Actors might base their decisions on their own experience with an exchange partner (dyadic learning) or on other actors' experiences (network learning). Dyadic and network learning effects have been studied extensively in experimental studies of trust games (for an overview, see Buskens and Raub, 2013). When these two effects are studied in isolation, it is typically found that trustors use both sources of information, and positive or negative experiences or feedback affect how much they trust particular trustees (e.g. Bolton et al., 2004). The results are less clear, however, when the two are studied simultaneously and their relative importance for trust is evaluated. Barrera and Buskens (2009) found that individual experience affects trustors' decisions on whether to trust, but trustors do not consider the behavior of exchange partners with other trustors. In a repeated trust game of two trustors and a trustee Buskens et al. (2010) found evidence for both effects.

Individuals in online markets face similar dilemmas to those experimentally analyzed using trust games. In many cases buyers must

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evaluate trustworthiness of competing sellers, considering information from their previous exchanges and feedback from other buyers. These environments are therefore convenient to test reputation effects observationally on a large scale. However, previous studies on reputation effects in online marketplaces and sharing economy platforms have rarely distinguished between information at the dyadic and network levels. Studies employing data from eBay (e.g. Kollock, 1999; Resnick and Zeckhauser, 2002; Diekmann et al., 2014), Taobao (e.g. Ye et al., 2013), accommodation- (e.g. Teubner et al., 2017) or meal-sharing platforms (ter Huurne et al., 2018) typically used the seller as the unit of analysis for the effects of aggregated feedback ratings on item prices and volume of sales. Such research designs do not shed light on the actual decision-making process that buyers face and cannot distinguish between dyadic and network learning effects. To the best of our knowledge, there are few studies of online markets that differentiate between third-party feedback and individual experience in their analyses (Przepiorka, 2013; Snijders and Weesie, 2009). Also in these studies, however, buyers' past experience with a seller was used as a proxy for the seller's overall reputation, and the two mechanisms were not studied in detail.

Information that individuals obtain from their own experience can complement or contradict information that they receive from others. What does a buyer do, when other market participants report being scammed by their favorite seller? Does a negative individual experience with a seller get ignored as a misunderstanding if other buyers in the marketplace leave only positive feedback? Answers to these questions can inform theories of dyadic and network learning in repeated exchanges – which effect is stronger when both of them affect actors' decisions at the same time, or how buyers weigh negative against positive evaluations depending on the source of this information. Such questions can only be answered by using a research design that focuses on buyers' decisions rather than sellers' market outcomes.

In this paper we analyze under what conditions buyers' individual experience and reputation information from third parties affect choices of sellers in an online marketplace for illegal drugs. Marketplaces on the Dark Web, or cryptomarkets, are online platforms that enable individual buyers and sellers to exchange in full anonymity by employing an anonymizing internet browser (TOR), cryptocurrencies for transactions and other technical means (Barratt and Aldridge, 2016). In their structure and layout, these websites copy major legal online marketplaces, such as eBay – buyers choose from a list of categorized items that are photographed and described by sellers, including standard

information on price and shipping options (Christin, 2013; see also Fig. 1). Ordered drugs are typically sent to buyers by regular mail and payments are handled in digital currencies. Cryptomarkets, like typical online marketplaces, also use 5-star rating systems, where buyers rate their experience with sellers after exchanges. Previous research shows that reputation has positive effects for sellers' market outcomes, similar to those found in legal online marketplaces (Przepiorka et al., 2017; Hardy and Norgaard, 2016; Duxbury and Haynie, 2018a; 2018b). However, cryptomarkets are mostly used for selling consumable goods – illegal drugs such as cannabis products, cocaine or heroin (Barratt and Aldridge, 2016). As a result, buyers are likely to exchange repeatedly with the same partners (Décary-Héту and Quesy-Doré, 2017).

Additionally, cryptomarkets are environments of extreme uncertainty – next to the usual problem of information asymmetry between buyers and sellers, contracts in cryptomarkets are not secured by the legal system, while the actors are at constant risk of being exposed to law enforcement. As a result, these drug marketplaces provide an excellent test bed for studying dyadic and network learning effects on trust simultaneously.

In contrast to previous research on reputation systems in online marketplaces, we focus on buyer choices rather than seller market outcomes. A somewhat similar design that incorporates individual buyers into the analyses was used by Duxbury and Haynie (2018a, 2018b). They found that buyers are more likely to select sellers with generally higher reputation in an ERGM model, although they did not differentiate buyers' prior individual experience with each seller and third-party feedback. Here we aim to reconstruct sets of seller alternatives each buyer had before making a purchase. We then analyze to what extent buyer's previous exchanges with each seller in the set, and each seller's overall market reputation affect buyer's subsequent decision. Having a full snapshot of active buyer profiles, seller profiles, and transactions between them allow us to distinguish between dyadic and network learning effects in a natural empirical setting and shed light on how reputation systems affect individual choices at the micro level.

We analyze data on 10,234 exchanges between 282 sellers and 3192 buyers of drugs over a period of 7 months. We first explore patterns of buyer-seller interactions in an online environment. Secondly, we use a buyer's choice model and construct which sets of alternatives were available for buyers at the time of the transactions to study how buyers' own experience with each available seller and their reputation in the marketplace affect buyers' choices.

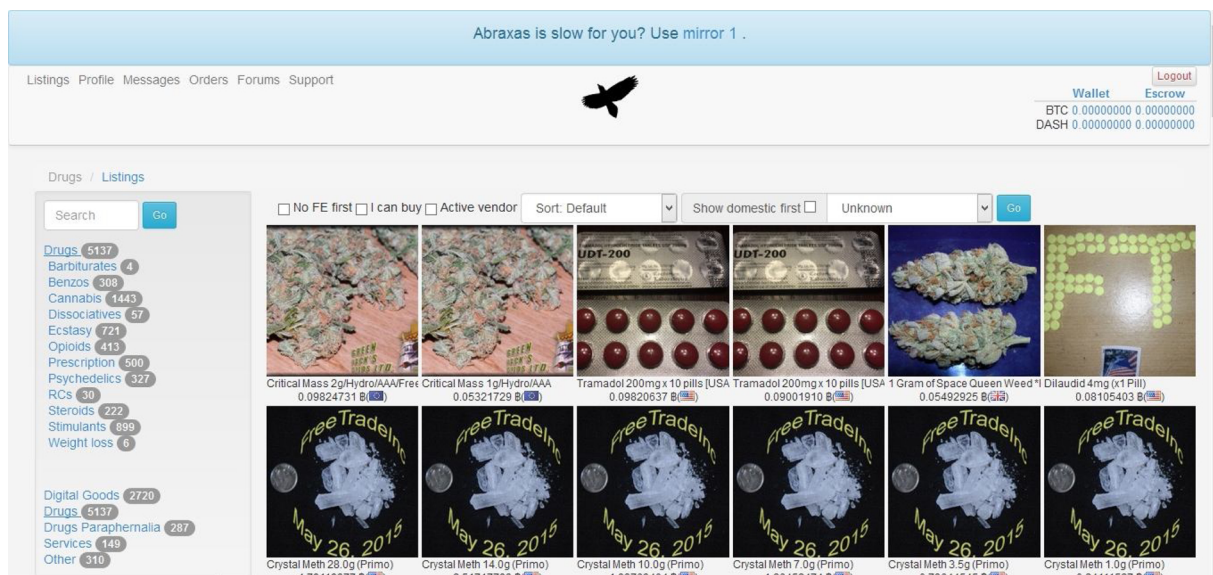


Fig. 1. Drug items in the analyzed Abraxas cryptomarket's 'Home' webpage.

2. Theory

2.1. The problem: cryptomarket exchanges and uncertainty

Cryptomarkets are peer-to-peer market platforms, where drug vendors trade directly with end users, bypassing local distributors and other middle-men that typically operate in offline drug supply chains (Martin, 2014; Barratt and Aldridge, 2016). Although buyers do not know the true identity of their exchange partners, they can identify specific sellers not only from their online nickname, but also from the person-specific encryption keys that sellers use to encrypt and secure their messages (PGP; Broséus et al., 2016). As a result, drug buyers in cryptomarkets can choose to repeatedly exchange with the same seller.

Typically, a cryptomarket exchange between a buyer and a seller has the following structure (see also Christin, 2013). Sellers list the goods they offer, often with textual descriptions, images and other details important for an exchange, such as price and weight. A buyer chooses a listing, contacts the seller directly and transfers money to the seller (or uses an escrow system, see below). The drug is then shipped to the buyer, concealed in a vacuum sealed packages or other type of masking (Aldridge and Askew, 2017).

This structure of exchanges makes buyers vulnerable to opportunistic behavior. Buyers choose a seller and are typically required to trust her with their money before actually receiving the goods. Contracts made in cryptomarkets are not secured by law enforcement, hence there are limited means to enforce them (Martin, 2014; Barratt and Aldridge, 2016). Buyers must also choose based on limited information about the truthfulness and professionalism of the seller, and quality of their goods. In such situations, buyers face high risk of getting a good of inferior quality than advertised, or not receiving the good at all (Aldridge and Askew, 2017). In the worst-case scenario, buyers face the risk of arrest due to seller's negligence¹.

To reduce asymmetry in information between buyers and sellers, cryptomarkets employ several safety mechanisms. Most cryptomarkets offer escrow systems, which make the marketplace itself a financial intermediary in an exchange between a buyer and a seller (Barratt and Aldridge, 2016; Christin, 2013). Cryptomarkets charge a fixed percent for each transaction, which leads sellers to offer a reduced price for goods in exchange for trading directly without the escrow (i.e. finalizing early; Moeller et al., 2017). Buyers can also abuse the escrow system by claiming they never received the item, which leads some sellers to require a direct transfer of money from the buyer (Morselli et al., 2017; Moeller et al., 2017).

Another mechanism that sustains cooperation is the reputation system, where buyers provide feedback about the seller and the quality of goods (Przeziorka et al., 2017; Kollock, 1993; Resnick and Zeckhauser, 2002). Buyers can observe seller's history of feedback messages, which reduces information asymmetry. Reputation systems allow buyers to make informed decisions not only based on their own trial-and-error process, but also on information from the experience of all other buyers. Sellers with high reputation have been found to sell more drugs for a higher price, compared to their lower-reputed competitors (Hardy and Norgaard, 2015; Przeziorka et al., 2017).

2.2. Reputation, embeddedness and learning

There are several theoretical mechanisms that have been argued to influence actors' trust under uncertainty, when information about partners' trustworthiness can be exchanged in a network of individuals (Buskens, 2002; Buskens and Raub, 2013; Barrera, 2008). In a dyadic exchange between a buyer and a seller, the buyer can control the seller

¹ See, for example: Branwen, G. (2018). DNM-related arrests, 2011–2015 (Updated 08 Jun, 2018). Retrieved 3rd October 2017 from: <https://www.guern.net/DNM-arrests>.

by retaliating after opportunistic behavior. Assuming that actors exchange repeatedly over a sufficiently long period of time, buyer's retaliation imposes potential future costs of opportunistic behavior on the seller, which incentivizes the seller to cooperate in the present. In an online environment, where identities are not fixed, the seller has an incentive to exit the market after receiving buyer's money and re-enter under a new alias, avoiding buyer's punishment, or simply to look for a new buyer.

Reputation systems provide an incentive for sellers to refrain from opportunistic behavior by embedding buyers and sellers in an information network². Buyers can exchange information about seller's trustworthiness, choose trustworthy sellers and avoid the opportunistic ones. Sellers face a larger cost of leaving the market, because reputation is costly to build and buyers choose sellers based on good reputation (Bolton et al., 2004; Diekmann et al., 2014; Przeziorka et al., 2017). Sellers also receive a larger premium for cooperation, since a good reputation might attract new buyers.

From the buyer's perspective, reputation systems enable network control and learning effects. Since reputation information is disseminated between all market actors, buyers can punish uncooperative sellers by leaving negative feedback. With a reputation system present, buyers can also learn from other buyers' feedback and evaluate trustworthiness of a seller with no individual transaction history. This effect might be especially relevant for buyers entering the market, when no individual experience is present, and other buyers are the only source of information to guide decisions.

Dyadic- and network learning and control effects have been studied in experimental settings, using trust games and survey studies (see Barrera, 2008; Raub and Buskens, 2008; Buskens et al., 2018 for reviews). It is generally found that both repeated dyadic exchanges and embeddedness within a network of information sharing increases trust placed in trustees. Evidence for both control and learning effects have been found, although it is often difficult to disentangle these effects, even in experimental designs (Buskens et al., 2010).

We expect that cryptomarket buyers will not be different and act conditional on own experience and information they retrieve from other buyers via the reputation system. Although we cannot disentangle control and learning effects in this environment, we expect that net of item price and other item properties, buyers will be more (less) likely to choose sellers that they have positive (negative) history of transactions with. We expect them to also be more (less) likely to choose sellers that have positive (negative) reputation based on third-party information.

H1. The likelihood that a buyer chooses a vendor increases (decreases) with the number of successful (unsuccessful) exchanges they had before.

H2. The likelihood that a buyer chooses a vendor increases (decreases) with the number of successful (unsuccessful) exchanges reported by other buyers.

2.3. Dyadic vs. Network learning

Studies that analyzed dyadic and network learning effects simultaneously (e.g. Snijders and Weesie, 2009; Barrera and Buskens, 2009; Barrera and Van den Bunt, 2009; Buskens et al., 2010) often assumed that these two sources of information are complementary. However, in situations where actors exchange repeatedly and also receive information about their partners from third parties, situations might occur in which individual experience contradicts that of other actors (Buskens

² Note that the network learning theory used throughout the paper does not assume any particular network structural effects. In online markets with a reputation system, information on sellers' past behavior is available to all buyers. It can be argued that buyers are embedded in a fully-connected information network, where everyone can exchange information with everyone else.

et al., 2018). For example, a buyer in a cryptomarket might have to choose whether to trust a seller in a situation, where the seller receives negative ratings from multiple buyers, even though the individual experience with that seller is extensive and only positive. Alternatively, a buyer's trust might be abused by a seller, who is reported to be perfectly trustworthy by other buyers.

There are several theoretical reasons to believe that the two sources of information might not be perfect substitutes for buyers making trust decisions. It has been argued that individual experience is always more salient than information gained from third parties (Granovetter, 1985; Glückler and Armbruster, 2003). Individual experience might have a larger impact on partner's choice because the information is more detailed and accurate. Granovetter (1985) also argued that individual experience is the more important source, because information is cheaper to obtain than network-based experience. The latter argument might not apply in the case of online reputation systems, where information sharing is virtually costless as the reputation system effectively disseminates information on past exchanges to all users.

Noise, on the other hand, might be particularly important in the context of online marketplaces and cryptomarkets in particular (Utz, 2009). Buyer feedback messages in online markets typically contain a numeric score (e.g. 1–5 stars) and, less frequently, a short text comment (Hijikata et al., 2007). Feedback messages might provide insufficient information for a buyer, since they usually refer to a particular aspect of an exchange, like product quality or reliability of the seller, and are therefore hard to summarize when the number of feedback messages and sellers is large (Hijikata et al., 2007; O'Donovan et al., 2007).

Exchanges in illegal marketplaces also contain an additional element of risk for both parties, namely, that goods might be confiscated during the shipping stage (Décary-Héту et al., 2016; Aldridge and Askew, 2017). Cryptomarket buyers cannot be certain that sellers are not responsible for such events, which would lead to increased prevalence of noise in feedback messages due to uncontrollable exogenous events (Kollock, 1993). As a result, information from other buyers might be considered noisy and less important than individual experience when choosing a seller.

Repeated economic relations might also develop into social bonds, which could diminish the relevance of third-party information (Granovetter, 1985). Individual experience might increase affect towards the person and reduce objectivity when evaluating third-party information (Sorenson and Waguespack, 2006; Lawler, 2001). Although users in online marketplaces are anonymous and the strength of social bonds in online marketplaces could be questioned (Diekmann et al., 2014), buyers and sellers in cryptomarkets frequently engage in non-market related conversations in discussion forums (Munksgaard and Demant, 2016; Barratt and Aldridge, 2016). Sellers' engagement in such discussions that could be considered cheap talk have been found to increase their market outcomes, regardless of their market reputation (Norbutas, 2020).

These theoretical arguments point towards the same prediction, namely, that buyer's individual experience, whether positive or negative, will have a stronger effect on their choice of exchange partners than information from other buyers' feedback.

H3. The effect of buyer's own successful (unsuccessful) experience with a seller on the likelihood of choosing the seller is larger than that of other buyers.

2.4. Negative asymmetry and end-game effects

It has been argued that negative information about an exchange partner has a stronger impact than positive information (Guido and Czapski, 1990; Taylor, 1991). While positive social relations, such as friendships, develop gradually over time, the strength of negative relationships develop much faster, resulting in quick categorizations of a person as "rival", compared to more detailed ranking of acquaintances

and friends based on their closeness (Labianca and Brass, 2006).

Although social and market relations might not necessarily be directly comparable, negative asymmetry has also been observed in online market exchanges. Studies on reputation effects in online marketplaces also show that the impact of negative ratings on buyer's trust is much larger than the trust-building effect of positive ratings (Standiford, 2001; Przepiorka et al., 2017). Although negative ratings are typically rare, they carry much more weight on actors' decisions.

There are also cryptomarket-specific reasons to expect that in the case of negative ratings, third-party feedback might have an additional effect on buyer's choices. Sellers are assumed to act cooperatively if the cost they face for abusing buyer's trust is larger than the expected benefit from future exchanges (Axelrod, 1984; Buskens and Raub, 2008). The number of repeated exchanges with buyers has to be sufficiently high to outweigh the benefits of scamming for the seller. Experimental research shows that in finitely repeated trust games, cooperative behavior of both actors decreases in the last rounds of the game, since trustors (i.e. buyers, in the case of online markets) know that trustees (i.e. sellers) no longer have an incentive to honor trust (e.g. Buskens et al., 2010; Barrera, 2008).

The end-game effect takes place when parties know about the approaching end of the game. In case of online markets, however, buyers can never be sure when a seller might be willing to leave the market. When a seller decides to leave, it becomes beneficial to abuse buyer's trust and take the money, since they no longer face potential costs of such actions. In legal online marketplaces, such seller's behavior is costly due to the threat of legal enforcement. In illegal marketplaces, on the other hand, occurrences of such behavior might be more frequent. Such cases where cryptomarket sellers build up a good reputation and suddenly disappear, also called 'exit scams', have been observed in multiple cryptomarkets (Moeller et al., 2017).

As a result, regardless of a seller's reputation, buyers cannot be certain about the shadow of the future. Negative feedback messages from third parties could be more informative in those cases than individual positive experience in the past, since they can reveal seller's intentions of leaving the market. Therefore, although we expect buyers to primarily be guided by personal experience from past exchanges (see Hypothesis 3), the asymmetry of negative ratings and the shadow of the future might outweigh this effect.

Based on these arguments, we formulate the following hypotheses. First, negative asymmetry implies that negative experience and third-party ratings will have a stronger effect on buyer's decisions than positive ones. Second, we expect that negative feedback messages will diminish the positive effect of buyer's positive individual experience with a seller. The increased likelihood of choosing a vendor with whom already successful exchanges were made, will diminish with every negative rating reported by other buyers. Note that we do not expect the effect of buyer's negative past transactions with a seller to be moderated by positive third-party ratings, since, based on the salience of personal experience and negative asymmetry arguments, buyer's personal negative experience should be the strongest predictor of buyer choices.

H4. Buyer's unsuccessful past transactions with a seller and negative third-party ratings have a stronger effect on choosing the seller than successful past transactions and positive third-party ratings.

H5. The positive effect of the number of buyer's successful past transactions with a seller on choosing the seller is weaker with the number of negative transactions reported by other buyers.

3. Data and methods

We use a dataset from the cryptomarket "Abraxas", collected by Branwen et al. (2015). The dataset contains semi-daily copies of the marketplace, collected over 7 months, using a website content retrieval package called 'wget'. The dataset and the methodology of data

collection are available publicly (Branwen et al., 2015). The first copy of the marketplace website in the dataset was collected before the first customer purchase in 2015. The last scrape in the collection is dated approximately 3 months before the marketplace was closed. The marketplace was mostly used for trading illegal drugs (Norbutas, 2018).

The structure of the website resembles that of other major online marketplaces and cryptomarkets (see Fig. 1). Sellers post items on the website, include a picture of the product, a description, price, possible shipping destinations and other information. Buyers can observe the list of items on sale, categorized by the type of drug they contain. A purchase is made by contacting item's seller and transferring the money directly to the seller or via the escrow system. All drug items are sent to buyers using regular postal services. When the package arrives, buyers can leave 0–5 stars rating and a comment about their experience. This information is then instantly published on the website – a list of all item-specific feedback can be observed in the webpage of each drug item; an aggregated list of feedback about all seller's items is provided in sellers' profile pages. An average reputational score of is also displayed next to sellers' nicknames wherever they are displayed.

In total, the data contain 7971 unique items, 463 seller profile pages, 3542 buyer profile pages, and 10,898 feedback messages. We use all items in the “Drugs” category to ensure comparability in our analyses. Excluded items contain digital goods (eBooks, software, etc.), which are difficult to compare to drug items, since digital goods contain no shipping stage and are sent directly to the buyer. After deletion, the dataset contains 79.9 % (6,374/7,971) of all items on Abraxas.

Feedback messages that were edited by the buyers were deleted, keeping only the most recent feedback message for every transaction. We do not expect this to have any effect on the results, since edits were typically made to add textual comments and were mostly made within 1–2 days after the original message had been posted. Buyers could not see the original messages after they were edited, which makes our final dataset similar to what most buyers were likely to observe on the website. After deletion of feedback messages, the subset contains 84.8 % feedback messages (9,244/10,898), 84.23 % seller profiles (390/463) and 90.11 % buyer profiles (3,192/3,542).

Item weights were provided by sellers in the title of each item. Since these data are highly unstandardized, item weights were recoded manually. For some items, weights were not available in the name or the description, resulting in missing values. We excluded these items from our analyses. After this deletion, the subset contains 43.78 % of all items in Abraxas (3,490/7,971) in 10 sub-categories, 53.93 % of seller profiles (259/463), 74.05 % of buyer profiles (2,623/3,542) and 70.17 % of all feedback messages (6,487/10,898).

The statistical models used to test the hypotheses require a dataset that represents buyers' choices at the time of each purchase. We derive this dataset by using details of the items that buyers actually purchased and adding all other items of the same drug type, within 200 % margin of weight that were available online at least 2 days before the date of buyer's purchase. Here we assume that it takes at least 2 days from the time a buyer places an order to the time the buyer receives the good via mail and leaves a feedback message. For example, if a buyer bought 1 g of marijuana on the 15th of June, we assume that a buyer chose from a set of all marijuana items that are 0.5 g–2 g in weight, were posted before 13th of June and last observed after 15th of June. We create these choice sets for every purchase in the data, which results in a nested dataset where item alternatives are nested in choice sets with 1 item actually selected by the buyer per set (see Fig. 2). These choice sets are further nested in buyer profiles and represent all transactions they made. Finally, we aggregate the alternatives to the seller-level, since sellers might offer multiple similar items and be over-represented in each set. We excluded 46 sets, where the buyer had only 1 option. The final dataset contains 6441 choice sets (69.68 % of all feedback messages), 181,423 total seller alternatives for 2614 unique buyer profiles and 258 unique seller profiles.

It is important to note that we derive buyer-seller exchanges based

on buyers' feedback messages. Since buyers can only post feedback after a purchase is made, we can be certain that each feedback message corresponds to an exchange. There can be, however, cases where the buyer leaves no feedback message. Previous research on cryptomarket feedback messages found that 88 % of all sales are reported by feedback messages (Aldridge and Décary-Héту, 2014). We will address this limitation further in the Conclusions section.

Finally, it should be noted that by using buyer choice sets, we assume that buyers have access to (i.e. actually choose from) the entire choice set as we model it. We do not have information about buyer search strategies in online drug marketplaces that could guide our assumptions on limiting the choice sets. We argue that it is not unreasonable to assume that buyers, having the means on the website to filter displayed items based on category, weight and other properties, chose from all the items satisfying the criteria outlined above.

3.1. Variables used in the models

The dependent variable, selected alternative, is a binary variable, indicating which seller alternative was selected by the buyer in each choice set (see also Table 1). Every set contains one selected seller and reflects one transaction in the marketplace (based on feedback messages; see Fig. 2).

Positive and negative individual experience with a seller were measured using the number of 5-star and non-5-star feedback ratings a buyer had awarded a particular seller before the time of exchange. These variables have different values for each seller alternative in the choice sets. If a buyer never had an exchange with a seller, both variables are equal to 0. We use 0–4 stars as a measure of negative experience, since reputation scores in online marketplaces, including cryptomarkets, tend to be extremely highly skewed with few ratings below 5 stars (Przepiorka et al., 2017). In the subset used in the analyses, 5-star ratings account for 96.12 % of all feedback messages, while 0–4 star ratings account for 0.7–1.3 % of feedback messages each. This suggests that ratings below the maximum value are posted in extraordinary cases. It also shows that sellers' average rating scores might not be helpful for buyers to differentiate sellers' quality, especially when the number of seller's total sales is high and the impact of each additional sub-5-star rating on the average reputation score decreases. The number of 0–4 star ratings could therefore be considered an indicator of buyers' negative experiences, regardless of the actual number of stars awarded. We test sensitivity of the results to different measurements in the section “Additional analysis”.

Positive and negative third-party ratings reflect, respectively, the number of 5-star and non-5-star feedback ratings from all exchanges for each seller alternative, at the time of observation. This variable reflects each seller's market reputation at the time a buyer chose between alternatives. The variable is constructed using all feedback ratings, including items that have been excluded from the analyzed subset ($N = 10,898$ feedback messages). Since both, buyers' individual experience and third-party ratings, are strongly left-skewed, we use a log-transformed version of the 4 variables. The correlation between positive individual experience and positive third-party ratings is 0.16, while correlation between negative experience and third-party ratings is 0.05.

To control for price differences across alternatives, we used two types of price variables. First, a dummy variable ‘lowest price seller’ indicates which seller offered the lowest priced item in the choice set. Secondly, we used an “average price (USD)” continuous variable, which indicates the average price of each seller's items in the marketplace at the time of buyer's selection. Since items in cryptomarkets can be sold multiple times, sellers who run out of stock for an item have been found to artificially increase item price (e.g. to 9999\$ per gram) to keep the item visible until they restock and are able to sell again (Décary-Héту and Paquet-Clouston, 2016). We excluded such “holding” items with artificially high prices when calculating the average price for the “average price (USD)” variable. To account for the fact that such items

1. Item-level alternatives

Buyer ID	Choice set	Seller ID	Drug type	Item weight (g)	Date	Selected
1	1	1	A	1	Bought on Feb 18	1
1	1	1	A	0.75	Feb 16-Mar 30	0
1	1	2	A	1.25	Jan 27-Feb 27	0
1	1	2	A	5	Jan 5 – Jul 30	0
1	2	3	B	4	Bought on Mar 9	1
1	2	3	B	5	Mar 8 – Jul 26	0
1	2	4	B	5	Jan 1 – Jul 20	0
1	2	4	B	5	Feb 20 – Dec 6	0

Items selected based on similarity to the selected item

2. Seller-level alternatives

Buyer ID	Choice set	Seller ID	Selected
1	1	1	1
1	1	2	0
1	2	3	1
1	2	4	0

Dependent variable

Fig. 2. Structure of the dataset used in the analyses. Choice sets are constructed by selecting similar alternatives for every buyer’s purchase (top). Item-level alternatives are then aggregated to the seller level (bottom).

Table 1
Variables used in the regression models.

Variable	N	Mean (Std. dev)	Min-max
Selected alternative	181,423	0.035	0/1
Positive individual experience	181,423	0.042 (0.45)	0–29
Negative individual experience	181,423	0.0007 (0.02)	0–1
Positive 3 rd -party ratings	181,423	36.626 (72.47)	0–605
Negative 3 rd -party ratings	181,423	1.000 (2.55)	0–33
Lowest price per gram	181,423	0.021	0/1
Average price per gram (USD)	181,423	34.476 (95.74)	0.15–22528
Ships worldwide	181,423	0.301	0/1
Geographic monopoly (destination)	181,423	0.048	0/1
Geographic monopoly (origin)	181,423	0.134	0/1
Number of seller’s items	181,423	2.840 (3.96)	1–46
Number of holding items	181,423	0.021 (0.15)	0–2
N(Buyers)	2614		
N(Sets)	6441		

might still affect buyers’ choices via visibility of these items in the website, we included a variable for the “number of holding items” each seller had online in each choice set. A total of 42.14 % choice sets (2714/6441) had at least one seller with holding items posted (2% of all alternatives).

We add dummies for seller’s offered shipping destinations, since this might limit buyers’ choices ([BLINDED]). We use a dummy variable that represents whether a seller offered shipping Worldwide, or to a limited set of countries (baseline category). 32 % of items that are not shipped worldwide, ship only to European countries, 18 % ship only to EU and 10 % only to Australia. Additional 22 % of items with restricted shipping locations are sent to multiple countries, while about 18 % are being shipped to all but 1 continent.

It is possible that in some cases buyers’ choices are constrained by few domestic sellers in a given country. Even if there are competing sellers who offer worldwide shipping, buyers might be unwilling to choose them, because they ship from a distant location, which might increase shipping fees and risk of detection. Since we cannot observe buyers’ geographic locations, we use sellers’ provided shipping origin

and destination locations to control for geographic constraints. We measure “geographic monopoly - origin” and “geographic monopoly - destination” using dummy variables that show whether each seller is the only one shipping to or from a country. Destination monopoly controls for cases where a seller is the only one that offers shipping to a country. Origin monopoly controls for cases where there is only one alternative that ships from a country, regardless of shipping destinations. For example, multiple sellers might offer shipping to Australia, but only one alternative might be shipping from Australia, which would make that alternative much more attractive to Australian buyers.

We control for the number of items each seller had posted online at the time of each exchange, to account for differences in visibility of items. Sellers use different strategies to increase their visibility on the website, such as making multiple listings of the same type with slightly different weights, or posting similar items under different names.

3.2. Analytical strategy

We estimate conditional fixed effects logistic regression model (clogit in Stata; [McFadden, 1974](#)) to model the likelihood an alternative is selected. These models treat choice among alternatives as a function of characteristics of the alternatives and not the individual making the choices. The model estimates the likelihood an alternative is selected conditional on other available alternatives in the set. By definition, the model does not estimate effects of buyer-specific predictors (constant across alternatives), since the analysis is done “within” choices by comparing alternatives. We use clustered standard errors to account for correlated standard errors in repeated choices made by the same buyer. A similar model was used in [Snijders and Weesie \(2009\)](#) to analyze a programmer’s market.

We estimate 3 models. The first model includes only the first exchange of every buyer in the cryptomarket to estimate the effect of third-party information when buyers have no individual experience. Model 2 uses all remaining exchanges of the buyers (i.e. the second and subsequent exchanges). This is the full model with repeated exchanges and is used to test hypotheses 1–4. Model 3 adds an interaction effect and tests hypothesis 5. Finally, we report sensitivity of the main results

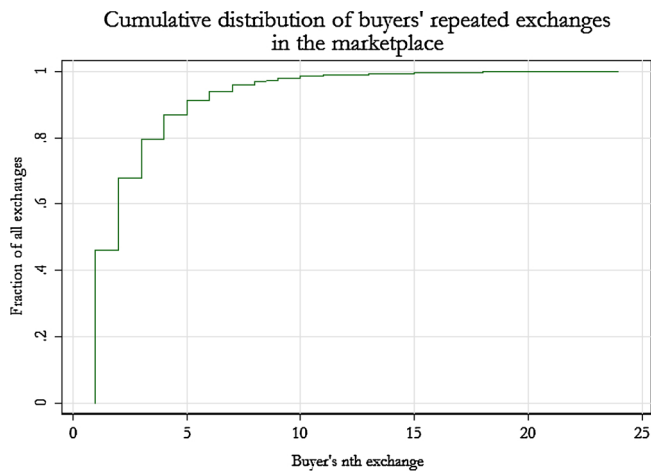


Fig. 3. Cumulative distribution of buyers' repeated exchanges in the marketplace.

to assumptions used throughout the models.

4. Results

4.1. Descriptive findings

In this section, we first focus on descriptive results of finalized buyer-seller exchanges, that is, alternatives in the choice sets that were selected by each buyer (N = 6441). The results show that 46.22 % of all analyzed transactions (2977/6441) are the first transactions for the buyers (market entrants). Accordingly, more than a half of all exchanges are made by returning buyers (see Fig. 3). Out of the 3464 exchanges that are made by returning buyers, 51.24 % (1775/3464) are made between buyers and sellers who had already exchanged in the past. On average, buyers who made at least two purchases on the market bought from 2.26 sellers and made 65.3 % of their exchanges with a single seller. These figures show a much stronger dyadic embeddedness between buyers and sellers of illegal drugs than found previously in another cryptomarket – on average 15 vendors per buyer and 31 % of exchanges with the most popular vendor (Décary-Hétu and Quessy- Doré, 2017). The difference might be caused by the data used in Décary-Hétu and Quessy- Doré (2017) that contained partially anonymized buyer nicknames. This could have led to an

Table 2

Conditional fixed-effects logistic regression models. Buyers' choices of sellers.

Independent variables	Model 1 1st exchange	Model 2 Full model (all subsequent exchanges)	Model 3 Model 2 + interaction
Positive individual experience (log)		33.530** (3.24)	44.168** (4.93)
Negative individual experience (log)		1.391 (0.86)	1.713 (0.93)
Positive 3 rd -party ratings (log)	1.470** (0.02)	1.202** (0.02)	1.188** (0.02)
Negative 3 rd -party ratings (log)	0.878** (0.03)	1.047 (0.03)	1.151** (0.04)
Positive individual experience (log) * Negative 3 rd -party ratings (log)			0.724** (0.06)
Lowest price per gram	1.176 (0.11)	1.368* (0.16)	1.367* (0.16)
Average price per gram (USD; log)	0.611** (0.03)	0.522** (0.03)	0.515** (0.03)
Ships worldwide	0.872** (0.03)	0.980 (0.05)	0.969 (0.05)
Geographic monopoly (origin)	0.734** (0.05)	0.810** (0.05)	0.817** (0.05)
Geographic monopoly (destination)	1.490** (0.10)	1.343** (0.13)	1.338** (0.13)
Number of seller's items	1.050** (0.00)	1.033** (0.00)	1.035** (0.00)
Number of holding items	0.935 (0.13)	1.065 (0.17)	1.094 (0.17)
N obs.			
Level 1: Alternatives	76,976	104,447	104,447
Level 2: Choice sets	2977	3464	3464
Level 3: Buyers	2614	1199	1199
Explained variance (Pseudo R ²)	0.075	0.355	0.357

* p < 0.05.

** p < 0.01. Odds ratios reported, standard errors in parentheses.

underestimation of the number of buyer accounts (i.e. multiple accounts with similar nicknames analyzed as a single account) and an overestimation of the number of sellers per buyer.

Buyers make choices that are almost entirely conditional on positive individual history with that seller. Out of the analyzed 3464 repeated exchanges, only 0.78 % (or 0.42 % of all exchanges) are made with sellers, who buyers have reported having negative experience with in the past, which shows that buyers very rarely come back to a seller after posting negative feedback. This is almost perfectly in line with the expected rational retaliation behavior. In contrast, buyers have up to 29 repeated exchanges with sellers they had positive exchanges with in the past. Interestingly, buyers are likely to repeatedly exchange with the same seller even if the seller has negative ratings reported by other buyers - buyers exchange more than once with sellers that have up to 25 negative ratings reported by other buyers (2.64 negative ratings on average).

In dyads where the same two actors exchange repeatedly (N = 1119), 73.64 % of exchanges are made for the same drug type, while in a quarter of these exchanges buyers return to the same seller for a different type of drug. This result indicates that buyers return to sellers not only because of the quality of a specific product, but possibly due to trust in the seller.

The number of seller-alternatives varies substantially across the analyzed choice sets. In the 6441 choice sets, buyers on average choose from 28 different sellers, ranging from 2 to 75 alternatives per set. The number of alternatives varies by drug category due to differences in popularity of these drugs. Buyer purchases of items in the “Weed” category have the largest average number of alternatives (43 alternatives per set), followed by “Cocaine” (26.5 alternatives per set), while choice set sizes in “Ketamine” and “Mushrooms” categories are significantly lower (3.8 and 4.1 seller-alternatives respectively).

Strong embeddedness in buyer-seller dyads cannot be fully explained by a lack of seller alternatives. When making the first exchange, buyers on average select out of 28 seller alternatives. Returning buyers with 1–3 exchanges on average choose out of 13 alternatives. Finally, buyers who have more than 3 exchanges choose from 16 alternatives.

4.2. Hypotheses testing

The results of Model 1 (see Table 2) are based only on buyers' first exchanges and exclude individual experience effects. The results show that the number of positive third-party feedback messages increases the likelihood of a seller to be chosen in a choice set (OR = 1.470,

$p < .01$). In contrast, the number of negative feedback messages decreases the odds of a seller to be chosen ($OR = 0.878, p < .01$). For the first exchange, buyers choose based on both positive and negative ratings of each seller, as reported by previous buyers. Results also show that reputation considerations might be more important than price, as the seller who offers an item for the lowest price in the set is not significantly more likely to get selected at buyers' first exchange ($OR = 1.176, p > .05$). On the other hand, price still plays a role, as sellers with higher average price are significantly less likely selected ($OR = 0.611, p < .01$). Sellers that are the only ones shipping from a particular country in a choice set are less likely selected ($OR = 0.734, p < .01$). For buyers' first exchange, sellers who are the sole option for shipping to a particular country are more likely selected ($OR = 1.490, p < .01$). These geographic effects remain significant throughout all models. The odds of being selected also rises with the number of items the sellers had posted in the marketplace ($OR = 1.050, p < .01$), which could be related to seller's visibility in the website.

Results in Model 2 include only buyers' second and subsequent exchanges, when the effect of individual experience becomes possible. The model shows that buyers are overwhelmingly likely to choose sellers with whom they interacted in the past. Every positive experience with a seller increases the odds that same seller is chosen by a factor of 33.5 ($p < .01$), which is in line with Hypothesis 1. Interestingly, negative individual experience does not significantly affect the likelihood of (not) choosing the same seller in the future ($OR = 1.391, p > .05$). We therefore find only partial evidence for Hypothesis 1. Once buyers' individual experience is taken into account, the effect of positive third-party information decreases only slightly ($OR = 1.202, p < .01$), while the effect of negative feedback becomes statistically insignificant ($OR = 1.047, p > .05$). These results are in line with Hypothesis 2 only for positive third-party experience.

The two variables that measure individual experience increase the explained variance in Model 2 by 24.4 %. This figure is based on comparing Model 2 with the same model that excludes the two individual experience variables (not shown). The pseudo- R^2 of this model is equal to 11.1 %. The results of a likelihood ratio test that compares the fit of the two models also shows a significant improvement of Model 2 over the model, which excludes the two individual experience variables. These results are in line with Hypothesis 3. Model 2 suggests that both, individual and third-party negative ratings are not statistically significant. We therefore reject Hypothesis 4.

Finally, Model 3 includes the interaction effect, which tests Hypothesis 5. Although negative 3rd-party ratings do not directly affect buyers choices as shown in Model 2, it decreases the effect of buyer's positive experience with a seller ($OR = 0.724, p < .01$). While buyers are not less likely to choose sellers with more negative ratings based on findings in Model 2, they are less likely to come back to the same seller after positive exchanges if other buyers report negative experiences with that seller. These results are in line with theoretical expectations and confirm Hypothesis 5.

4.3. Additional analyses

The previous analyses were made under an assumption that only 5-star ratings are considered a positive signal, while 0–4 star ratings are a signal of negative or poor reputation. This assumption was based on the skewed distribution of ratings. In the following analyses, we test this assumption by varying the operationalization of negative ratings and changing it to 0–3 star, 0–2 star and 0–1 star ratings, while keeping the positive ratings at 5 stars.

Fig. 4 shows the results of Model 2 repeatedly run with the different operationalizations of negative ratings. The estimated odds ratios for different operationalizations are marked by different colors. The results show, that as the operationalization of negative ratings becomes more extreme (i.e. approaches 0–1 ratings), the estimated odds ratios change towards the hypothesized directions. The positive effects of

positive individual experience and positive third-party ratings become larger, while the negative effects become negative. The results for negative third-party ratings are only statistically insignificant for the original operationalization (0–4 ratings) and become negative and statistically significant in all other models. This shows that buyers might not consider all 0–4 star ratings a negative signal, or there might be individual heterogeneity in these considerations. These results provide further support for Hypotheses 1 and 2.

Fig. 5 shows the same procedure of alternative operationalizations applied to the interaction effect tested in Model 3. The top left panel shows the interaction effect in the original model, which shows that buyers are slightly more likely to choose sellers with whom they have no positive experience, the more negative ratings these sellers have. These results are counter-intuitive and in line with the previous interpretation – it is possible that buyers consider a fraction of “negative” 0–4 star ratings as a positive signal. The same interaction effect becomes increasingly more negative for all groups once more extreme operationalizations of negative ratings are taken into account. The interaction effects are statistically significant throughout the 4 different operationalizations in Fig. 4. The direction of the effects is stronger in the hypothesized direction, the more extreme the measure of negative ratings is used, which provides further support for Hypothesis 5.

Finally, the previous models used in the analyses cannot account for the fact that buyers, after receiving negative ratings are likely to leave the marketplace, instead of switching to another alternative within the marketplace (e.g. switch to buying drugs offline). This strategy could provide an alternative explanation for the null results of negative individual experience on seller's choice. We estimated a Cox proportional hazard model to analyze whether buyers are more likely to leave the market after at least one negative experience with any seller (see Fig. 6). Time is operationalized as the number of buyer's exchanges. Failure is operationalized as the date of the final observed exchange, if the feedback message was left at least 4 weeks before the end of data selection. We operationalize market exit as not making any orders for one month or more. The results show that buyers who have negative experience have a larger hazard of leaving the market, especially during initial exchanges in the marketplace (haz. ratio = 1.344, $p < .05$). The gap becomes smaller in subsequent exchanges.

5. Conclusions and discussion

In this paper, we analyzed how reputation affects buyers' trust in sellers, in a highly uncertain environment – a cryptomarket for illegal drugs. We add to the previous literature on reputation in online markets by focusing on decisions of buyers, instead of sellers' market outcomes. This allowed us to distinguish between two different levels of reputation effects - buyers' individual experience and third-party information effects. We add to the literature on embedded trust by studying dyadic and network learning mechanisms simultaneously in an empirical setting on a large scale.

Our results are generally in line with the main predictions of dyadic and network learning effects (Buskens and Raub, 2002). Buyers are more likely to trust sellers with whom they had positive experience in the past, or if they observe positive feedback from other buyers. The evidence is relatively weaker for negative experience - although buyers react to negative ratings from other buyers before making their first purchase, the effect of negative information on trust becomes less pronounced in subsequent exchanges.

Perhaps more importantly, we find that dyadic embeddedness effects on trust are stronger than those of network learning. Buyers' individual history of exchanges is a stronger predictor of their subsequent trust decisions than the third-party reputation information they observe. Despite having a rich set of seller alternatives and a significant amount of information about trustworthiness of each option on the market, buyers tend to repeatedly exchange with the same sellers they trusted in the past. Although cryptomarkets enable unprecedented

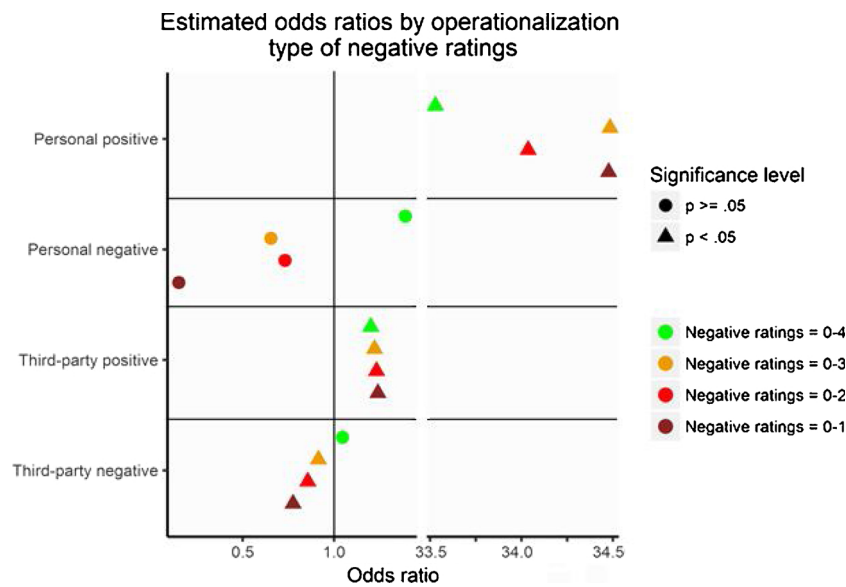


Fig. 4. Estimated Model 2 odds ratios by different operationalizations of negative ratings.

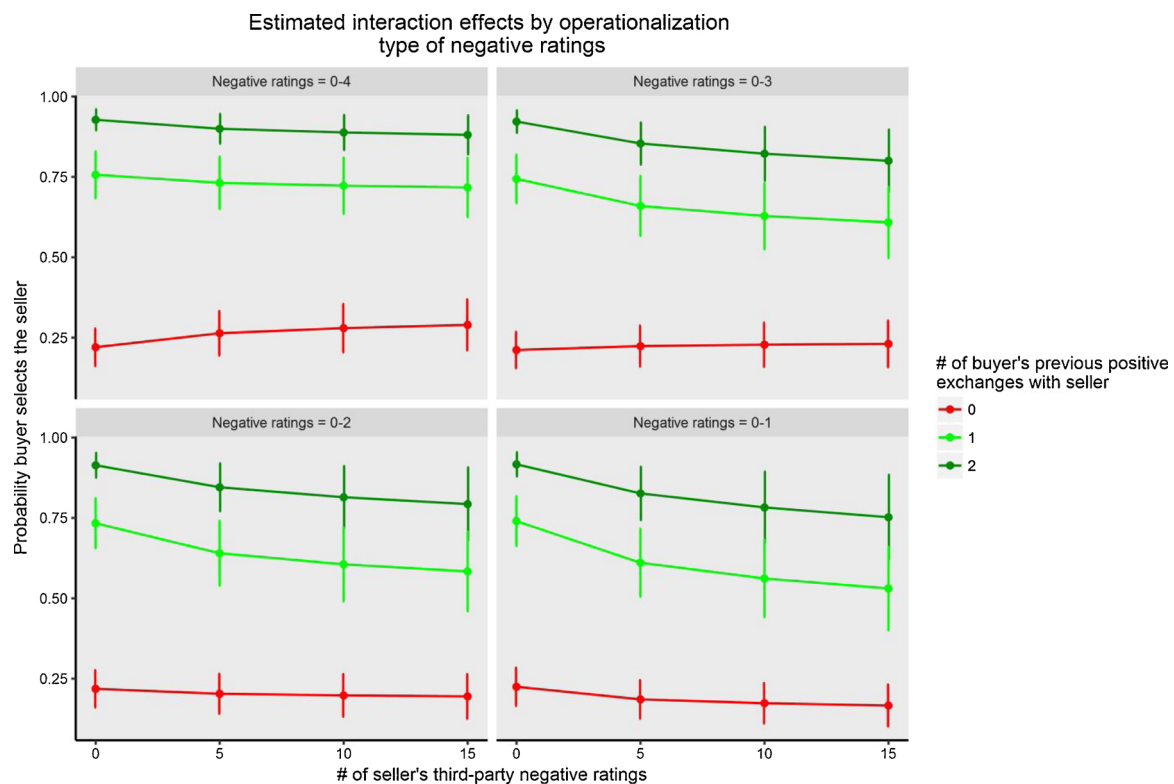


Fig. 5. Estimated Model 3 interaction effects by different operationalizations of negative ratings.

access to multiple sources of illegal substances to end-users, it might be that high uncertainty pushes buyers to choose exchanges with few trusted sellers, much like they do in offline drug markets (Beckert and Wehinger, 2013; Chalmers and Bradford, 2013; Jacques et al., 2014).

This finding echoes those of Romero et al. (2016), who showed that the structure of communication networks between stock traders tends to “turtle up” when uncertainty increases – individuals cluster and focus their communication on strong ties and trusted company insiders, instead of reaching out to weak ties to obtain as much information as possible. In our case, similarly, buyers have the option to reduce their reliance on a single source of drugs, which is relevant given the reported police arrests and seller scams (Décary-Héту and Quessy-Doré,

2017). Instead, online drug exchanges tend to “turtle up” as well, as buyers focus on few individually trusted market ties. Even though analysis of whether this tendency becomes stronger as uncertainty increases (e.g. after law enforcement marketplace shutdowns) is outside the scope of this paper, cryptomarkets offer a wide variety of cases where the effect of external shocks on trust and exchange network structure could be analyzed empirically.

Although, in line with dyadic learning theory, buyers reward cooperative sellers by choosing them repeatedly, we do not find the predicted retaliation effect after negative experiences. Instead of choosing a different seller, buyers become more likely to exit the marketplace. The use of the term ‘exit’ in this paper slightly differs from

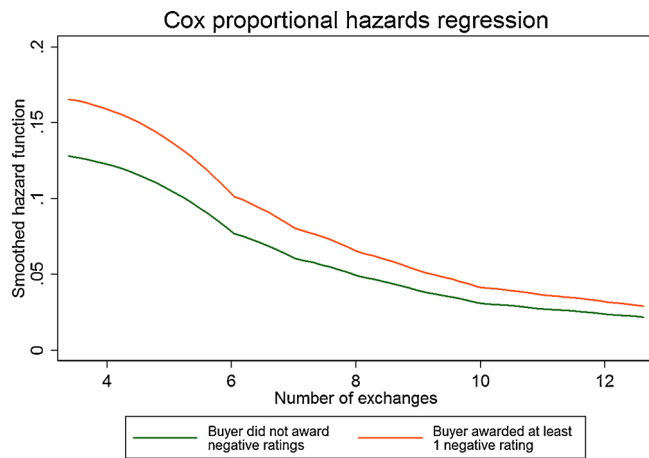


Fig. 6. Cox proportional hazards model of buyer leaving the marketplace based on having negative experience with at least 1 seller.

the one used in experimental research on Trust games (e.g. Buskens and Raub, 2002; Buskens, 2003) or Prisoner's dilemma games (e.g. Schuessler, 1989; Yamagishi et al., 1984) played in networks of actors, where it refers to the ability to select a different partner within a game. In our case, instead of choosing another partner, buyers opt out of the game for good. It is possible that after facing an abuse of trust, buyers turn to less risky sources for the same product. Given that online drug markets constitute a relatively small portion of global drug trade (Global Drug Survey, 2016), buyers might turn to offline sources, which could be interpreted as an 'exit' by selecting an offline drug dealer, instead of an online drug seller. It is difficult to test predictions about such behavior in this environment, since we cannot observe product and search costs of offline alternatives that buyers have (Yamagishi, 1988). An interesting future research avenue could be a test of whether cryptomarket buyers in countries with high "street" prices of specific drugs are less likely to leave cryptomarkets after negative experiences.

Interestingly, a tendency to leave the marketplace after receiving a negative rating has been found for sellers in a similar online environment (Norbutas, 2020). Sellers have an incentive to leave the marketplace early on if they receive a negative rating, since re-entering with a new nickname is less costly than rebuilding damaged reputation. This tendency might also partially explain why we do not find strong effects of negative third-party ratings on buyers' behavior – the 'worst' sellers might leave the market and no longer show up on buyers' list of alternatives. Taken together, these findings show that the 'exit' option is an important behavioral alternative to consider when analyzing reputation effects in risky environments.

We also find that negative signals from third parties can indirectly erode buyer's ongoing trust relation with a seller. The trust-decreasing effect of observed negative ratings is stronger for those, who have a positive exchange history with a given seller. We show that network learning not only directly affects trust of the buyer towards specific sellers, but also by moderating the effect of dyadic learning. Positive individual experience still outweighs the effect of information from other actors, however, since buyers are highly likely to return to a trusted seller with up to 15 observed negative ratings.

Taken together, our findings show that reputation effects play a crucial role in establishing trust in an uncertain market environment. However, not all reputation information is equally important when making trust decisions – individual history of exchanges plays a much stronger role than third-party information, and subsequently translates into strong dyadic embeddedness of actors in the exchange network.

Appendix A

See Table A1

Negative experiences can be especially detrimental and lead actors to leave the market, instead of looking for alternatives. We show that cryptomarkets are a useful empirical environment with high uncertainty and non-trivial risks for the actors involved, excellent for testing social theories on trust and cooperation.

5.1. Limitations

As mentioned previously, our analysis relies on a measure of transactions that is based on buyers' feedback messages. The usage of this measure leads to possible selectivity bias in our results, since buyers might systematically avoid leaving feedback after specifically positive or negative exchanges. Selectivity bias could partially explain the lack of findings regarding negative reputation and personal experience effects. We do not expect selectivity to have a strong impact on our findings regarding positive effects of dyadic embeddedness on trust, since buyers were previously found to be reluctant to leave feedback for the same seller more than once (Diekmann et al., 2014). Additionally, previous research on cryptomarkets has shown a strong correlation between each seller's number of sales reported in the website and the number of feedback messages (Aldridge and Décary-Héту, 2014; Przepiorka et al., 2017; Hardy and Norgaard, 2016). Ideally, data on actual buyer-seller exchanges rather than feedback messages should be used in future studies.

Due to the nature of the TOR network, we also could not identify cases where individuals use several accounts. Although this problem holds for most analyses of online marketplaces, the use of multiple accounts for security purposes could be somewhat more prevalent in illegal contexts. This could also partially explain the high number of single-exchange buyer accounts found in the results. Future research should ideally obtain exchange data from cryptomarkets or other online marketplaces, to analyze the scope of this shortcoming in more detail.

The data set used here is a part of a larger collection of cryptomarket scrapes collected by Branwen et al. (2015), which is known to suffer from incompleteness (Décary-Héту & Giommoni, 2017). Daily copies of cryptomarket websites have been found to have partially missing item pages. We compared the number of scraped item pages in every daily copy of Abraxas to the total number of items reported in the website's homepage. The average completeness of collected marketplace items across the daily scrapes is 92.4 % (range: 26%–100%). Since every marketplace item is typically collected more than once in daily scrapes, we addressed this issue by using the most recent collected copy of each item's page. We also aggregated individual items to the seller level in our analyses. Nevertheless, some seller level alternatives in choice sets might contain missing information on part of the items. We do not expect the missingness to be systematic, since it is caused by errors during automated scraping of webpages, rather than actions of the cryptomarket administrators or users. The results of this study should ideally be replicated with a fully complete set of cryptomarket items.

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Table A1
Conditional fixed-effects logistic regression models with seller account dummies. Buyers' choices of sellers.

Independent variables	Model 1 1st exchange	Model 2 Full model (all subsequent exchanges)	Model 3 Model 2 + interaction
Positive individual experience (log)		33.159** (3.13)	48.017** (5.50)
Negative individual experience (log)		1.545 (0.74)	1.861 (0.82)
Positive 3 rd -party ratings (log)	1.126** (0.04)	1.039 (0.04)	1.007 (0.04)
Negative 3 rd -party ratings (log)	0.766** (0.04)	0.818** (0.05)	0.934 (0.06)
Positive individual experience (log)*Negative 3 rd -party ratings (log)			0.648** (0.06)
Lowest price per gram	1.392** (0.15)	1.215 (0.16)	1.227 (0.16)
Average price per gram (USD; log)	0.628** (0.05)	0.568** (0.05)	0.567** (0.05)
Ships worldwide	1.305* (0.15)	1.497** (0.19)	1.508** (0.19)
Geographic monopoly (origin)	0.935 (0.07)	1.082 (0.09)	1.085 (0.09)
Geographic monopoly (destination)	1.331** (0.13)	1.167 (0.15)	1.152 (0.15)
Number of seller's items	1.013* (0.00)	1.031** (0.00)	1.031** (0.00)
Number of holding items	0.498** (0.10)	0.526** (0.09)	0.532* (0.10)
Seller dummies (N = 257)		Omitted	
N obs.			
Level 1: Alternatives	76,976	104,447	104,447
Level 2: Choice sets	2977	3464	3464
Level 3: Buyers	2614	1199	1199
Explained variance (Pseudo R ²)	0.167	0.418	0.243

* p < 0.05.

** p < 0.01. Odds ratios reported, standard errors in parentheses.

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