International Journal of Drug Policy 56 (2018) 92–100

Contents lists available at ScienceDirect

International Journal of Drug Policy

journal homepage: www.elsevier.com/locate/drugpo

Research Paper

Offline constraints in online drug marketplaces: An exploratory analysis of a cryptomarket trade network

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ARTICLE INFO

Keywords:
Cryptomarkets
Online drug trade
Network analysis
ERGM
Dark web
Online markets

ABSTRACT

Background: Cryptomarkets, or illegal anonymizing online platforms that facilitate drug trade, have been analyzed in a rapidly growing body of research. Previous research has found that, despite increased risks, cryptomarket sellers are often willing to ship illegal drugs internationally. There is little to no information, however, about the extent to which uncertainty and risk related to geographic constraints shapes buyers' behavior and, in turn, the structure of the global online drug trade network. In this paper, we analyze the structure of a complete cryptomarket trade network with a focus on the role of geographic clustering of buyers and sellers.
Methods: We use publicly available crawls of the cryptomarket Abraxas, encompassing market transactions between 463 sellers and 3542 buyers of drugs in 2015. We use descriptive social network analysis and Exponential Random Graph Models (ERGM) to analyze the structure of the trade network.
Results: The structure of the online drug trade network is primarily shaped by geographical boundaries. Buyers are more likely to buy from multiple sellers within a single country, and avoid buying from sellers in different countries, which leads to strong geographic clustering. The effect is especially strong between continents and weaker for countries within Europe. A small fraction of buyers (10%) account for more than a half of all drug purchases, while most buyers only buy once.
Conclusion: Online drug trade networks might still be heavily shaped by offline (geographic) constraints, despite their ability to provide access for end-users to large international supply. Cryptomarkets might be more "localized" and less international than thought before. We discuss potential explanations for such geographical clustering and implications of the findings.

Introduction

Recent years saw an increase in scholarly attention to the growing number of online marketplaces for illicit goods and services called cryptomarkets (Barratt & Aldridge, 2016; Martin, 2014). Cryptomarkets are online trading platforms that bring together individual buyers and sellers. Anonymity of marketplace users is guaranteed by the Tor network and digital currencies used for financial transactions (e.g. Bitcoin; Nakamoto, 2008). These online marketplaces enable buyers and sellers of illicit drugs to interact in relative safety from the law enforcement agents.

Cryptomarkets provide an opportunity for researchers to access large-scale data related to drug trade and use (Barratt & Aldridge, 2016). A rapidly growing body of research has analyzed various aspects of such marketplaces, including buyers' behavior in terms of popular types of drugs and volume of sales (Christin, 2012; Soska & Christin, 2015), prevalence of wholesale trading (Aldridge & Décary-Hétu, 2014, 2016a; Demant, Munksgaard, & Houborg, 2016), or social mechanisms and technical innovations that ensure buyers' trust in sellers (Hardy & Norgaard, 2015; Przepiorka, Norbutas, & Corten, 2017; Tzanetakis, Kamphausen, Werse, & von Laufenberg, 2016).

An important question with regards to the role of cryptomarkets in global drug trade is whether these marketplaces merely move conventional offline drug trade channels online, or also have the potential to transform localized and fragmented retail trade networks by bringing goods to markets, where their availability had previously been limited (Aldridge & Décary-Hétu, 2016b; Christin 2014; Martin, 2014). While online marketplaces theoretically offer buyers and sellers easy access to international markets, shipping of orders across national borders results in higher risk and longer waiting times. This could potentially limit users' willingness to trade internationally (Broséus, Rhumorbarbe, Morelato, Staehli, & Rossy, 2017; Décary-Hétu, Paquet-Clouston, & Aldridge, 2016).

Previous literature examined geographical patterns of online drug

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https://doi.org/10.1016/j.drugpo.2018.03.016
Received 26 May 2017; Received in revised form 11 March 2018; Accepted 15 March 2018

trade using sellers' self-reported origin country and shipping destination data (Broséus et al., 2017; Cunliffe, Martin, Décary-Hétu, & Aldridge, 2017; Décary-Hétu et al., 2016). Based on information from Silk Road, Décary-Hétu et al. (2016) found that 69% of analyzed listings, mostly illicit drugs, were open for international orders. Sellers who offered international shipping held 61% of total market revenues. Although it is unclear what share of these revenues came from internationally shipped items, the findings suggest that a significant share of drug sellers were willing to ship internationally. Broséus et al. (2017) and Cunliffe et al. (2017) found that trade of illegal drugs is primarily domestic in Australia, while a larger proportion of sellers from the United States, Canada, Netherlands, Germany and China offered international shipping.

Analyses of international flows of drugs that are based on geographical information provided by cryptomarket sellers suffer from several significant sources of bias. First, many sellers do not disclose their origin country for security reasons. In previous research such cases were either excluded from the analyses or, due to missing information on origin countries, could not provide information about whether these sellers trade internationally. For example, Décary-Hétu et al. (2016) excluded 8% of their collected sample of item listings due to ambiguous sellers' origin locations. Broséus et al. (2017) found that about 37% of sellers of illicit drugs in Evolution market listed "Worldwide" as their country of origin. Van Buskirk et al. (2016) found that 21% of analyzed drug listings were shipped from undeclared locations in Agora. This issue could have an impact on the reliability of previous results, especially if sellers' willingness to disclose their origin country is associated with willingness to ship internationally.

Secondly, previous research on geographical patterns in cryptomarkets did not incorporate information on the buyers. Information on sellers' origin countries and shipping destinations cannot reveal what fraction of items that have an option for international shipping are bought by foreign-based and not domestic buyers. This could lead to an underestimation of domestic drug trade in cryptomarkets.

We address these issues by analyzing a complete cryptomarket drug trade network, using a social network analysis approach. We construct a network of exchanges between buyers and sellers of illicit drugs and analyze network clustering patterns that might emerge due to geographic constraints. Analysis of a cryptomarket exchange network has several advantages. We can incorporate data on sellers and their items with missing or ambiguous origin countries (e.g. 'Worldwide'), since buyers' and sellers' positions in the global network structure can be a strong signal of their geographic location. Emergent structural patterns of a global buyer-seller exchange network can also be considered a more reliable representation of drug trafficking flows than sellers' willingness to ship internationally, since they are based on completed exchanges rather than sellers' intentions.

Social network analysis has been used to study the structure of offline drug trafficking networks (Kenney, 2007; Morselli, 2009; Malm & Bichler, 2011; Natarajan, 2006; Wood, 2017), online discussion forums of hackers (Holt, Strumsky, Smirnova, & Kilger, 2012; Lu, Luo, Polgar, & Cao, 2010) and stolen data markets (Monsma, Buskens, Soudijn, & Nieuwbeerta, 2013; Motoyama et al., 2011). This approach has also been used to study trust considerations between opioid buyers and sellers in a cryptomarket (Duxbury & Haynie, 2017, 2018). The results show that the opioids' exchange network is highly clustered, but not geographically − buyers tend to exchange with few well-reputed sellers. The lack of any geographic structure in this network is counter-intuitive, given that a significant share of sellers in many cryptomarkets only ship domestically (Décary-Hétu et al., 2016; Broséus et al. , 2017). This finding could be heavily influenced by the relatively small subset of the total cryptomarket network analyzed, especially given that the absolute majority of analyzed sellers were from a single country.

Here we use a complete buyer-seller trade network data set from a cryptomarket Abraxas (Branwen et al., 2015). To our knowledge, apart from the anonymous cryptomarket analyzed by Duxbury and Haynie (2017), this is the only marketplace where buyer identifiers are available for each transaction. We construct a full buyer-seller trade network with information on almost 11,000 trades of drugs between 463 sellers and 3542 buyers, over a period of 7 months in 2014–2015. These unique data allow us to explore the structure of online drug trade in detail and shed light on possible mechanisms that underlie formation of such networks.

Structure of offline and online retail drug trade networks

To operate efficiently, markets must minimize the amount of uncertainty for its actors, to make assessment of costs and benefits of a potential exchange possible (Beckert & Wehinger, 2012). Contracts in illegal markets are not secured by law, which increases potential risks for market actors and makes them turn to alternative strategies to minimize uncertainty and potential losses (Reuter, 1983).

The level of uncertainty and the resulting behavior of buyers and sellers might differ depending on whether illegal market exchanges take place online or offline (Brynjolfsson & Smith, 2000; Cambini et al., 2011). Buyers and sellers in offline retail drug trade networks face uncertainty with regards to true intentions of their exchange partners. Face-to-face contacts lead to increased risk of violence and potential exposure to law enforcement for both, buyers and sellers (Bouchard & Ouellet, 2011; Jacques & Wright, 2011). Additionally, buyers face uncertainty with regards to quality and purity of purchased drugs, since drug markets are "markets for lemons", characterized by substantial information asymmetry between buyers and sellers with regards to true quality of the goods (Akerlof, 1970; Reuter & Caulkins, 2004). Information about trustworthiness of sellers and quality of their goods is scarce, which makes it costly for buyers to look for market alternatives (Galenianos, Pacula, & Persico, 2012).

The risk of violence and exposure to law enforcement, product quality uncertainty and a lack of information about trustworthiness often lead actors in offline retail drug markets to form "closed", "overembedded" or highly clustered trade networks, where they form small, fragmented groups, consisting of long-lasting dyads of repeated interactions (May & Hough, 2004; Uzzi, 1997). Drug sellers have been found to screen potential customers for trustworthiness and incentivize long-term clients by offering credit or discounts (Chalmers & Bradford, 2013; Jacques, Allen, & Wright, 2014). The geographic area of retail drug sellers' activity might be limited deliberately to prevent additional exposure to law enforcement (Reuter, 1983). Since illegal drugs are consumer goods, buyers, learning from their successful transactions with a seller in the past and facing high search costs for alternatives, have an incentive to maintain existing cooperation (Buskens & Raub, 2002).

Online drug markets, just like online markets for legal goods, might reduce many of these uncertainties and lead to more dynamic, open and efficient retail drug trade networks (Brynjolfsson & Smith, 2000; Cambini et al., 2011). Cryptomarkets increase information availability for buyers − complete lists of items and sellers on the market can reduce search costs and make it easier to choose the best market alternative (Cambini et al., 2011). Buyers and sellers gain easy access to international markets, where drugs are sold, which are not available locally (Van Buskirk, Naicker, Roxburgh, Bruno, & Burns, 2016). Due to absence of face-to-face contact and increased anonymity, sellers can be more expansive − exposure to more buyers no longer increases risk of being arrested (Morselli, Giguère, & Petit, 2007; Reuter, 1983). Finally, cryptomarket buyers can assess sellers' trustworthiness and product quality via reputation systems, which publicly disseminate buyers' feedback based on their past transactions with each seller (Hardy & Norgaard, 2016; Przepiorka et al., 2017).

An important source of risk in online drug markets that might diminish their ability to transform localized and dyadically embedded offline drug trade networks, is the shipping stage of online exchanges (Aldridge & Askew, 2017). International shipping of packages leads to

increased risk of potential interceptions by the law enforcement (Décary-Hétu et al., 2016). Branwen (2017) found that a substantial fraction of arrests of cryptomarket buyers and sellers were related to international orders. Cryptomarket users also identify shipping stage as the main source of risk of being arrested (Aldridge & Askew, 2017). Having this risk in mind, some sellers choose to sell their goods only domestically (Décary-Hétu et al., 2016).

Buyers must also consider shipping time when choosing a seller as an additional cost. All else equal, an international seller, especially from a geographically distant location, might be a less desirable option than a domestic one. Together these aspects might lead to increased geographical clustering of buyers and sellers − a formation of buyer-seller groups limited by national or regional borders – and limit cryptomarkets' ability to globalize retail drug trade.

Aims

The aim of this paper is to analyze the structure of an exchange network between buyers and sellers of illicit drugs in a cryptomarket Abraxas, with a focus on geographic constraints. Firstly, background information and descriptive statistics are provided regarding the number of buyers, sellers and transactions in the marketplace over time. Secondly, geographic clustering patterns between buyers and sellers in the marketplace are analyzed by using exponential random graph models (ERGM).

Method

We use data from Abraxas, a cryptomarket that was active from December 2014 to November 2015. The data set collected by Branwen et al. (2015) contains data from the period between December 2014 and July 2015, with an average of 1 crawl every 2–3 days. The first data collection point is dated several days after the start of the market, with only several active sellers and no active buyers. This allows us to observe the growth of marketplace activity from its very beginning.

The data contains copies of item listings, seller profiles and customer profiles. A customer profile becomes visible only after a customer leaves a feedback message on an item page after an exchange. We can therefore only observe active buyers after their first purchase. Item pages contain detailed information, including seller's nickname, price, description and feedback of previous buyers. Each feedback message contains a date, a 0- to 5-star rating and the original price for which the item was bought.

The data set collected by Branwen et al. (2015) contains information on multiple cryptomarkets and is known to suffer from incompleteness (Décary-Hétu & Giommoni, 2017). Daily copies of marketplaces might contain information on only a fraction of items and user profiles. To get a better assessment of this problem in our case, we compared the number of crawled item pages in the data to the actual number of items displayed in the home page of Abraxas at each date. The average percentage of collected items across all crawls is 92.4%, ranging from 26% to 100% for each crawl. While the average coverage of the data is rather high, it might still pose a significant problem for the reliability of our analysis. To minimize the impact of this issue, we aggregated information across all daily crawls of item pages and profiles (N = 91[1]), maintaining only the most recent version of every page. During the observed period of 7 months, the aggregated data contains 11,814 item pages, 463 seller and 3542 buyer accounts, and a total of 10,898 transactions.

Each collected feedback message needs to be attributed to a particular buyer to construct a network data set of exchanges between individual buyers and sellers. While this poses a problem in many cryptomarket data sets due to partially or fully hidden buyer nicknames, Abraxas contained unique buyer profile identifiers for each feedback message, which was located in the HTML code of item pages. We used these buyer identifiers to aggregate feedback messages left by each buyer account. While we were able to identify purchases of individual buyer accounts, the data did not include buyers' country of residence. Although we cannot observe buyers' geographic location directly, inferences about geographic clustering in the marketplace can be drawn based on buyers' selection of sellers located in particular countries. We will discuss this approach in the following section. It is also important to note that while we can attribute feedback messages to individual buyer accounts, some buyers could have used multiple accounts for different purposes. For the sake of clarity, we will use the terms "buyer account" and "buyer" interchangeably.

To exclude items that are irrelevant for this paper (e.g. fake documents or eBooks), we use a subset of the aggregated data set, which contains buyer profiles[2] and transactions of items in the "Drugs" category. This category contains data on 390 sellers (84.23%), out of which 282 sellers made at least 1 sale, 3192 buyers (90.11%) and 10,234 transactions (93.90%). The category contains items that are further divided into 11 subcategories: benzodiazepines, cannabis, dissociatives, ecstasy, opioids, prescription drugs, psychedelics, RCs, steroids, stimulants and mixed drugs. We hand-coded weight of every item with at least 1 sale, based on the name and description. There were 83 items[3] (purchased 342 times) that had no information on weight.

We use this information to construct the network data set for our analysis. The network contains a set of nodes that represent individual profiles in Abraxas, and ties between nodes that represent market transactions. We constructed a bipartite network, which represents two types of nodes: buyers and sellers (Newman, 2010).

Exponential random graph models

To assess geographic clustering in the network, we use Exponential Random Graph Models (ERGMs) for bipartite networks (Robins, Pattison, Kalish, & Lusher, 2007; Robins, Snijders, Wang, Handcock, & Pattison, 2007). These models are designed for network data and take network connections as the dependent variable. ERGMs take into account structural interdependence between network actors, which is not possible in ordinary logistic regression models. ERGMs allow to model the effects of exogenous actor-level attributes (e.g. seller's geographic location) and endogenous structural factors (e.g. buyer's position in the network) on tie formation. The resulting model estimates can be interpreted as a comparison of likelihood of tie formation to random chance, given a certain property of a network node or a dyad. For example, a zero effect of seller's reputation on tie formation would show that it does not change the likelihood of a seller being selected by a buyer from random chance, while a positive effect would show that highly reputed sellers are more likely to be selected. The likelihood of occurrence of certain structural features in the observed network, such as inter-connected cliques, can also be modelled. We used the *statnet* package in R to implement the models (Handcock, Hunter, Butts, Goodreau, & Morris, 2008).

To analyze geographic clustering, we model the occurrence of *geographically homogenous and heterogeneous buyer-seller 2-stars* in the network (see Fig. 1). A 2-star is a structural pattern in the network that represents a buyer with connections to two sellers. A buyer might have multiple 2-stars if she is connected to more than 2 sellers. These sellers might be from the same or different countries, resulting in the two types of 2-stars. Unfortunately, given the data availability, we cannot directly

[1] We excluded 3 crawls (2015-04-07; 06-04; 07-01), since contained very incomplete information on only several items.

[2] Customer accounts contain aggregate information on the number of purchases, refunds, amount of money spent in Bitcoin. We did not include this data in our analysis, since we could not distinguish which part of this information refers to orders of illegal drugs.

[3] We use "items" and "listings" interchangeably.

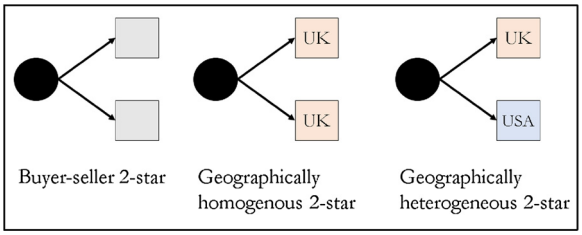

Fig. 1. An example of buyer-seller 2-star structures used in the ERG models. Circles represent buyers and squares represent sellers.

observe the geographical location of buyers. However, if strong geographical clustering is present in the cryptomarket, we would observe positive estimates of buyers making purchases from multiple sellers in the same country (homogenous 2-stars), and negative estimates of buyers purchasing from multiple sellers from different countries (heterogenous 2-stars).

There might be several explanations for the occurrence of homogenous 2-stars. We argue that the most likely explanation is buyer's residence in the same country as the sellers (domestic transactions). There might also be cases where a buyer chooses multiple sellers from the same foreign country, for example, in cases where a particular type of drug is mostly available in a single foreign country. This would result in homogenous 2-stars that are in fact international exchanges. While we cannot distinguish between these two cases with our data, we argue that the latter scenario should be much less prevalent, given that concentration of sellers and items of specific types of drugs in particular countries is generally low in cryptomarkets (Broséus et al., 2017; Van Buskirk et al., 2016).

Descriptive results

The number of buyers and sellers grew steadily over time (see Fig. 2a). Although Abraxas started operating in December 2014, the first observed feedback message was posted on 14th January 2015. The most rapid increase in the total number of users and items began in March 2015. This increase might be related to sellers' migration from a major cryptomarket Evolution following an exit scam, which took place around 14th March 2015.

In total the network of drug exchanges during the entire period of data collection contains 10,234 wted ties, or market transactions, between 282 sellers (72.31%) and 3192 buyers. Tie weight represents the number of repeated transactions in the same buyer-seller dyads. Once we exclude repeated exchanges, a total of 5644 ties are observed, which show that almost half of all interactions are repeated between the same users. 108 sellers (27.69%) who had posted drug items in the market had no sales. The full network consists of 15 connected components with 3474 (98.9%) users in the largest component. The remaining connected components consist of 1 buyer and 1 seller on average. This result shows that buyers tend to purchase from various sellers over time, which leads to formation of a large group of interconnected users with very few isolated buyer-seller cliques. We will further focus on this largest component in our analysis.

Fig. 2b shows the cumulative distribution of unweighted degree among buyers (N = 3192) and sellers (N = 282). Unweighted degree refers to the number of user's ties, excluding repeated exchanges with any seller. For buyers this measure reflects the number of sellers she has bought from, and vice versa for sellers. The figure shows that 60% of buyers only interacted with a single seller, an additional 21.4% of buyers bought from 2 different sellers. Percentage of buyers with higher degree decreases rapidly after this point, with a maximum value of 22 sellers. This shows that most buyers only purchase from a single seller and it is a relatively small group of buyers whose ties maintain the largest network component connected.

The same distribution for cryptomarket sellers is much less skewed − 50% of all sellers exchanged with 8 or fewer buyers. Sellers' degree distribution has a long tail and the highest degree of 297 (not shown in Fig. 2b), which shows that there is a small outlier group of highly popular sellers. These numbers reinforce findings of Soska and Christin (2015), who showed that only a small fraction of all sellers generate significant revenue.

Marketplace characteristics

Table 1 shows transaction statistics by drug category. Drug items have been found to get misclassified by cryptomarket sellers and the categories provided in the website often contain multiple types of drugs (Aldridge & Décary-Hétu, 2016a). Drug items were re-classified to sub-categories (column 2), using regular expressions based on item names and the categorization provided in Abraxas (column 1). To reduce the size of the table, drug items in smaller sub-categories were merged.

Based on the total volume of sales, Abraxas was a relatively small cryptomarket compared to other cryptomarkets operating at the time (e.g. Evolution, Agora or Nucleus). Evolution, for example, totaled for around $350,000 in daily volume of sales based on the last known estimate from February 2015 (Soska & Christin, 2015). In comparison, Abraxas on average made $15,200 per day in sales of illegal drugs during the most active month in June 2015. The volume of sales had been increasing steadily up to this month, however, and there are reasons to believe that Abraxas became one of the largest cryptomarkets before closing, since two of the largest competing cryptomarkets − Evolution and Agora, had both been closed before this time (Branwen, 2017).

In terms of the most popular drugs, Abraxas is relatively similar to other cryptomarkets, such as Silk Road 1 (Aldridge & Décary-Hétu, 2016a; Christin, 2012) or Agora (Van Buskirk et al., 2016). The most popular categories in terms of number of items on sale are cannabis

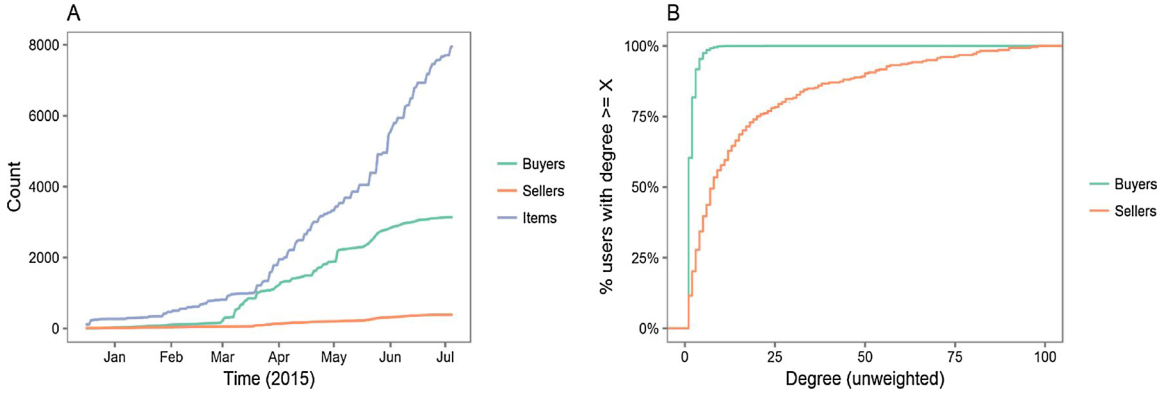

Fig. 2. A. Number of buyers, sellers and drug items over time. B. Cumulative distribution of unweighted degree (number of individual contacts) by market user type.

Table 1
Market item and transaction statistics by drug category in Abraxas.

Category	Sub-category (recoded)	Number of items	Number of sellers	Number of buyers	Number of transactions	Volume of transactions (USD)	Avg. weight of purchased items (g)*
Cannabis	Marijuana	1591	126	435	3230	327,547	11.16
	Cannabis products[a]	530	57	79	257	18,884	3.71
	Hashish	457	49	123	722	43,122	6.86
Opioids	Misc. prescription opioids[b]	278	51	62	306	25,787	5.73
	Heroin	247	35	77	481	214,400	1.45
	Oxycodone	105	25	30	215	37,046	0.32
	Buprenorphine	33	9	14	74	10,621	0.06
Stimulants	Cocaine	626	87	151	1015	178,330	1.77
	Amphetamine	374	56	107	699	48,777	16.81
	Misc. prescription stimulants[c]	318	48	38	101	7822	1.21
	Methamphetamine	214	39	70	354	45,589	2.07
Ecstasy	Ecstasy pills	604	61	141	627	73,694	8.54
	MDMA	467	72	125	589	90,762	6.64
	Mephedrone	60	14	18	83	14,069	10.39
Psychedelics	LSD	235	34	71	448	22,321	3.00
	Misc. psychedelics[d]	223	29	52	199	10,933	0.65
	Mushrooms	69	22	27	71	3453	8.22
Benzodiazep.[e]		509	53	97	483	21,386	0.17
Prescription	Misc. other prescription[f]	422	14	35	67	2291	1.40
	Misc. relaxants[g]	139	43	11	27	2410	24.51
Dissociatives	Ketamine	66	14	18	93	9737	2.20
	Misc. dissociatives[h]	57	12	11	42	2174	13.98
Steroids		260	13	11	26	1253	0.77
RCs[i]		69	13	7	23	822	1.41
Packages of mixed drugs		8	5	2	2	179	1.12
Total		7961	390	3,192	10,234	1,213,457	6.70**

* Calculated only for items with sales and available weight information, N = 2079.
** Weighted average (price weighted by number of transactions in each category; item weight weighted by number of items in each category).
[a] Contains drug infused candy and chocolate, concentrates.
[b] Fentanyl, hydrocodone, tramadol, codeine, etc.
[c] Adderall, dextroamphetamine, Ritalin, etc.
[d] Synthetic psychedelics (25D-NBOMe, 2C-B, etc.), dimethyltryptamine.
[e] Xanax, Valium, Diazepam, Etizolam, etc.
[f] Viagra, Cialis, Prozac, etc.
[g] Etizolam, Zolpidem, etc.
[h] GHB, methoxetamine.
[i] A-PVP, ethylphenidate, Modafiendz.

(N = 2578), stimulants (N = 1532) and ecstasy drugs (N = 1131). The same pattern holds if we consider the number of unique buyers in each category. If we consider the value of transactions, opioids closely follow cannabis products with an estimated transaction volume of $287.854, with heroin accounting for 74.5% of this figure. While heroin has relatively few buyers compared to other major drugs (N = 77), the number of transactions per buyer in this category is among the highest (6.24 purchases per buyer). This suggests that a small number of opioid buyers make frequent purchases and generate a relatively large volume of trade.

Purchase volume distribution

The distribution of the total volume of purchases is highly skewed among buyers (Fig. 3). The total value of purchases per buyer ranges from $0.23 to $10888.69. About 50% of buyers spent less than $150 and made only a single purchase over the period of data collection. Around 5% of buyers spent more than $1200 on an average of 10 purchases. The total value of purchases (in USD) made by the top 10% accounts for 50% of the entire market turnover of drug purchases during the observed period. The distribution of the relative number and volume of purchases across drug categories are similar for the top 10% and bottom 90% buyers. The top 10% of buyers on average buy larger quantities of most drugs: cannabis (18.4 g vs. 6.9 g), ecstasy (16.7 g vs. 4.6 g) and opioids (2.8 g vs. 1.0 g) being the largest differences between the groups. This result shows that market activity is as skewed among buyers, as it is among sellers (Soska & Christin, 2015) − a small group of users account for most transactions. A fraction of these transactions are purchases of large quantities of drugs.

Network structure and geographic clustering

Fig. 4a and b display the structure of Abraxas trade network visually − the nodes represent buyers and sellers and network ties represent market exchanges. We used "ForceAtlas 2" algorithm in Gephi (Jacomy, 2009), which aims to represent connected nodes closer to each other, while pushing unconnected nodes away simultaneously. The resulting layout shows that the trade network has several large clusters.

In Fig. 4b, sellers are colored by their stated geographic origin. Sellers' geographic location is coded based on their provided "shipping from" locations in item pages. If more than one value was provided (e.g. "Italy" and "EU"), we used the value of the "lowest" geographical level value (e.g. country instead of region). To get a better picture of geographical trends in our analyses, we reduced the number of categories by merging countries with few sellers into larger categories (see Table 2).

The resulting network structure shows that buyer-seller network is highly fragmented across geographical borders. Sellers from the same countries are depicted closer to each other, because there are many buyers who make orders from each one of them, and fewer or no orders

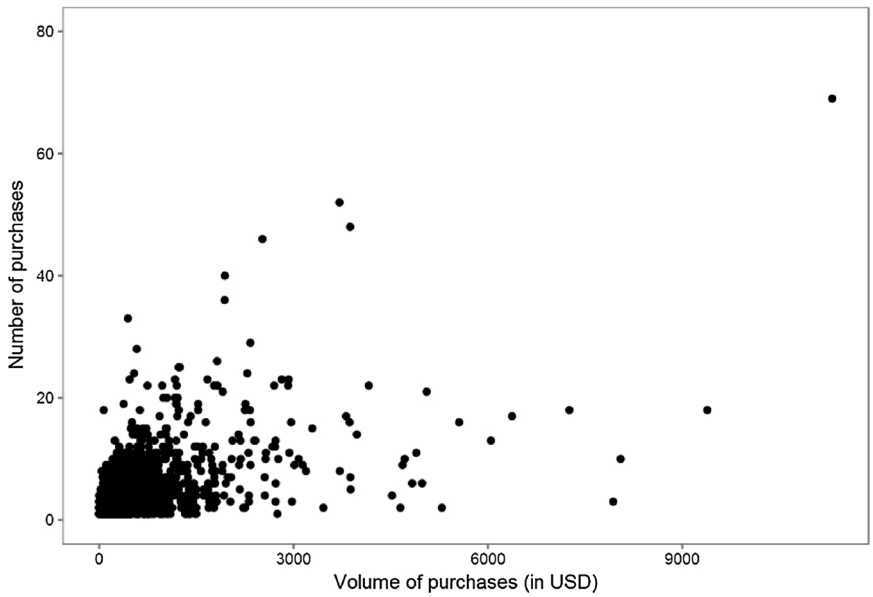

Fig. 3. Distribution of number and volume of purchases among drug buyers in Abraxas.

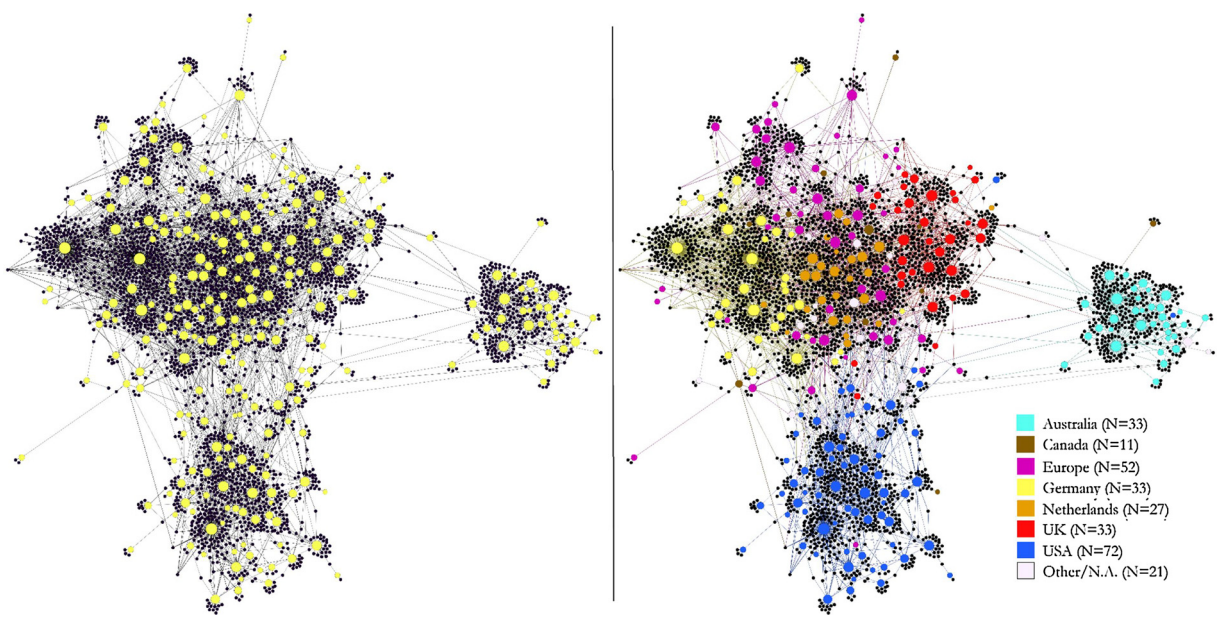

Fig. 4. A. (left): Network of market trades between drug buyers (blue) and sellers (yellow). Node size reflects the total number of seller's sales. B. (right): The same network of drug buyers and sellers; sellers colored by geographical location ('Ships from'). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

from sellers in other countries. As mentioned previously, buyers might prefer sellers from one specific country for several reasons (see also the Discussion section). The visualization also does not provide the extent to which this preference applies after controlling for other key factors (e.g. reputation, types of drugs). We will therefore analyze geographical clustering in more detail.

ERGM results for geographic clustering patterns

In order to apply bipartite ERG models, we excluded repeated ties between the same buyers and sellers (N = 5644). We used the same coding of sellers' countries of origin provided in Table 2. We do not explicitly model the structural effects for sellers in the "Other/N.A" category, in order to decrease the number of parameters in the model.[4] In total, the model includes 28 possible combinations of buyer-seller 2-stars.

We include several control variables in our ERG model. *Edge* variable is the baseline likelihood of tie formation, which is often included in ERG models and can be interpreted as the intercept term, or a baseline likelihood of a tie occurring in a network. We control for the general tendency of buyers to form *2-stars* and the *number of buyers with multiple (> 2) purchases*. These structural terms are used to improve

[4] Please note that while we exclude 2-star parameters with sellers in the "Other/N.A." category, network connections between these sellers and their buyers are still included in the data.

Table 2
Recoding scheme of Abraxas' sellers' locations.

Original value	Number of sellers	Recoded value	Number of sellers
Australia	33	Australia	33
Canada	11	Canada	11
Netherlands	27	Netherlands	27
Germany	33	Germany	33
UK	33	UK	33
USA	72	USA	72
Belgium	3	Europe	52
Bulgaria	1		
Czech Republic	1		
Denmark	2		
Europe	26		
France	3		
Hungary	1		
Italy	2		
Norway	1		
Poland	1		
Spain	7		
Sweden	3		
Switzerland	1		
China	1	Other/N.A.	21
Columbia	1		
Mexico	1		
South Africa	1		
Not Available	17		

Table 3
Descriptive statistics of variables used in the ERG model.

Variable name	N	Mean (std. dev)	Min/Max
Seller origin			
USA	282	0.255 (0.43)	0/1
Europe	282	0.184 (0.38)	0/1
Australia	282	0.117 (0.32)	0/1
United Kingdom	282	0.117 (0.32)	0/1
Germany	282	0.117 (0.32)	0/1
Canada	282	0.039 (0.19)	0/1
Netherlands	282	0.095 (0.29)	0/1
Other non-Europe/NA	282	0.074 (0.26)	0/1
Seller's reputation	282	4.744 (0.73)	0 – 5
Seller's number of items			
Weed	282	0.393 (1.81)	0–17
Ecstasy	282	0.109 (0.59)	0–6
Opioids	282	1.124 (3.01)	0–26
Psychedelics	282	0.687 (2.06)	0–13
Stimulants	282	0.375 (1.62)	0–18
Benzodiazepines	282	0.567 (1.66)	0–13
Number of sellers	3192		
Number of buyers	282		
Number of edges (unweighted/undirected)	5644		

model fit.

We include the main effects of *seller's location* to control for the likelihood of buyers to form a tie with a seller from a particular country (see Table 3). *Seller's reputation* has been found to affect buyer's trust in previous research (Przepiorka et al., 2017; Duxbury & Haynie, 2017). We averaged seller's ratings over all feedback messages, including non-drug items that have been excluded from our data. This variable has a theoretical range of 0–5, based on the 5-star feedback system. Finally, to account for the effect of the kind of drugs sold on tie formation, we include a variable for the number of seller's items in the 6 largest drug categories: *marijuana, ecstasy, opioids, psychedelics, stimulants and benzodiazepines*.

The model results for the occurrence of buyer-seller 2-stars are displayed in a matrix in the first part of the table (Table 4a). The results on the diagonal cells are the estimates of geographically homogenous 2-stars, where a buyer is connected to 2 sellers from the same country. The results show that geographically homogenous 2-stars are more likely to appear than would be expected by chance. This applies to all countries, except Germany, where the result is statistically insignificant (log-odds = 0.103, p = 0.07). In contrast, the estimates for geographically heterogenous 2-stars below diagonal are all negative and statistically significant for most country combinations. These results show that buyers in Abraxas are unlikely to order from sellers in multiple countries and are especially likely to order from multiple sellers within the same country. These two effects, working together, give rise to the clustering observed in Fig. 4b.

The negative estimates of geographically heterogenous 2-stars below the diagonal are especially highly negative for 2-stars that contain sellers from Australia and USA, while estimates are closer to zero for 2-stars with sellers from different European countries. This result suggests that the largest amount of geographical clustering is observed between continents, while simultaneous purchases from several European sellers, although unlikely, occur more often. Most estimates are statistically insignificant for 2-stars that contain Canadian sellers. This result might be partially explained by the small number of Canadian sellers in the marketplace (N = 11).

The estimates of the control variables (Table 4b) in the model show that, generally, the likelihood of buyer-seller 2-star formation in the network, and the number of buyers with more than a single purchase are lower than could be expected by chance. This is in line with the skewed degree distribution of buyers in Fig. 1b, which shows that many buyers only exchange with a single seller. The results also show that, all else equal, sellers from Australia, the UK and Germany are more likely to form exchange relations than their competitors in the United States, while sellers from Canada, the Netherlands and other analyzed European and uncategorized countries are less likely to attract buyers.[5] Finally, in line with previous research, we observe a positive effect of sellers' reputation on the number of exchange relations.

Discussion

Cryptomarkets provide unprecedented access for researchers to data not only on macro-level structure of large-scale drug trade networks, but also on individual buyer decisions and buying patterns. In this paper, we made the first attempt to shed light on the structure of a complete online drug trade network and the shaping factors.

Analysis of the Abraxas trade network illuminates several important structural characteristics. First and foremost, we find that the network is largely shaped by geographical boundaries. Buyers tend to make orders from multiple drug sellers from a single country, and avoid ordering from multiple countries. This effect is especially strong for continental boundaries – buyers are more likely to simultaneously order drugs from sellers from several European countries, than from sellers in different continents. This structural aspect of cryptomarket networks has not been observed in previous studies that analyzed subsets of a cryptomarket network (Duxbury & Haynie, 2017, 2018).

There might be several explanations for this geographic clustering. Buyers might be more willing to order domestically to avoid increased risks of package interception, possibility of getting arrested and long shipping times. This might also be amplified by sellers' risk aversion and unwillingness to ship internationally (Décary-Hétu et al., 2016). Another explanation could be buyers' tendency to buy specific types of drugs from particular countries, regardless of their own geographic location (e.g. due to drug availability being limited to few countries). We argued that this explanation might not be the primary one, since supply of all types of drugs is relatively well distributed across different countries in cryptomarkets (Broséus et al., 2017; Van Buskirk et al., 2016). Unfortunately, we were not able to test these explanations

[5] Please note that this result does not necessarily reflect the general distribution of purchases across sellers in these countries, since the model takes structural effects, reputation and other covariates into account. Sellers from the United States on average have more sales and buyers per person than sellers in Australia, UK and Germany.

Table 4a
ERG model estimates − likelihood of geographically homogenous (diagonal) and heterogenous buyers 2-stars. The matrix represents all possible combinations of buyer-seller 2-stars. Geographically homogenous 2-stars (both sellers from the same country) are presented on the diagonal of the matrix.

Seller 1 \ Seller 2	Australia	Canada	Europe	Germany	Netherlands	UK	USA
Australia	**0.288*** (0.05)**						
Canada	-0.750 (0.46)	**1.084*** (0.07)**					
Europe	**-2.400*** (0.39)**	0.123 (0.08)	**0.195*** (0.06)**				
Germany	**-4.491*** (1.01)**	**-0.631** (0.21)**	**-0.250*** (0.06)**	0.103† (0.05)			
Netherlands	**-3.494*** (0.95)**	0.029 (0.13)	-0.009 (0.06)	**-0.286*** (0.06)**	**0.378*** (0.04)**		
UK	**-2.038*** (0.29)**	-0.169 (0.18)	**-0.328*** (0.06)**	**-0.925*** (0.08*)**	**-0.179* (0.07)**	**0.311*** (0.04)**	
USA	**-2.686*** (0.36)**	-0.299 (0.18)	**-0.868*** (0.09)**	**-1.441*** (0.11)**	**-1.432*** (0.16)**	**-1.686*** (0.16)**	**0.161*** (0.05)**

Table 4b
ERG model estimates − effects of the control variables on likelihood of ties.

Variable name	Coefficient	Std. Err.
Edges	−4.984***	0.175
Buyer 2-stars	−0.097*	0.049
Buyers > 1 purchases	−1.946***	0.077
Seller origin		
USA	Ref.	
Europe	−0.332***	0.061
Australia	0.404***	0.059
United Kingdom	0.277***	0.052
Germany	0.583***	0.054
Canada	−1.312***	0.185
Netherlands	−0.394***	0.070
Other non-Europe/NA	−1.347***	0.135
Seller's reputation	0.231***	0.033
Seller's number of items		
Weed	−0.034***	0.007
Ecstasy	0.009	0.017
Opioids	0.085***	0.002
Psychedelics	0.076***	0.005
Stimulants	0.076***	0.008
Benzodiazepines	0.102***	0.005
AIC/BIC	61816/62343	

***p < 0.01.

directly, since buyers' geographic locations were not available in the cryptomarket website, and this aspect remains an important venue for future research.

These results show that cryptomarkets are heavily affected by offline factors and geographic boundaries. Their ability to internationalize retail drug trade could therefore be more limited than shown by sellers' willingness to ship internationally in previous studies (Décary-Hétu et al., 2016; Broséus et al., 2017). Even though cryptomarkets technically provide its users an easy access to information and worldwide markets, rational cost and benefit considerations of market actors might push them to exchange in "local" niches.

Additionally, the network analysis suggests that trade volume distribution is as skewed for buyers, as it has previously been found among sellers (Christin, 2012; Soska & Christin, 2015). We find that around 10% of buyers accounted for a half of marketplace's entire trading volume, while 50% of buyers never spent more than $150 and purchased only once. If such pattern is consistent across larger cryptomarkets, the growth and prospects of cryptomarkets might be overestimated with only a small fraction of buyers using such markets on a constant basis. Décary-Hétu and Quessy-Doré (2017) found, in contrast, that 91% of buyers made more than a single purchase. Although the overall distribution of purchases across buyers was not analyzed, it could be the case that results of this paper are limited due to a short period of time used in the analyses. Alternatively, the result of Décary-Hétu and Quessy-Doré (2017) could be overestimated. They matched buyer accounts using partially anonymized nicknames, which could have led to a large underestimation of distinct buyer accounts (i.e. attribution of purchases from different buyers to the same case in the analysis). It should also be noticed that our data is based on buyer accounts and not individual buyers. If buyers tend to use multiple accounts (e.g. for security reasons), the true concentration of purchases could be even larger.

Limitations and policy implications

There are several limitations of this paper. First, the data do not include buyers' geographic location, which prevents us from directly testing the effect of geographic homophily between buyers and sellers and alternative mechanisms that lead to it. The data set is also too small to analyze drug-type specific geographic clustering patterns.

Secondly, Abraxas is a relatively small market and the extent to which our findings can be generalized to other cryptomarkets should be further evaluated. While virtually all cryptomarkets anonymize buyer nicknames in feedback messages, which makes our findings hard to replicate, there could be opportunities in new marketplaces. We encourage researchers to put more emphasis on individual-level buyer and seller interactions. Such large-scale granular data can be very valuable to answer important questions, such as what drives buyers' trust in sellers, what kind of buyers stay in cryptomarkets for the long term, how individual drug use patterns change over time or why do some actors end up being so important.

The findings of this paper contribute to the debate on the international nature of cryptomarkets, previously raised by Décary-Hétu et al. (2016). Based on the structure of trade network in Abraxas, it might be more fruitful to analyze cryptomarkets as conglomerations of regional sub-markets rather than as uniform international market entities. While the threat of law enforcement undeniably plays a significant role in increasing the risks of international shipping, relatively high clustering of European sellers and low frequency of inter-continental trade by the same buyers might suggest that other factors, such as considerations of shipping speed, could play a sufficient role in "localizing" cryptomarket

exchanges. Our findings suggest that for monitoring and enforcement coordination purposes, data on buyers' behavior is crucial to capture the scope and potential growth of cryptomarkets as an international phenomenon. Finally, additional research is needed to better understand the conditions under which buyers are likely to order internationally.

Funding

This research benefited from the support of the Netherlands Organisation for Scientific Research (NWO) Talent Grant [grant number: 406-15-106].

Conflicts of interest

None.

Acknowledgements

I would like to thank Rense Corten, Stijn Ruiter and Brian Keegan for their valuable advice during the course of writing this paper. This research also benefited from the support of the Netherlands Organisation for Scientific Research (NWO).

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