J Quant Criminol
DOI 10.1007/s10940-017-9359-4

ORIGINAL PAPER

The Network Structure of Opioid Distribution on a Darknet Cryptomarket

Scott W. Duxbury[1] **· Dana L. Haynie**[2]

Abstract

Objectives The current study is the first to examine the network structure of an encrypted online drug distribution network. It examines (1) the global network structure, (2) the local network structure, and (3) identifies those vendor characteristics that best explain variation in the network structure. In doing so, it evaluates the role of trust in online drug markets.
Methods The study draws on a unique dataset of transaction level data from an encrypted online drug market. Structural measures and community detection analysis are used to characterize and investigate the network structure. Exponential random graph modeling is used to evaluate which vendor characteristics explain variation in purchasing patterns.
Results Vendors' trustworthiness explains more variation in the overall network structure than the affordability of vendor products or the diversity of vendor product listings. This results in a highly localized network structure with a few key vendors accounting for most transactions.
Conclusions The results indicate that vendors' trustworthiness is a better predictor of vendor selection than product diversity or affordability. These results illuminate the internal market dynamics that sustain digital drug markets and highlight the importance of examining how new anonymizing technologies shape global drug distribution networks.

Keywords Drug distribution · Online drug markets · Social networks · Trust · Tor network

✉ Scott W. Duxbury
duxbury.5@osu.edu

Dana L. Haynie
haynie.7@osu.edu

[1] Department of Sociology, The Ohio State University, 238 Townshend Hall, 1885 Neil Avenue Mall, Columbus, OH 43210, USA

[2] Department of Sociology, The Ohio State University, 202 Townshend Hall, 1885 Neil Avenue Mall, Columbus, OH 43210, USA

Published online: 08 June 2017

Introduction

Drug trade has gone digital. Users and curious individuals have turned to online venues to seek out drug information and to make drug purchases, both legal and illegal (Walsh 2011; Eurobarometer 2014; UNODC 2016). Consequently, online drug marketplaces have proliferated on both the Clearnet—all websites that can be accessed through a mainstream search engine—and the 'Tor network'—an encrypted Internet network only accessible via anonymous Tor browsers (Barratt et al. 2013). The Tor network employs an anonymizing 'darknet' that obscures Tor users' IP addresses and enables users of Tor markets to connect and make anonymous economic transactions (Barratt 2012).[1] Tor markets[2] typically specialize in illicit materials, most frequently drugs. They engage in trade akin to Clearnet markets (e.g. *Ebay*), incorporating transaction rankings, private messaging, and bidding systems. Unlike Clearnet markets, however, they use anonymous currency to protect vendors and customers involved in the illegal sale and purchase of drugs from potential identification.

Unsurprisingly, the Tor network has gained infamy as a criminal enclave. The '*Silk Road*,' the first widespread drug Tor market, contributed to the development of this reputation by gaining public notoriety for its libertarian trade practices. It offered drugs, stolen credit cards, counterfeit items, and various other contraband for purchase (Barratt et al. 2013, 2014), earning itself the moniker 'E-bay for drugs' (Barratt 2012). In many ways, the *Silk Road* provided a blueprint for how a 'successful' Tor marketplace can function. Despite being shut down in 2013 by the FBI, the *Silk Road* ushered in an era of Tor markets. The void left by the *Silk Road* was quickly filled by innumerable Tor markets, many of which are much larger than the *Silk Road* was at its height (Dolliver 2015; Van Buskirk et al. 2016). Recent research estimates a 50% increase in the number of drug users who have purchased from a Tor market over the last two years (Barratt et al. 2014; Van Buskirk et al. 2016). Further, some of the larger Tor markets generate over $180 million US in revenue per year (Soska and Christin 2015), with over half of all generated revenue coming from wholesale purchases above $1000 US (Aldridge and Decary-Hetu 2016). This indicates that both distributors and consumers are turning to Tor markets for drug procurement. In this regard, Tor markets are no longer 'an E-bay for drugs,' but instead are a "paradigm shifting criminal innovation" (Aldridge and Décary-Hétu 2014, p. 1). The Tor network currently acts as a medium for other real world crime rings, including jihadist terrorist groups, child pornography trade, assassination services, and firearm exchange (ibid).

Tor markets present a rare opportunity to observe drug markets in action (Van Buskirk et al. 2016). As Barratt and Aldridge (2016) highlight, research into online drug markets can provide insight into internal trade dynamics that stabilize and facilitate the growth of drug markets. As such, identifying how buyers select vendors and how those selection processes impact the overall network structure is critical for understanding the behavior of online drug markets and the burgeoning trend of online drug distribution. The current study will provide insight into the micro-interactions that sustain drug markets and contribute to their growth. It will also identify the specific individual-level and network-level traits that explain variation in the formation of digital drug distribution networks.

[1] Colloquially, anonymous activity on Tor and other encrypted networks are often referred to as activities on the 'darknet,' although this is not technically correct.

[2] Most literature in this field refers to Tor markets as 'cryptomarkets.' We use the term Tor marketplace to avoid confusion with the specific marketplace we examine, *Cryptomarket*.

This article has two goals: (1) to characterize the network structure of a Tor drug distribution network and (2) to evaluate what individual-level and network-level characteristics predict vendor selection. In particular, we direct attention to the role of trust in explaining internal market dynamics and the structure of the distribution network. Following Papachristos (2014; also see Papachristos 2009; Papachristos et al. 2013), we employ network methods and theory to identify internal market dynamics of an online drug distribution network. We apply descriptive and analytic network techniques to a unique dataset of transaction data collected from an active opioid distribution network on one large Tor marketplace. We conclude with a discussion of the implications of our results for online drug market disruption, drug abuse, and theories of criminal coordination.

Trust and Tor Markets

Research in criminal and co-offending networks shows that trust is a key component in the organization of criminal groups (Baker and Faulkner 1993; Morselli et al. 2007; Tremblay 1993; Weerman 2003; von Lampe and Johansen 2004; Smith and Papachristos 2016). Trusted connections limit the risk of detection by reducing the probability of working with informants, undercover agents, or reckless affiliates (Tremblay 1993; Weerman 2003). Trust is particularly important as networks grow in size (Weerman 2003). Large criminal networks are comprised of many connections and so the opportunity for informants, reckless affiliates, or undercover agents to enter the network increases. In the case of drug exchange networks—which Weerman (2003) highlights as a form of co-offending—a digital medium offers to connect buyers and vendors across the globe, increasing the size of the network and potentially underscoring the importance of trust.

While trust plays an important role in illegal online exchange (Van Hout and Bingham 2013; Decary-Hetu and Laferriere 2015), it is hard to evaluate exactly how important trustworthiness is to anonymous co-offenders who cannot incriminate one another. Recent research suggests a few noteworthy considerations. First, some studies show that one large appeal of Tor markets may be the opportunity for extensive illegal drug experimentation. Tor markets expose buyers to an array of drugs that may not be available in their immediate local context (UNODC 2016; Barratt et al. (2016a). In this regard, the appeal of a vendor may not be their trustworthiness, but the variety of drugs that they offer (Stephen and Toubia 2009). Another potential explanation is drug affordability. Van Hout and Bingham (2014) highlight this, citing competition between both large and small drug vendors vying to offer the lowest prices. Quantitative analyses support this competitive dynamic, demonstrating that vendors with lower reputation scores tend to be more willing to take on the risk of international shipping, presumably to attract more customers (Decary-Hetu et al. 2016).[3]

These purchasing patterns suggest a unique network configuration. Buyers may switch between vendors rapidly to either get the best deal or to experiment with different drugs offered by different vendors. In this configuration, the network will be relatively interconnected with either low localized subgroup formation or high subgroup formation with all subgroups being comparably sized.

While buyers may still be concerned with the trustworthiness of vendors in these scenarios (Dolliver and Kenney 2016), it is also possible that trust may outweigh other

[3] Decary-Hetu et al. (2016) note that risk is greater in international distribution because sanctions are harsher than domestic distribution and because contraband crossing national boarders is more likely to be seized than contraband traveling within national borders.

factors. Even with anonymizing technology, the risk that a buyer is purchasing from a federal agent or a scammer is unknown prior to the purchase. Like targeted intervention, exchange with a scammer poses significant risk to the network in that it threatens to disrupt all exchanges routed through that vendor and to deter future potential buyers (e.g. Stafford and Warr 1993). The presence of trustworthy vendors may facilitate network activity and also make it more difficult for disingenuous vendors to impact the overall network structure. In this regard, trust may be the key component stabilizing Tor markets.

Recent findings suggest that Tor purchasers may be particularly concerned with vendor trustworthiness (van Hout and Bingham 2013). This concern with secure transactions may influence the relatively high drug prices that buyers are willing to pay (UNODC 2016) and even the design of Tor markets (Tzanetakis et al. 2016). Buyers who select into this network may be relatively affluent, and so the appeal of a non-violent drug market may outweigh any price concerns (e.g. Barratt et al. 2016b). Similarly, since Tor marketplaces connect buyers from around the globe (Aldridge and Decary-Hetu 2016), the network may be sufficiently large that trust concerns outweigh other considerations, such as cost and product diversity (e.g. Tremblay 1993; Weerman 2003).

This second network configuration suggests a transaction network where trust dominates vendor selection. Here, the network will exhibit high localized clustering around trustworthy vendors, and subgroups of dramatically different sizes, where most purchases will be directed towards a select few trustworthy vendors.

While we can evaluate the overall network structure with structural analyses, statistical modelling of social networks allows us to directly compare the effects of the explanations proposed in prior research (described above) on the formation of the overall network structure (Robins et al. 2007; Lusher et al. 2013). In the analysis below, we draw on a unique dataset of 763 Tor marketplace users who were involved in drug exchange with opioid vendors to answer two questions: what is the social structure of the Tor opioid distribution network? And, what is the role of trust in vendor selection? Our analysis proceeds in three steps. First, we describe the global network characteristics and traits of buyers and sellers. Second, we perform community detection analysis to evaluate the extent of subgroup formation in the transaction network and to characterize the localized network structure. Finally, we use exponential random graph modelling (ERGM) to evaluate which characteristics identified in prior research significantly predict variation in vendor selection in the Tor opioid distribution network.

Data

We collected our data by first identifying one of the largest Tor markets ('Cryptomarket') involved in drug sales.[4] Next, we identified all active vendors in the opioid vendor network operating on April 1st, 2016. To code data, we downloaded webpages for every vendor, which included identifiers for all vendors as well as identifiers of all buyers who purchased drugs from the vendors over a 6-month period, stretching between October 2015 and April 2016. This allowed us to recreate the complete transaction network for all opioid vendors on *Cryptomarket* operating during the time period of October 2015 through April 2016 by

[4] *Cryptomarket* was also selected for data collection because it is the only large Tor market that provides the entire username for both vendors and buyers, allowing network ties to be identified. Most other Tor drug markets encrypt usernames to preserve anonymity. The ability to match identifiers is necessary to reconstruct the network.

coding which buyers purchased from which vendors and how frequently buyers purchased from given vendors during this time frame.

The network we analyze is weighted by the frequency with which buyers purchase from specific vendors. Whereas binary network data shows the structure of buyers' selection of initial vendors, weighting the network by the frequency of buyers' purchases captures repeat transactions, and thus the extent to which buyers return to specific vendors. This allows us to examine the effects of repeat transactions in our analyses.

We chose opioid vendors for two reasons. First, it is the second largest sub-category of drug listings (after marijuana) on *Cryptomarket.* Second, the severe legal consequences of scheduled opioid trafficking makes it ideal for analyzing how buyers choose vendors when risk is high (i.e., when trust considerations are most salient). Because some vendors sold other drugs in addition to opioids, not all drug exchanges in our network are opioid transactions, though all vendors sell some type of opioid. As such, we identified different products in transactions when coding webpages into a compiled data set. Roughly half of all exchanges are opioid transactions, with one quarter of overall transactions being Schedule 1 opioid sales.[5] All opioid sales were coded by hand to verify that the substance being listed as an opioid was actually an opioid.[6]

Network measures were constructed based on users' evaluations of transactions. Buyers evaluate transactions on a ranked scale of -5 through 5, where lower scores indicate a poor transaction and higher scores indicate a positive transaction.[7] These evaluations are tracked and recorded at the top of a vendors' webpage, providing a cumulative reputation score for each vendor. Unlike Clearnet markets (e.g. *Ebay*) where purchase evaluation is optional, *Cryptomarket* employs a mandatory evaluation policy where all purchases are ranked with visible comments from each buyer. Buyers are required to submit an initial evaluation within two weeks of initializing a sale or their account may be banned. This evaluation is listed as a visible comment on the vendors' webpage. Buyers are then free to revisit and edit their comments at any time in the future. These comments indicate the identity of the product that was sold, the price of the sale, and the purchaser's evaluation score of the sale for all vendors' active listings. Together, these measures allow us to determine the average cost of vendor's listings, vendor's cumulative reputation, the products vendors sold, and vendors' country of origin.[8] We establish the presence of network ties based on these comments. Each comment is evidence of a transaction, and so we coded a tie of value '1' for every time a buyer purchases from a given vendor. Because comments are only active for 6 months, our network reflects the trade structure of *Cryptomarket* cross-sectionally as a product of transactions over a 6-month period.

For listings that were no longer active or were removed at the time of data collection, the price of the sale and the product sold in the transaction were unavailable.[9] These data are still included because they reflect a drug transaction that occurred during the 6-month

---

[5] Schedule 1 is the highest degree of control in the US. It is reserved for substances with high abuse potential and no approved medical usage.

[6] Many vendors miscategorize their listings purposely to advertise to users who typically use different drugs. We classified each drug according to their chemical category, rather than how they were listed on *Cryptomarket.*

[7] Reasons for poor transactions include long shipment times, products not being delivered as described, poor communication between vendors and sellers, and non-delivery of items.

[8] Unfortunately, the country of origin for buyers is not listed on *Cryptomarket.*

[9] It is important to clarify here that all vendors were still active, even though the listing may not be. For example, when the webpages were downloaded, the vendor may no longer sell a particular drug, even though the vendor had sold that drug at some point in the prior 6 months.

time frame, but the nature of that explicit transaction cannot be ascertained. In these cases, we coded for the presence of the transaction and the buyers' evaluation of the transaction; other variables were treated as missing.[10] To measure the cost of the product being sold, it was necessary to convert the price of sales from Bitcoins (a type of cryptocurrency required for purchasing from *Cryptomarket*—see Barratt 2012) to US currency using the exchange rate at the time of data collection. Because this rate fluctuates, prices of older listings may be less accurate. However, because most listings over 1 month old were no longer active, these prices were unavailable and therefore not used in the analyses. Prices were determined based on the amount that buyers paid for a product, rather than the amount listed by the vendor.

Methods

To interrogate both the structure of the Tor drug distribution network and the processes that form this structure, we employ three analytic strategies: descriptive statistics of the network and the data, community detection analysis, and ERGM. All analyses were conducted using the *statnet* and *igraph* packages for *R* statistical software.

Descriptive Network Analysis

Given that we are analyzing a transaction network, our analysis will use directed ties, meaning that the tie from i to j is not necessarily reciprocated (i may purchase from j, while j does not purchase from i). A transaction is regarded as a tie, y_{ij}, where $y_{ij} = 1$ if a transaction has occurred between actor i and actor j and $y_{ij} = 0$ if not. Since our data is weighted, y_{ij} may be greater than 1 if multiple transactions have occurred between buyer i and seller j.

Similar to attributes of probability samples, descriptive measures for a network provide insight regarding the structure of a social network (see Knoke and Yang 2008; Wasserman and Faust 1994). We focus on four primary network measures: density, transitivity, reciprocity, and centralization. A network's density measures the total number i to j ties divided by the number of possible ties in the network. Density reflects the overall interconnectedness of the network—how many possible i to j transactions between a buyer and vendor actually occur. High densities indicate that buyers tend to purchase more than once and switch vendors regularly; low densities indicate that buyers tend to only purchase from a single vendor or purchase infrequently. Reciprocity is the proportion of i to j ties that are also j to i ties divided by the total number of ties in the network. Reciprocity would indicate whether vendors purchase drugs from buyers to whom they have previously sold drugs. Transitivity measures the total number of closed triangles in the network (when i is connected to j, j is connected to a third actor, k, and k is connected to i) divided by the total number of potential or 'open' triangles in the network (e.g. when i is connected to j, and k is connected to i, but k and j are not connected). Transitivity would indicate that buyers have purchased drugs from one vendor and have also sold drugs to another member of the network. This allows us to examine the extent to which *Cryptomarket* vendors use

[10] This did not result in any missing ties in the network data. Missing ties are the source of most missing-data based estimation problems in network analysis (Robins et al. 2004; Wang et al. 2016). Missing tie *values* were present for 37% of ties, but did not impact ERGM results when we reran the models without the affordability variable—the only variable based on tie values.

Cryptomarket to procure substances as well as distribute them (see Dolliver and Kenney 2016 for a related study).

Centralization measures how much influence a few actors exert over the network structure. In this study, it indicates how much influence a few vendors (indegree centralization) or buyers (outdegree) exert over the global opioid Tor drug market network structure. Centralization is measured by calculating the degree centrality of each actor in the network (the number of transactions in which a vendor or buyer is involved).[11] The sum of the differences between the actor with the highest centrality score and all other actors in the network is then divided by the largest possible sum of differences retrieved from a theoretical matrix of the same size. The resulting value ranges between 0 and 1, where higher values indicate greater central tendency in the network (Wasserman and Faust 1994). Formally, this can be represented as:

$$Centralization = \frac{\sum[C^* - C_i]}{max\sum[C^* - C_i]}$$

where, C^* is the largest centrality score in the network, C_i is the observed centrality score for a random actor in the network, and the denominator reflects the greatest possible value of $\sum[C^* - C_i]$ for a network of the same size as the empirical network. Since our network is directed, we calculated separate measures for outdegree and indegree centralization.

Community Detection Analysis

Global network measures help us understand the aggregate features of a network; however, they cannot answer questions related to the extent of clustering in the network (i.e. localized or subgraph clusters) and whether features of localized clusters are distinct from the global network. To determine the extent of subgroup clustering in the *Cryptomarket* opioid distribution network, we employ the walktrap community detection algorithm (Pons and Latapy 2005; Newman 2010). The walktrap approach performs a series of random walks—a connecting path of adjacent ties—on the network. Walks are more likely to stay within the same community in areas where the network is densely clustered. The walktrap algorithm identifies multiple potential community structures based on a random series of walks (steps). Each step partitions the graph into two separate communities, merging communities in which the distance between the two communities is small enough (described in Pons and Latapy 2005). The walktrap approach is ideal for large directed networks, where other algorithms may fail or provide uninterpretable results.

To evaluate the goodness of fit of the resulting community structure, a modularity score *Q,* can be used. Formally, modularity is calculated as:

$$Q = \sum\left(e_{bd} - a_b^2\right)$$

where e is the fraction of ties connecting community b and community d, and a is the fraction of ties connected to community b. Q is equal to zero when there are no within group ties and equal to one when all ties are within group (Newman and Girvan 2004; Newman 2006). Higher values indicate better fit of the community structure; $Q > 0.3$ indicates acceptable fit or 'significant' community structure (Newman and Girvan 2004).

Together, the community detection algorithm and modularity score allow us to identify how many communities exist within the global Tor network and whether this fit

[11] An actor's degree score and degree centrality are synonymous.

significantly reflects the network structure. We evaluate the composition of the communities by calculating descriptive network statistics for each localized community in the overall Tor network.

Exponential Random Graph Models

While descriptive measurements and community detection offer interesting insights about the structure of a network, they cannot identify processes through which a network forms (e.g. why buyers select certain drug vendors). ERGM has been developed to identify correlates between ties and the actors or network contexts in which those ties occur. Although a relatively recent technique, ERGM has been fruitfully applied in analyses of crime and violence (Papachristos 2009; Papachristos et al. 2013) as well as research into social structure of prison inmates (Schaefer et al. 2017). Particularly, Papachristos (2009) describes the global structure of gang violence relations and then underscores these group-level characteristics by using ERGM to identify structural features that render a gang vulnerable to attack. The combination of ERGM and descriptive network measurements offer a powerful tool to criminologists to understand the structure of criminal affiliations and/or collaborations, as well as those dynamic group and actor-level processes through which such global structures may emerge (Kreager et al. 2016).

ERGMs treat the network as the dependent variable, where coefficients indicate the log-odds of tie formation (Robins et al. 2007). Alternative methods, such as logistic regression, are insufficient when using network data because network data violate the assumption of independent observations. Thus, the main benefit of ERGM is that the analytic strategy allows for inferential parameter estimates and assumes dependent rather than independent observations. Consequently, important characteristics of the network, such as degree parameters, can be examined and included as controls (Lusher et al. 2013). Formally, ERGMs simulate the probability of observing a set of ties given a set of actors and their attributes as:

$$P(Y = y) = \frac{1}{c}\exp\left(\sum_{k=1}^{K} \theta_k z_k(y)\right)$$

The $z_k(y)$ terms represent model covariates, which are any set of K network statistics, such as the vendors' degree score, calculated on y and included in the model. The θ coefficients are estimated from the data, and reflect the impact of variables on the likelihood of tie formation (making a purchase). c is a normalizing constant that constrains the probabilities to sum 1. The ERGM equation can be rewritten to predict the log-odds of tie formation:

$$logit\left(P(Y_{ij} = 1|Y_{ij}^{c})\right) = \sum_{k=1}^{K} \theta_k \delta z_k(y)$$

where Y_{ij}^{c} denotes all dyads other than Y_{ij}, and $\delta z_k(y)$ is the amount by which $z_k(y)$ changes when Y_{ij} changes from 0 to 1. The θ coefficient indicates the log-odds of tie formation.

Dyadic dependence models—models that include network features, like degree scores, as explanatory variables—use Markov chain Monte Carlo (MCMC) simulation for maximum likelihood estimation (Snijders 2002; Robins et al. 2007). A probability distribution of networks is simulated from the results of a logistic regression (Snijders 2002). The log-likelihood of the ERGM is evaluated iteratively until it reaches convergence. The MCMC procedure is often repeated many times to ensure that the log-likelihood solution is accurate.

ERGM Specification

Our key predictor variables are vendors' trustworthiness, vendors' affordability, and vendor's product diversity. We measure vendors' trustworthiness with vendors' cumulative reputation score—a common measure of trust in similar research (Diekmann et al. 2014; Dupont et al. 2016).[12,13] Since buyers evaluate the quality of transactions after a sale, the composite reputation score indicates the quality of previous transactions, where high values indicate smooth transactions and low values indicate problematic ones. We measure vendor's affordability as the average cost of products sold by that vendor in the preceding last 6 months.[14] The average cost of actual products sold is a more accurate estimate than the average cost of vendors' listings because some listings are deliberately over or under priced so that vendors attract clientele even though the vendor may not actually sell the cheaper product listed. We measure product diversity based on the types of opioids a vendor sells. Because we oriented collection to opioid vendors, we restrict our measure of product diversity to only opioid listings.

We control for vendors' country of origin. Geographic proximity often accounts for drug 'tastes' because some drugs are more common in specific regions (e.g. Coomber 2004). Similarly, increased shipping costs may be an additional constraint on buyers not captured by the average cost of transactions with a vendor.

ERGM allows us to disentangle the independent effects of a vendor's reputation and the count of sales in which they have engaged. These effects are difficult to parse out in non-ERGM analyses because buyers evaluate sales after a transaction. In ERGM, these effects can be specified separately as the vendors' reputation score and their degree score, which indicates the count of transactions in which a vendor has been involved. We control for the degree scores of both buyers and sellers. Omission of degree parameters can overestimate the effects of actor-level attributes on tie formation (Lusher and Ackland 2011). Controlling for the degree scores of buyers allows us to account for highly active buyers when selecting vendors.

Results

The Structure of Tor Network Opioid Distribution

The Global Structure

As Table 1 shows, the *Cryptomarket* opioid distribution network consists of 763 different actors, comprised of 57 vendors and 706 buyers connected to one another through 1132

[12] To make interpretation easier, we added '6' to every vendor's reputation score so that 0 becomes the lowest score possible, indicating vendors who have not made a sale in the past 6 months. We compared this decision to z-score and logarithmic transformations of the reputation score to verify the robustness of our results.

[13] We also ran the ERGM with an average evaluation per sale measure for vendors, finding the same pattern as that presented below. Because the ERGM controls for the number of sales made to each vendor, we used the cumulative reputation score in our models.

[14] We reran the model measuring vendors' affordability as the average price per gram of drug for a vendor (e.g. average of \$40 for a 1 g drug transaction), encountering the same results: vendors' reputation was positively correlated ($p < 0.001$) with making a sale and affordability was non-significant. We elected to use the more parsimonious measure to restrict missing data in the model.

Table 1 Network characteristics and descriptive statistics

	Mean (SD) or %	Range
Global network characteristics		
Total actors	763	
Total vendors	57	
Isolates	13	
Total buyers	706	
Total edges	1132	
Density	0.002	
Reciprocity	0	
Transitivity	0	
Indegree centralization	0.201	
Outdegree centralization	0.008	
Buyer characteristics		
Outdegree	1.82	1 to 25
Buyers who have purchased from more than one vendor	5.6%	
Buyers who have purchased more than once	18.3%	
Vendor characteristics		
Indegree	30.71	1 to 254
Vendor's reputation	148.53 (219.29)	−5 to 1152
Average cost of transactions with a vendor (In US dollars)	46.29 (13.80)	17 to 149
Product listings		
Heroin only	15.9%	
Prescription opioids only	70.4%	
Both heroin and prescription opioids	13.6%	
Geographic region		
USA	60.9%	
France	9.7%	
Netherlands	7.3%	
UK	12.2%	
Germany	2.4%	
Canada	9.7%	

transactions. Of these vendors, 13 are isolates—actors who are listed as vendors and currently listing drugs for sale at the time of data collection, but who have not made a sale within the last 6 months in which data were collected.

Like many criminal networks, the *Cryptomarket* opioid distribution network is relatively diffuse with extremely low network density (0.002) (see Raab and Milward 2003; Morselli et al. 2007), indicating that only 0.2% of all possible unique transactions (when a buyer and seller exchange for the first time) occur. For the sake of comparison, the density of the jihadist networks studied by de Bie et al. (2017)—a type of network widely reputed to be especially diffuse (Krebs 2001; Morselli et al. 2007)—ranges from 0.2 to 0.4. The low observed density may be a product of buyers' unwillingness to branch out to new vendors. Indeed, while few buyers purchased more than once in the past 6 months (18.3%), only 30.6% of those who did sought out new vendors.

One consequence of buyers' unwillingness to branch out to new vendors is that relatively few active vendors account for most traffic. While the average indegree for vendors is roughly 31 sales, the most prolific of vendors have engaged in up to 254 trades in the last 6 months. This extreme skew yields a relatively high indegree centralization of 0.201, with many buyers connecting to only a handful of high profile vendors. Since centralization measures tend to decrease dramatically as network size increases (Wasserman and Faust 1994; Knoke and Yang 2008), an indegree centralization score of 0.201 should be viewed as substantial in a large social network of over 750 actors. For comparison, the centralization of one 87 actor mafia network is 0.5 (Morselli et al. 2007). There is less disparity among buyers than among vendors. Whereas the average buyer purchases just twice (average outdegree = 1.82), the most enthusiastic buyers have bought over 20 times in the last 6 months (range from 1 to 25). While there are some very active buyers who contribute to much market activity, the disperse outdegree centralization (0.008) of the network indicates that buyers tend to purchase infrequently. Therefore, individual buyers tend not to yield much influence on the global network structure.

The relatively high number of isolates[15] (13 of 57 vendors) suggests that a clientele base may be difficult to establish in the network. Although a few central vendors direct a high degree of traffic, many vendors struggle to cement one sale or to even establish a regular base of buyers. This may result from buyers' perceptions of vendors' trustworthiness. The average cumulative reputation score of a vendor is roughly 149 with a standard deviation of 219.29; the range of vendors' cumulative reputation scores stretches from −5 to 1152. This substantial variation in vendors' cumulative reputation suggests that vendors with the highest reputation may attract the most customers because buyers perceive them to be trustworthy (explored further in the analyses below).

An additional insight that can be gleaned from the descriptive network measurements is that vendors likely have real-world drug connections. As Table 1 shows, the lack of transitivity and reciprocity in the Tor opioid market indicates very few multiple-degrees of connection between actors. In other words, there are no buyers who are also vendors in the network, and so vendors are not procuring products wholesale through *Cryptomarket* and then redistributing them in the same Tor drug network (see Dolliver and Kenney 2016 for a related study).[16] Since there are no transactions between vendors, we treat the network as bipartite (two-mode) for all analyses.[17,18]

The Local Structure

While global structural analyses give insight into the broad patterns of relations in the network, it takes only a glance at Fig. 1 to notice that much action appears to be occurring at the local level. Community detection analysis allows us to examine the localized

[15] It is important to note here that only vendors can be isolates, as buyers could only enter the network after a connection (transaction) has been made. Thus, there are 57 vendors total, but only 44 vendors who have made a sale in the last 6 months.

[16] This may be due to vendors using different accounts to purchase. However, we have found no source, scholarly or otherwise, to corroborate this.

[17] Technically, bipartite networks are not directed. However, we continue to use the language of indegree/outdegree for the sake of consistency.

[18] All network statistics provided are calculated by treating the network as bipartite, with the exception of transitivity, which cannot exist in a bipartite network.

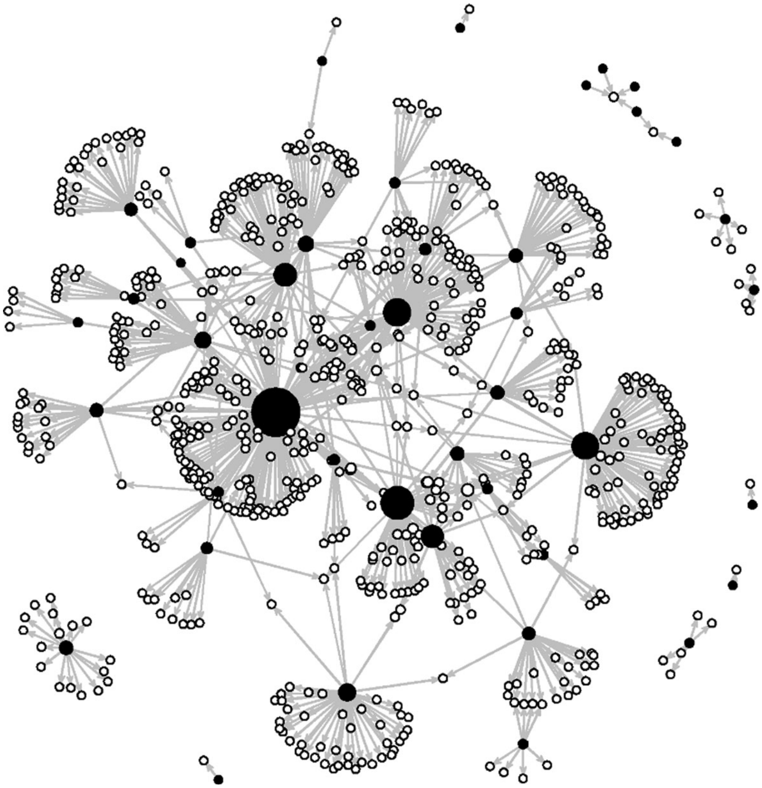

Fig. 1 Opioid distribution network on *Cryptomarket*. *Black nodes* are vendors, *white nodes* are buyers; larger nodes engage in more sales (scaled for visual appeal)

composition of the opioid distribution network and to compare these compositional characteristics to the global trade structure.

Community detection of our opioid Tor marketplace reveals 36 unique communities formed around prolific vendors with a modularity score of 0.76, indicating good model fit and significant community structure (Newman and Girvan 2004). The largest of these communities possesses 142 members, whereas the smallest 18 communities have fewer than 10. Indeed, the leading 10 communities account for 75.6% of the actors within the network. The high preferential attachment revealed in this network corroborate the important role of trust in network organization. As shown in Fig. 2, while the largest vendors share some buyers, most small communities coalesce around small-time vendors who are completely isolated from the main activity of the distribution network. As a result, overlap between communities tends to only occur between large subgroups.

The community composition revealed through community detection analysis reveals much about the largest communities. Of all communities, those with the most members tend to have high average vendor reputation scores. Moreover, these are the only communities where, on average, more than one transaction occurs between a community buyer and a community seller. These are also the communities with the largest number of vendors. This indicates that the largest communities in the network structure tend to form

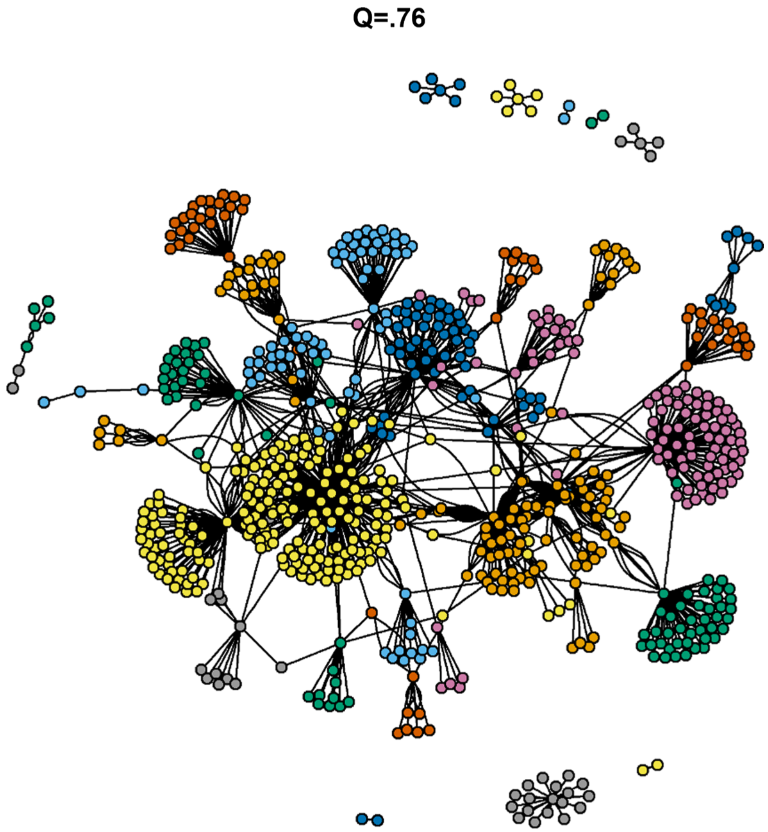

Fig. 2 *Cryptomarket* opioid drug distribution network *colored* by community membership (isolates removed) (Color figure online)

around a few desirable vendors who share clientele. In other words, those rare buyers who do branch out to different vendors (5.6% of the network) tend to select only a handful of alternate vendors. This may be due to name recognition or mutual recommendations between vendors. Interestingly, the local outdegree centralization scores across communities are not remarkably different than the global outdegree centralization. This indicates that once a buyer finds a trustworthy vendor, a second purchase does not necessarily follow (Table 2).

While the global network analysis shows a diffuse structure, community analysis indicates high, and particularly dense, local clustering. Most purchases tend to stay within a community, and only two communities (1 and 5) showed evidence of buyers switching between communities (buyers average outdegree <1, density <1). Evidence that buyers rarely switch between communities of vendors suggests that price or product diversity may yield less of an effect on buyers' purchasing patterns than vendors' trustworthiness. We test the extent to which buyers consider price, product diversity, and vendor trustworthiness in the ERGM below.

Table 2 Vendor community composition of the 10 largest communities

	1	2	3	4	5	6	7	8	9	10
Vendors and buyers										
Mean indegree for vendors[a]	28.5	13.0	52.0	32.7	29.0	66.0	42.0	33.0	73.0	22.0
Vendors' average reputation	216	75	475	480	115	639	293	219	596	124
Number of vendors	2	2	3	3	1	1	1	1	1	1
Mean outdegree of buyers[a]	0.97	1.00	1.05	1.21	0.94	1.00	1.00	1.00	1.00	1.00
Community										
Community size	61	26	142	73	32	70	43	34	74	23
Outdegree centralization	0.017	0.040	0.007	0.026	0.001	0.000	0.001	0.001	0.000	0.002
Density	0.52	0.54	0.37	0.47	0.94	0.96	1.0	1.0	1.0	1.0
Within community transactions	57	26	156	98	29	66	42	33	73	22

We exclude the 26 smallest communities for the sake of visual appeal. These results are available from the authors upon request

[a] Values are for within community only

Table 3 ERGM predicting vendor selection: effects of vendors' trustworthiness, product diversity, and affordability

	Coefficient	Standard error
Vendor reputation	0.003***	0.000
Average price	0.001	0.001
Product listings (only selling heroin is referent)		
Prescription opioids	−0.252	0.130
Heroin and prescription opioids	−0.123	0.168
Vendors' degree	−9.061***	0.061
Buyers' degree	2.986***	0.167
Location of vendor (US is referent)		
France	0.882***	0.128
Netherlands	−0.173	0.177
UK	0.317**	0.120
Germany	0.409	0.220
Canada	−0.157	0.169
Edges	−5.027***	0.147
AIC	6734	
BIC	6892	

$N = 763$

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

What Makes a Vendor Desirable?

Descriptive measures of one Tor opioid distribution network show a network where trust may yield great influence over buyers' purchasing patterns. However, while the global and localized structures give us information on the patterns of transactions between buyers and vendors, they cannot identify the key drivers of vendor selection in multi-dimensional space. We turn to ERGM to evaluate which of our measures are associated with a tie between a buyer and a vendor. Particularly, we compare the effects of reputation, product diversity, and affordability, controlling for the regionality of vendors and vendors' and buyers' history of prior transactions. We provide evaluations of model fit in the Appendix.

Table 3 shows the results of ERGM predicting the log-odds of vendor selection.[19] Compared to the US, vendors located in France ($p < 0.001$) and the UK ($p < 0.01$) are significantly more likely to make sales.[20] The statistically significant degree score for vendors indicates that the odds of making more than one sale is extremely low for vendors ($p < 0.001$). On the other hand, the odds of buyers making more than one purchase is particularly high as indicated by buyers' degree score ($p < 0.001$).[21]

[19] We reran this model without the mean transaction variable—the only variable influenced by missing data—with little difference in statistical significance, standard errors, and coefficient size.

[20] Prior research has highlighted that many vendors list their geographic location as 'worldwide' to avoid identification. Eight of our 57 vendors were listed as worldwide. This information was not included in our vendors' location variable. As one reviewer pointed out, there may be self-selection among vendors who do not list their country of origin.

[21] While unintuitive given our descriptive findings, this merely reflects that the only buyer level variable in our model is their degree score, which tends to be significant if no other controls are included in the model (Lusher and Ackland 2011), and that all buyers in our network have a degree score >1.

We find that vendor's reputation significantly predicts tie formation. A one unit increase in vendors' reputation score is associated with a 0.3% increase in the odds of selecting a given vendor for a drug purchase ($p < 0.001$). Across a range of reputation scores ranging from 1 to 1158 (after transformation), this association explains significant variation in desirability for vendors. Interestingly, neither the average monetary value of transactions with a vendor or the diversity of vendors' products significantly predict tie formation.

ERGM results indicate that vendors' trustworthiness yields a large effect in attracting new customers as well as retaining old ones. Price of product and product diversity are less effective tools for capturing buyers' interest. Combined with results from community detection and global network analysis, we find that trust plays a predominant significant role in explaining Tor network drug purchasing behavior and Tor drug distribution network structure. Results from global analysis suggest that buyers tend to stick with a select few trustworthy sellers when making purchases. Further, when explaining vendor selection, vendors' apparent trustworthiness (measured as reputation) predicts purchasing behavior more so than the affordability or products or even which products the vendor offers. We discuss and review these results in more detail below.

Discussion

A description of this opioid network's characteristics reveals a very large and diffuse network structure absent of transitivity and reciprocity. This indicates that vendors are not procuring substances through the same Tor drug distribution network and may be drawing on real-world connections to drug organizations to distribute drugs. The average opioid vendor engages in a substantial amount of transactions over a 6-month period, whereas buyers tend to only participate in a handful of sales. The high centralization of vendors' degree scores in the network shows a unique configuration for a drug distribution network with a few key actors anchoring most relationships in the network. This is an important discussion point for drug market disruption. A large distribution network with only a handful of active distributors may make the Tor opioid distribution network particularly vulnerable to focused deterrence (Kennedy 2008), which explicitly targets high profile actors in criminal networks (discussed further below). A rife ground for future research would be to evaluate how online drug distribution rings react to exogenous shocks and the removal of high profile distributors.

One clear trend from the global network analysis is that most network activity is highly localized. We evaluate the localized network structure and community composition using community detection methods. We find a network with strong community structure ($Q = 0.76$) and 36 communities, with the largest 10 communities accounting for 75.6% of the networks' actors and significant variation in community size. This finding reflects the large impact trust has on distributional patterns: buyers rarely make purchases outside of their own community of 1–3 established vendors. It also indicates, in contrast to descriptions by vendors themselves (Van Hout and Bingham 2014), high-profile vendors may eclipse small time vendors in transactions because small time vendors have not established their own trustworthiness.

Statistical analysis of the processes that form the network structure indicate that vendors' reputation score is a significant predictor of vendor selection. However, neither the affordability or the diversity of vendors' products are significant predictors of tie formation, once reputation, regionality, and other network characteristics are accounted for. The importance of trust for online drug exchange is consistent with prior research on criminal and co-offending networks (Baker and Faulkner 1993; Tremblay 1993; Weerman 2003; Morselli et al. 2007) and reflects the role trust plays in online illicit materials markets more broadly (e.g. Decary-Hetu and Laferriere 2015).

In terms of internal market dynamics, which are of interest to drug researchers (e.g. Barratt 2012; Van Hout and Bingham 2014; Aldridge and Decary-Hetu 2016), problematic transactions (i.e. those which receive low evaluations) may hurt new vendors far more so than established vendors because their cumulative reputation score is much lower. Inversely, well-established vendors may be more robust to poor reviews because they have an established clientele base and have gathered high cumulative reputation scores, which limit the impact of low evaluations. Still, even for these well-established vendors, buyers' evaluations of recent transactions are available to view, and so a string of poor purchases may deter additional transactions.

The role of trust in Tor opioid distribution warrants further discussion. The high vendor centralization suggests that the market may be especially susceptible to focused deterrence approaches (e.g. Kennedy 2008). Removing a few active vendors would serve the dual purpose of curbing most drug market activity and damaging internal market dynamics because few trustworthy vendors would remain from whom buyers could purchase. The 'power vacuum' effect seen with other forms of crime, such as gangs, where a crime boss' removal results in multiple other key players struggling for their position of influence, may even be reduced when high profile vendors disappear because the few remaining vendors would lack the necessary reputation to jockey for new customers. This may also indicate that online drug distribution networks may be slow to recover from focused deterrence, with the caveat that a significant amount of high profile vendors would have to be removed simultaneously. Of course, identifying those high-profile vendors is a challenge when transactions occur in an anonymous space.

Thinking broadly, the most effective way to reduce online drug trafficking may be to focus prevention efforts on markets in their nascent stages. After a market attracts many vendors and customers, website members can more easily identify trustworthy vendors (via user review comments, reputation scores, and discussion posts). However, while a market is first emerging, it may be easier to target vendors as they register, preventing them from establishing trust in the first place and undermining the market itself. Thus, the most effective way to curb Tor network drug trafficking may be to simply target emerging vendors' reputation. For example, law enforcement may be able to make a few small transactions with emerging vendors and give negative evaluations. This may prevent the vendor from establishing a clientele base and free up more intensive law enforcement efforts to focus on the high-profile vendors in prolific markets. This is consistent with research in offline drug market disruption, which suggests that drug markets are easiest to control in their nascent stages (Caulkins and Reuter 2010).

Results also indicate that trust may yield different effects on network structure in online drug distribution networks compared to real-world ones. Prior research on real-world crime networks suggest that trust is reflected in dense or multiplex relationships (Baker and Faulkner 1993; Smith and Papachristos 2016). Our findings show that when trust acts as a measurable attribute that participants can evaluate, such as a reputation score, this attribute becomes extremely desirable, potentially providing a barrier to entry for new vendors. This suggests that as online drug distribution networks continue to operate, they may grow increasingly centralized (as reputation scores accumulate among a few vendors), with a decreasing amount of vendors accounting for most traffic.

Regarding criminal coordination, our results suggest that Internet encryption may complicate our understanding of drug distribution networks. Prior research has emphasized a hierarchical drug distribution network structure that insulates high profile drug dealers (Natarajan 2006; Tenti and Morselli 2014; Wood 2016). Our findings indicate that this network structure changes when drug distribution is coordinated through encrypted technologies. In this study of one Tor opioid distribution network, the hierarchy collapses and many buyers connect directly to prolific distributors. However, in contrast to prior research, this concern with secure transactions does not impact the Tor opioid distribution network structure in a way that hinders efficient exchanges. Buyers connect directly to prolific vendors with no intermediaries. While our study does not directly test the 'security/efficiency trade off' (Raab and Milward 2003; Morselli et al. 2007), it will be important for future studies to evaluate whether digital crime networks use new anonymizing technologies to increase security and efficiency simultaneously.

Further, some research suggests that a large supply of trustworthy co-offenders increases the length of criminal careers (Tremblay 1993; Weerman 2003; Andresen and Felson 2010; Schaefer et al. 2014). Extending this to drug use, a stable supply of trustworthy distributors may promote lengthier cycles of abuse or drug dependency. Future research can address this by examining the consumption patterns of Tor network drug buyers over time.

Future research can also extrapolate on our findings by using longitudinal network analysis to determine the effect that removing high profile vendors has on the overall network structure and also how low vendor reputation scores impact future sales. Such insights offer a more universal understanding of both the organization and operation of Tor network drug distribution and how focused deterrence impacts crime organized in cyberspace.

Acknowledgements We would like to thank Benjamin Gilbert for assistance in data coding, and David Melamed for helpful methodological suggestions.

Appendix

In line with Hunter et al. (2008), we evaluate the goodness of fit of ERGM by comparing a distribution of degree statistics from networks simulated from ERGM parameters to the degree statistics of the empirical network. Figure 3a indicates how well the simulated networks match the degree score of the empirical network. Figure 3b indicates how well ERGM coefficients predict the degree scores observed in the empirical network.

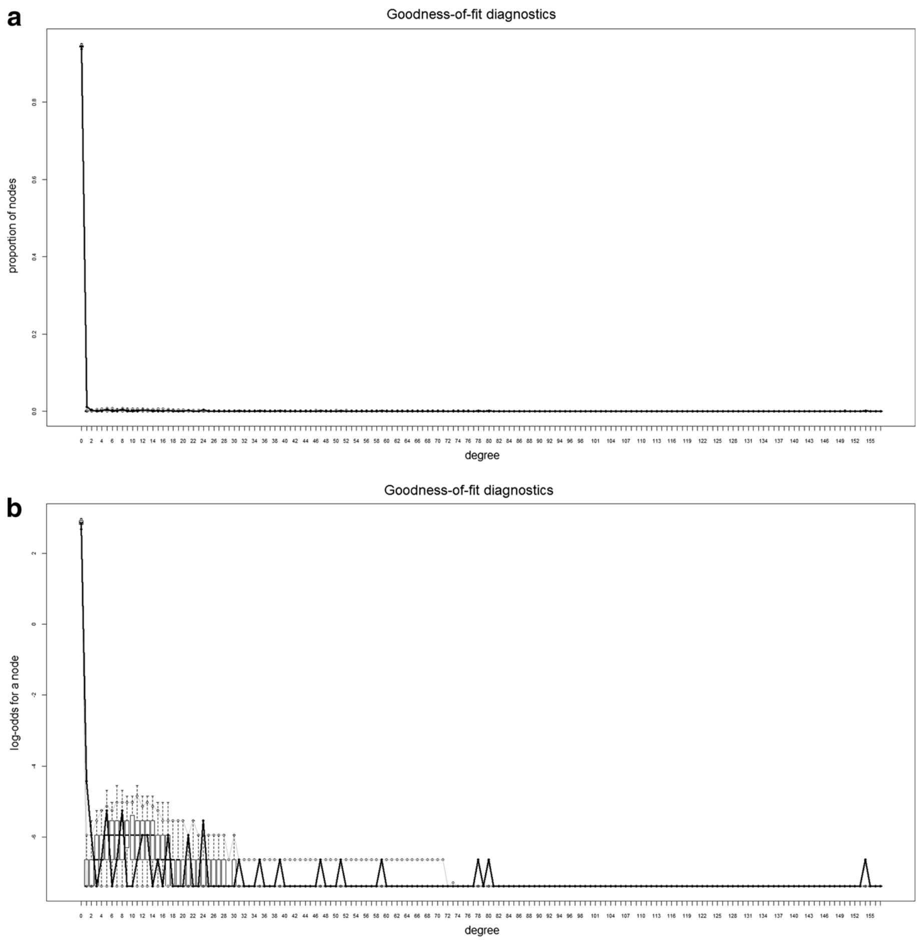

Fig. 3 **a** Goodness of fit for ERGM, degree. **b** Goodness of fit for ERGM, log-odds of degree

References

Aldridge J, Décary-Hétu D (2014) Not an 'Ebay for Drugs': The cryptomarket 'Silk Road' as a paradigm shifting criminal innovation. doi:10.2139/ssrn.2436643

Aldridge J, Decary-Hetu D (2016) Hidden wholesale: the drug diffusing capacity of online drug cryptomarkets. Int J Drug Policy. doi:10.1016/j.drugpo.2016.04.020

Andresen M, Felson M (2010) The impact of co-offending. Br J Criminol 50(1):66–81

Baker WE, Faulkner RR (1993) The social organization of conspiracy: illegal networks in the heavy electrical equipment industry. Am Sociol Rev 58:837–860

Barratt MJ (2012) Silk road: EBay for drugs. Addiction 107(3):683

Barratt MJ, Aldridge Judith (2016) Everything you always wanted to know about drug cryptomarkets* (*but were afraid to ask). Int J Drug Policy 35:1–6

Barratt MJ, Lenton S, Allen M (2013) Internet content regulation, public drug websites and the growth in hidden Internet services. Drugs Educ Prevent Policy 20:195–202

Barratt Monica J, Ferris Jason A, Winstock Adam R (2014) Use of silk road, the online drug marketplace, in the United Kingdom, Australia and the United States. Addiction 109:774–783

Barratt MJ, Lenton S, Maddox A, Allen M (2016a) 'What if you live on top of a bakery and you like cakes?' Drug use and harm trajectories before, during, and after the emergence of the Silk Road. Int J Drug Policy. doi:10.1016/j.drugpo.2016.04.006
Barratt MJ, Ferris JA, Winstock Adam R (2016b) Safer scoring? Cryptomarkets, social supply and drug market violence. Int J Drug Policy. doi:10.1016/j.drugpo.2016.04.019
Caulkins J, Reuter P (2010) How drug enforcement affects drug prices. Crime Justice 39(1):213–271
Coomber R (2004) Drug use and drug market intersections. Addict Res Theory 12(6):1–5
de Bie JL, de Poot CJ, Freilich JD, Chermak SM (2017) Changing organizational structures of jihadist networks in the Netherlands. Social Networks. 48:270–283
Decary-Hetu D, Laferriere D (2015) Discrediting vendors in online criminal markets. In: Maim Ali, Bichler Gisela (eds) Disrupting criminal networks: network analysis in crime prevention. Lynne Rienner, Boulder
Decary-Hetu D, Paquet-Clouston M, Aldridge J (2016) Going international? Risk taking by cryptomarket drug vendors. Int J Drug Policy 35:69–76
Diekmann A, Jann B, Przepiorka W, Wherli S (2014) Reputation formation and the evolution of cooperation in anonymous online markets. Am Soc Rev 79:65–85
Dolliver DS (2015) Evaluating drug trafficking on the Tor Network: Silk Road 2, the sequel. Int J Drug Policy 26:1113–1123
Dolliver DS, Kenney JL (2016) Characteristics of drug vendors on the Tor network: a cryptomarket comparison. Vict Offenders 11(4):600–620
Dupont B, Cote A, Savine C, Decary-Hetu D (2016) The ecology of trust among hackers. Glob Crime 17(2):129–151
Eurobarometer (2014) Young people and drugs: Results per country. Retrieved from http://ec.europa.eu/public_opinion/flash/fl_401_en.pdf
Hunter DR, Goodreau SM, Handcock MS (2008) Goodness of fit of social network models. J Am Stat Assoc 103(481):248–258
Kennedy D (2008) Deterrence and crime prevention: reconsidering the prospect of sanction. Routledge, London
Knoke D, Yang S (2008) Social network analysis, 2nd edn. Sage, Thousand Oaks
Kreager DA, Schaefer DR, Bouchard M, Haynie DL, Wakefield S, Young J, Zajac G (2016) Toward a criminology of inmate networks". Justice Q 33:1000–1028
Krebs V (2001) Mapping networks of terrorist cells. Connections 24(3):43–52
Lusher D, Ackland R (2011). A relational hyperlink analysis of an online social movement. J Soc Struct 12(5):1–35
Lusher D, Koskinen J, Robins G (2013) Exponential random graph models for social networks: theory, methods, and applications. Cambridge Press, Cambridge
Morselli C, Giguere C, Petit K (2007) The efficiency/security trade-off in criminal networks. Soc Netw 29(1):143–153
Natarajan M (2006) Understanding the structure of a large heroin distribution network: a quantitative analysis of qualitative data. J Quant Criminol 22:171–192
Newman MEJ (2006) Modularity and community structure in networks. Proc Natl Acad Sci 103:8577–8582
Newman MEJ (2010) Networks: an introduction. Oxford University Press, Oxford
Newman MEJ, Girvan M (2004) Finding and evaluating community structure in networks. Phys Rev E 69:026113
Papachristos A (2009) Murder by structure: dominance relations and the social structure of gang homicide. Am J Sociol 115:74–128
Papachristos A (2014) The network structure of crime. Sociol Compass 8(4):347–357
Papachristos A, Hureau D, Braga A (2013) The corner and the crew: the influence of geography and social networks and gang violence. Am Soc Rev 78(3):417–447
Pons P, Latapy M (2005) Computing communities in large networks using random walks. In: Physics and society. arXiv:physics/0512106v1
Raab J, Milward BH (2003) Dark networks as problems. J Public Adm Res Theor 13(4):413–439
Robins G, Pattison P, Woolcock J (2004) Missing data in networks: exponential random graph (p*) models for networks with non-respondents. Soc Netw 26(3):257–283
Robins G, Pattison P, Kalish Y, Lusher D (2007) An introduction to exponential random graph (p*) models for social networks. Soc Netw 29:173–191
Schaefer DR, Rodriguez N, Decker S (2014) The role of neighborhood context in youth co-offending. Criminology 52(1):117–139
Schaefer DR, Bouchard M, Young JTN, Kreager DA (2017) Friends in locked places: an investigation of prison inmate network structure. Soc Netw. doi:10.1016/j.socnet.2016.12.006

Smith CM, Papachristos AV (2016) Trust thy crooked neighbor: multiplexity in Chicago organized crime networks. Am Sociol Rev 81(4):644–688

Snijders TA (2002) Markov chain Monte Carlo estimation of exponential random graph models. J Soc Struct 3(2):1–40

Soska K, Christin N (2015). Measuring the longitudinal evolution of the online anonymous marketplace ecosystem. In: Proceedings of the 24th Usenix security symposium

Stafford MC, Warr M (1993) A reconceptualization of general and specific deterrence. J Res Crime Delinq 30:123–135

Stephen A, Toubia O (2009) Explaining the power-law degree distribution in a social commerce network. Soc Netw 31(4):262–270

Tenti V, Morselli C (2014) Group co-offending networks in Italy's illegal drug trade. Crime Law Soc Change 62:21–44

Tremblay P (1993) Searching for suitable co-offenders. In: Clarke RV, Felson M (eds) Routine activity and rational choice. Transaction Books, New Brunswick, pp 17–36

Tzanetakis M, Kamphausen G, Werse B, von Laufenberg R (2016) The transparency paradox. Building trust, resolving disputes, and optimizing logistics on conventional and online drug markets. Int J Drug Policy 35:58–68

United Nations Office on Drugs and Crime (2016) World drug report. https://www.unodc.org/doc/wdr2016/WORLD_DRUG_REPORT_2016_web.pdf

Van Buskirk J, Roxburgh A, Bruno R, Sundresan N, Lenton S, Sutherland R, Whittaker E, Sindicich N, Matthews A, Butler K, Burns L (2016) Characterising dark net marketplace purchasers in a sample of regular psychostimulant users. Int J Drug Policy. doi:10.1016/j.drugpo.2016.01.010

Van Hout MC, Bingham T (2013) 'Silk Road', the virtual drug marketplace: a single case study of user experiences. Int J Drug Policy 24:385–391

Van Hout MC, Bingham T (2014) Responsible vendors, intelligent consumers: Silk Road, the online revolution in drug trading. Int J Drug Policy 25:183–189

Von Lampe K, Johansen PO (2004) Organised crime and trust: on the conceptualization of trust in the context of criminal networks. Glob Crime 6:159–184

Walsh C (2011) Drugs, the internet, and change. J Psychoact Drugs 43(1):55–63

Wang C, Butts CT, Hipp JR, Jose R, Lakon C (2016) Multiple imputation for missing edge data: a predictive evaluation method with application to Add Health. Soc Netw 45:89–98

Wasserman S, Faust K (1994) Social network analysis: methods and applications. Cambridge University Press, Cambridge

Weerman F (2003) Co-offending as social exchange. Br J Criminol 43(2):398–418

Wood G (2016) The structure and vulnerability of a drug trafficking collaboration network. Soc Netw 48:1–9. doi:10.1016/j.socnet.2016.07.001