Social Networks 52 (2018) 238–250

Contents lists available at ScienceDirect

Social Networks

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

Building them up, breaking them down: Topology, vendor selection patterns, and a digital drug market's robustness to disruption☆

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ARTICLE INFO

Article history:
Available online 11 September 2017

Keywords:
Crime
Deterrence
Drug markets
Disruption
ERGM
Cryptomarket

ABSTRACT

Drug distributors are increasingly turning to online markets to deliver and procure illegal drugs. Online venues allow drug vendors to span broad audiences, reshape organizational structure, and remain relatively anonymous. Such trends raise fundamental questions regarding the structural robustness, topological characteristics, and tie formation patterns in online drug distribution networks. We examine one online illegal opioid transaction network. We characterize the network's topology, evaluate selection dynamics that sustain and facilitate the growth of the drug market, and investigate network vulnerability. Results support the existence of trust-based preferential attachment and give insight to how the network reacts to disruption.

Drug trade has gone digital. Users and curious individuals have turned to online marketplaces to make drug purchases, both legal and illegal (Aldridge and Decary-Hetu, 2013; Eurobarometer, 2014; UNODC, 2016). Consequently, online drug marketplaces have proliferated on both the surface web—all websites that can be accessed through a mainstream search engine—and the darknet[1]—an encrypted region of the Internet only accessible via anonymous 'Tor' browsers. These 'Tor markets'[2]; engage in trade similar to that of the surface web, incorporating transaction rankings, private messaging, and bidding systems. Unlike surface web markets, however, they use anonymous currency to protect vendors and customers involved in illegal drug exchange from potential identification.

The relative accessibility of drugs through the Internet and the decreased risk associated with drug purchasing (e.g. Barratt et al., 2016a) has contributed to a rapid growth in online drug trade. Recent research estimates a 50% increase in the number of drug users worldwide who have purchased from a Tor drug market over the last two years (Barratt et al., 2014; Van Buskirk et al., 2016).[3] Similarly, roughly one quarter of drug users report using Internet markets for illegal drug purchasing (UNODC, 2016). Many of these markets generate large amounts of revenue. Some larger Tor drug 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), indicating that both mid-level retailers and users have turned to Tor markets to procure drugs (Aldridge and Decary-Hetu, 2016).

Digital drug trade sits at the intersections of two growing networks-related research areas: online commerce (Stephen and Toubia 2009; Diekmann et al., 2014) and criminal networks (DellaPosta 2017; Morselli, 2009; Raab and Milward, 2003; Smith and Papachristos, 2016)—particularly drug distribution networks (Natarajan, 2006; Wood, 2017). Network analysis of digital drug markets provides rare insight to new forms of illicit trade, online offending, and the interactive dynamics of an active drug market (Barratt and Aldridge, 2016). Examination of these dynamics will help elucidate the resilience of digital drug markets and the relational processes that sustain and facilitate the growth of illicit online trade.

Further, online drug markets are an opportunity to evaluate how Internet venues affect the structure and operation of criminal networks. Some research shows that criminal groups use social media

☆ This research was supported by the National Science Foundation (1729067). We would like to thank David Melamed and Eric Schoon for helpful feedback and Benjamin Gilbert for coding assistance.

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1 Technically, the 'Tor network' employs an anonymizing 'darknet.' Most references to darknet activity refer to activity on the Tor network—currently the most popular anonymous web service. We use the term darknet here as it is more recognizable by broad audiences.

2 Much of the current literature refers to Tor markets as 'cryptomarkets.' We use the term 'Tor market' to avoid confusion with the specific market we study, named *Cryptomarket*.

3 Van Buskirk et al. (2016) report 9.6% of global drug users interviewed use Tor markets for drug procurement.

http://dx.doi.org/10.1016/j.socnet.2017.09.002
0378-8733/

to co-ordinate over a much larger distance, draw on more resources, and engage in more crime than their offline counterparts (Patton et al., 2013, 2016). Similarly, terrorist organizations are increasingly turning to Internet venues to advance political agendas and recruit participants (Chen et al., 2008; Berton and Pawlak, 2015). Just as the Internet raised fundamental questions related to the social structure of everyday friendship networks (e.g. Lewis et al., 2008, 2012; Dunbar et al., 2015), crime groups' usage of the Internet to coordinate offending and recruit participants is now raising important questions regarding the behavior and structure of offending networks. What are the topological characteristics of online drug distribution networks? What actor-level behaviors explain the formation of this topology? And, how do online drug markets fare against disruption?

In this article, we evaluate hypotheses drawn from research on criminal networks and online commerce. We analyze one bipartite Tor opioid exchange network consisting of 1132 illegal drug transactions.[4] We characterize the topology of the network, utilize exponential random graph models (ERGM) to identify vendor selection patterns in the network, and evaluate the network's robustness to disruption. Results have implications for drug market disruption, co-offending, illegal commerce, criminal networks, and the growing body of literature on online drug trade (see Barratt and Aldridge, 2016 for a review).

Hypotheses

Topology

Network topology gives insight to network resilience and network behavior. Prior research on criminal networks suggests that security concerns and constraints on efficient mobilization generate unique network structures among criminal groups (Baker and Faulkner 1993; Raab and Milward 2003; Morselli et al., 2007). Many drug distribution networks rely on a hierarchical network structure, where high profile distributors insulate themselves from the brunt of the network activity by connecting to only a few actors (Natarajan 2006; Morselli et al., 2007; Breiger et al., 2014). This network structure constrains the behaviors of participants by reducing the efficiency of criminal activities while simultaneously limiting the risk of network disruption by protecting key actors.

Alternatively, social commerce networks often form through preferential attachment, where highly desirable vendors attract a broad base of customers (Diekmann et al., 2014; Stephen and Toubia, 2009). Networks that form through preferential attachment exhibit a degree scaling property, where the probability of degree k is $p(k) \propto k^{-\gamma}$ and $\gamma \geq 1$ is the distribution parameter (Barabasi and Albert, 1999). In these cases, the degree distribution of the network follows a power-law and is said to be scale-free. This network structure is somewhat unintuitive for a criminal network, as hubs in a scale-free network are easy to identify and their removal tends to yield a pronounced disruptive effect on the entire network (Albert et al., 2004).

Still, there is some rationale for anticipating that *online* black markets may exhibit a scale-free network structure. First, research into online commerce finds that legitimate social commerce networks often exhibit a degree scaling property (Stephen and Toubia, 2009). This is because certain vendors span broad audiences (Stephen and Toubia, 2009) while others are perceived to be particularly reputable (Diekmann et al., 2014), both attracting a wide array of buyers. Second, some case studies show that illicit commerce networks may exhibit higher centralization than one would expect in a criminal network. Decary-Hetu and Laferriere (2015) use descriptive network analysis on a stolen credit card market, finding that a few key vendors have particularly high degree centrality. This is suggestive of preferential attachment in online illicit materials markets. Since relative anonymity reduces the risk of detection for online offending (Aldridge and Decary-Hetu 2013; Tzanetakis et al., 2016), we expect that the Tor opioid network topology will exhibit degree scaling.

Hypothesis 1. The drug distribution network on the Tor network will be scale-free.

Preferential attachment

Barabasi and Albert's (1999) seminal paper on scale-free networks presents preferential attachment as the mechanism that forms scale-free networks. However, research since then has determined that power-law degree distributions may arise even when preferential attachment is not present (Newman et al., 2001; Vazquez, 2003). In the case of online commerce networks, Stephen and Toubia (2009) demonstrate that selling diverse products may drive the development of a power-law distribution in an online commerce network because it opens the vendor up to a wide audience of buyers. In such cases, a scale-free network topology does not necessarily reflect preferential attachment in the market, but rather is a product of certain vendors spanning broad consumer bases.

Alternatively, trust often plays an important role in establishing trade on online markets (Diekmann et al., 2014). Similarly, much tie formation in criminal and covert networks is driven by trust (Charette and Papachristos, 2017; Morselli et al., 2007; Smith and Papachristos, 2016; Tremblay, 1993; Weerman, 2003). In the case of drug trade, Weerman (2003) suggests that trust between dealers and users facilitates future transactions and that dealers are more likely to repeat transactions with buyers whom they trust. Drawing from this line of reasoning, a scale-free network topology may reflect preferential attachment towards trustworthy vendors in a clandestine commerce network.

We expect trust to dwarf product differentiation in this instance. Even though the Internet reduces the risk associated with real world drug exchange (Barratt et al., 2016a), buyers are often concerned with the purity of their product (Bancroft and Reid, 2016), dealing with an undercover law enforcement officer (Aldridge and Askew, 2017), or being scammed (Van Hout and Bingham, 2013), and thus they may disproportionately select vendors whom they perceive to be credible (e.g. Cox, 2016).

Hypothesis 2. As vendors' trustworthiness increases, so do the odds of attracting customers.

Hypothesis 3. Vendors who are accused of fraud will be less likely to attract buyers.

Further, Tor drug purchasers often pay a higher premium on drug prices than real-world drug buyers (UNODC, 2016). This leaves two possibilities. The first is that buyers will seek to reduce costs even further, opting for the best deal. Alternatively, buyers may be less concerned with costs because cost may be taken as an indicator of quality or because buyers may expect to pay higher costs when purchasing drugs online. If there is little variation in the prices of drugs in the observed network, there may be little incentive for buyers to consider the price of products alongside the trustworthiness of vendors. Similarly, buyers may be willing to pay a premium to trustworthy vendors when there is high uncertainty about the quality of products (e.g. Bancroft and Reid, 2016).

[4] Throughout the article, we refer to the network as both a drug distribution network and drug market to indicate that while the network acts as a market, it is also a form of international drug distribution.

Hypothesis 4. Buyers will exhibit less preferential attachment towards price when compared to vendors' trustworthiness.

Robustness to disruption

A growing area of research examines how criminal networks—especially drug markets (Caulkins and Reuter, 2010; Kennedy, 2008)—respond to disruption (Duijn et al., 2014; Malm and Bichler, 2011; Morselli, 2009). Prior research suggests that crime networks avoid highly centralized topologies to reduce the risk of disruption (Morselli et al., 2007; Raab and Milward, 2003); alternatively, scale-free networks are often highly vulnerable to targeted disruption or vertex removal (Albert et al., 2004). Since a handful of highly connected actors account for most connections, the removal of a highly-connected vertex often fractures the network into numerous distinct components (Holme and Zhao, 2007; Newman, 2002). This suggests that a scale-free drug distribution network exhibiting preferential attachment may be particularly vulnerable to vendor removal.

Newman (2002, 2003) suggests that the structural vulnerability of scale-free networks is related to degree-mixing patterns. Newman (2002) argues that networks in which highly connected actors connect to other highly connected actors (assortative mixing) tend to be robust to vertex removal. On the other hand, networks in which highly connected actors tend to connect to low-k actors (dissortative mixing) are often vulnerable to key vertex removal (also see Alm and Mack, 2017). Dissortative mixing is a characteristic that has been observed in real-world drug distribution networks (Wood, 2017), rendering many real-world drug markets vulnerable to targeted disruption (Kennedy, 2008). We expect that the dissortative mixing in the Tor opioid distribution network will be relatively low. This is because there is relatively less risk in drug procurement when conducted through cyberspace (Barratt et al., 2016a), and many online drug market buyers report experimenting with a wider variety of drugs than they would otherwise (Barratt et al., 2016b). This suggests that buyers may be willing to both switch vendors and to make repeat purchases, creating a network that is neither highly dissortative or assortative.

Hypothesis 5. The Tor opioid distribution network will exhibit low dissortative mixing.

A common way to test the structural stability of a network is to remove vertices in descending order of k score and to measure the proportion of network components as a function of the actor's removal (Albert et al., 2004; Wood 2017; Alm and Mack, 2017). Precipitous declines in network cohesiveness indicate structural vulnerability. Kennedy (2008) argues that a more effective means to curb crime network activity—especially drug market activity—is to simultaneously remove multiple influential criminals in one effort. This 'focused deterrence' prevents the development of a power vacuum[5] and cuts off the bulk of network activity at its source.

Alternatively, some research suggests that those actors which bridge structural holes may be the most integral to many exchange, organizational, or political networks (Burt, 1992, 2004). McGloin (2005) echoes this point, suggesting that targeting gang members who span local network clusters may have a large disruptive effect on gang networks (also see Morselli and Roy, 2008). Extending this logic, vendors who span structural holes attract the most unique customers, and therefore may be integral to the cohesiveness of the market. Removing these vendors may yield a greater effect than focusing on the most active distributors.

[5] A power vacuum refers to when an influential criminals' removal results in multiple high profile criminals vying to fill in their position of influence.

Hypothesis 6. Removing brokers will have a greater disruptive effect on the Tor opioid distribution network than leading k removal.

Data

Our data comprises all transactions with opioid dealers on one large Tor drug distribution market ('*Cryptomarket*') during a six-month period (October 2015–April 2016). We focus on opioid dealers because, behind marijuana transactions, it is the second most highly trafficked class of drugs 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). Indeed, of the 574 transactions[6] with known products identified in the opioid vendor network, 253 were opioid exchanges. Of those, over half were Schedule 1[7] opioids (heroin and opium), while the rest were prescription only (e.g. fentanyl, oxycodone, methadone).

Cryptomarket was selected for three reasons: 1) it is one of the larger and more popular drug markets; 2) it is one of the few markets that shows complete website specific usernames for most buyers[8]; 3) it employs mandatory evaluations for all transactions. This third point is particularly important. Whereas most online markets employ optional product reviews, *Crytpomarket* requires that evaluator comments are completed within two weeks of a transaction or the account is banned. These publicly available comments offer information on which buyers purchased from which vendors, how the buyers evaluated the sale, the cost of the sale, and the product being purchased. Taken in sum, these comments allow us to recreate the complete transaction network for all opioid vendors on *Cryptomarket* during the observation period.

We collected data in a two-stage process. First, we identified every vendor who distributed opioids on *Cryptomarket.* We then downloaded the user-reviews for each individual vendor. Comments on user-reviews are available for six months after each transaction. As such, we were able to identify all transactions for this set of vendors over a six-month period.

Over the next three months we coded the comments for users' evaluations, the amount of money exchanged, and who purchased from whom. We coded vendor pages for attributional data, such as vendors' location, vendors' reputation score, whether vendors operated as a group or individually, and how frequently vendors had been accused of fraudulent practices (described in detail below).[9] We created the transaction network (e.g. who purchased from whom) based on these comment pages. It is important to note that although all vendors distributed opioids, opioids were not the only drug being exchanged in this network. Since there are no transactions between vendors in the network, we treat the network as bipartite for all analyses.[10] Table 1 presents characteristics of the network.

[6] While our total transaction network contains 1132 unique transactions, some listings are taken down while the user evaluation is still active. In these cases, information on the product being sold or its cost was unavailable.

[7] Schedule 1 is the highest regulation of drugs in the US.

[8] Of our sample of 771 actors, 8 were 'anonymous' users who paid extra to conceal their usernames. These are not included in our analyses.

[9] Manual coding allows us to create variables which may be hard to automate with machine learning. For example, our scam-to-sale ratio (discussed below) or the chemical category of drugs, which vendors often mislabel to expand their viewership. While manual coding may introduce some human error in data collection, this procedure is not remarkably different from entering the results of a survey questionnaire into a datasheet.

[10] We note that it is possible for vendors purchase from one another; however, it was not observed in our network.

Table 1
Network Characteristics.

Network measures	
Total actors	763
Isolates	13
Total edges	1132
Total unique edges	874
Density	0.002
Opioid transactions	44.01%[a]
Vendors	
Total	57
Mean k	30.71
$k_{\min}$	0
$k_{\max}$	254
Buyers	
Total	706
Mean k	1.82
$k_{\min}$	1
$k_{\max}$	25

[a] This does not include missing data for the product being exchanged, which were present for 51.14% of transactions.

Methods

Our analytic strategy proceeds in three steps. First, we characterize the topology of the observed network. Second, we use exponential random graph models (ERGM) to test preferential attachment in our network. Since we are interested in both initial and repeat transactions between buyers and vendors, we utilize both Bernoulli (e.g. Robins et al., 2007) and Poisson ERGMs (Krivitsky, 2012). Third, we report degree mixing and use vertex removal simulations to gauge the robustness of the network to targeted disruption.

Topology

Scale-free networks follow a power-law degree distribution (Barabasi and Albert, 1999; Newman et al., 2001). One way to test for a power-law distribution is to fit the network's degree distribution to a regression line in log–log space. This approach is common in social networks research (Moody, 2004; Stephen and Toubia, 2009). However, it is not without draw-backs (see Jones and Handcock, 2003). Clauset et al. (2009) critique that the method relies on 'qualitative' appeals, rather than quantitative analysis. Instead they propose a method that uses Kolmogorov-Smirnov tests to determine the goodness of fit of the power-law distribution to the empirical degree distribution. The resulting test statistic (KS-stat) determines fit of the distribution, whereas the p value indicates whether the empirical data could come from a power-law. In the case of the former, a smaller KS-stat indicates better fit. Typically, a KS-stat of 0.10 is considered adequate. In the latter, a small p indicates that the data does not follow a power-law. Further, Clauset et al. (2009) recommend comparing the fitted distribution to alternative degree distributions using log-likelihood ratio (Vuong) tests. This confirms the robustness of the results, as many degree distributions may be fit to power-laws without the power-law distribution offering the best fit. We follow Clauset et al.'s (2009) recommendations to evaluate the topology of our network.

ERGM

We use ERGM to test for 1) preferential attachment in the Tor opioid market and 2) mechanisms driving preferential attachment. ERGMs treat the realization of a given network as the result of stochastic processes (Robins et al., 2007). The unique benefit of ERGM is to model the likelihood of ties forming in the network based on actors' attributes and network characteristics.

Our interest is in both repeat purchases and initial vendor selection. Preferential attachment in the drug market may be a blend of characteristics that attract new buyers as well as certain practices that retain old ones. Thus, we utilize a Bernoulli ERGM of a binary network (e.g. Robins et al., 2007) as well as a Poisson ERGM where the edge values are weighted by the frequency with which buyers purchase from certain vendors (Krivitsky, 2012). Since the endogenous effects for Poisson and Bernoulli ERGMs are not always the same, we review the exogenous variables used in both models and the endogenous effects in the Poisson and Bernoulli ERGMs separately.

Exogenous variables

Much research in clandestine networks suggests that trust is a key component guiding network selection patterns (e.g. Morselli et al., 2007; Smith and Papachristos, 2016; Tremblay, 1993; Weerman, 2003). We use two measures of vendors' trustworthiness. The first is vendors' cumulative reputation score—a common measure of trust in similar research (Decary-Hetu and Laferriere, 2015; Diekmann et al., 2014; Dupont et al., 2016; Van Hout and Bingham, 2014). After a transaction, every buyer evaluates the sale on a scale from −5 to 5. The sum of these values is listed as a cumulative reputation score for buyers to view, where negative values indicate low trust and positive values indicate smooth transactions and vendor reliability. We use this composite measure to evaluate vendor trustworthiness.[11] Our second is a measure of perceived fraudulent practices. We constructed a continuous scam-to-sale ratio (ranging from 0 to 1). The scam-to-sale ratio is a measure of how many times a vendor has been accused of scamming by buyers divided by their total amount of sales.[12] Higher values indicate that the vendor has been accused of fraud more frequently relative to the amount of transactions they have conducted, lower values indicate the opposite.[13]

We compare the effects of trust to other mechanisms that may generate a power-law distribution. One obvious counter-point to the role of trust may be that buyers simply shop for the best deal, and so high reputation vendors may have high reputation because they make the most sales and list the lowest prices. We control for vendors' affordability by creating a measure of average transaction cost for vendors. This measure was constructed by dividing the sum value of all transactions with a given vendor by the total amount of sales for which price data were available.[14] Fig. 1 shows the frequency distribution of cumulative reputation score, number of sales, and average transaction cost for all vendors. Our final predictor is a binary variable indicating whether a vendor sells more than one class of drug (e.g. hallucinogen, opioid, stimulant).[15] This variable captures whether preferential attachment is actually present,

[11] Because the lowest ranked vendor had a reputation of −5, we added an arbitrary value of six to everyone in the matrix. This allowed us to maintain zero as a meaningful category for all buyers and to give all vendors a minimum reputation score of '1.' We determined the robustness of this decision by comparing it to z-score, logarithmic, and square root transformations. All transformations yielded comparable results.

[12] We created a rate variable instead of a binary variable because vendors who make many sales may be more likely to be accused of scamming simply because they have more customers.

[13] Examples of fraud accusations include failure to deliver a drug, a drug not being delivered as described in the listing, or shipping smaller portions of the drug than the buyer paid for.

[14] We reran the models measuring vendors' affordability as the average unit price for a vendor, encountering the same results (described below). We elect to use average transaction cost to restrict missing edge values, which were more common when working with the unit size of purchases.

[15] Since many vendors may miscategorize their listings or may be uninformed about which drugs belong to certain chemical categories, we hand-coded this vari-

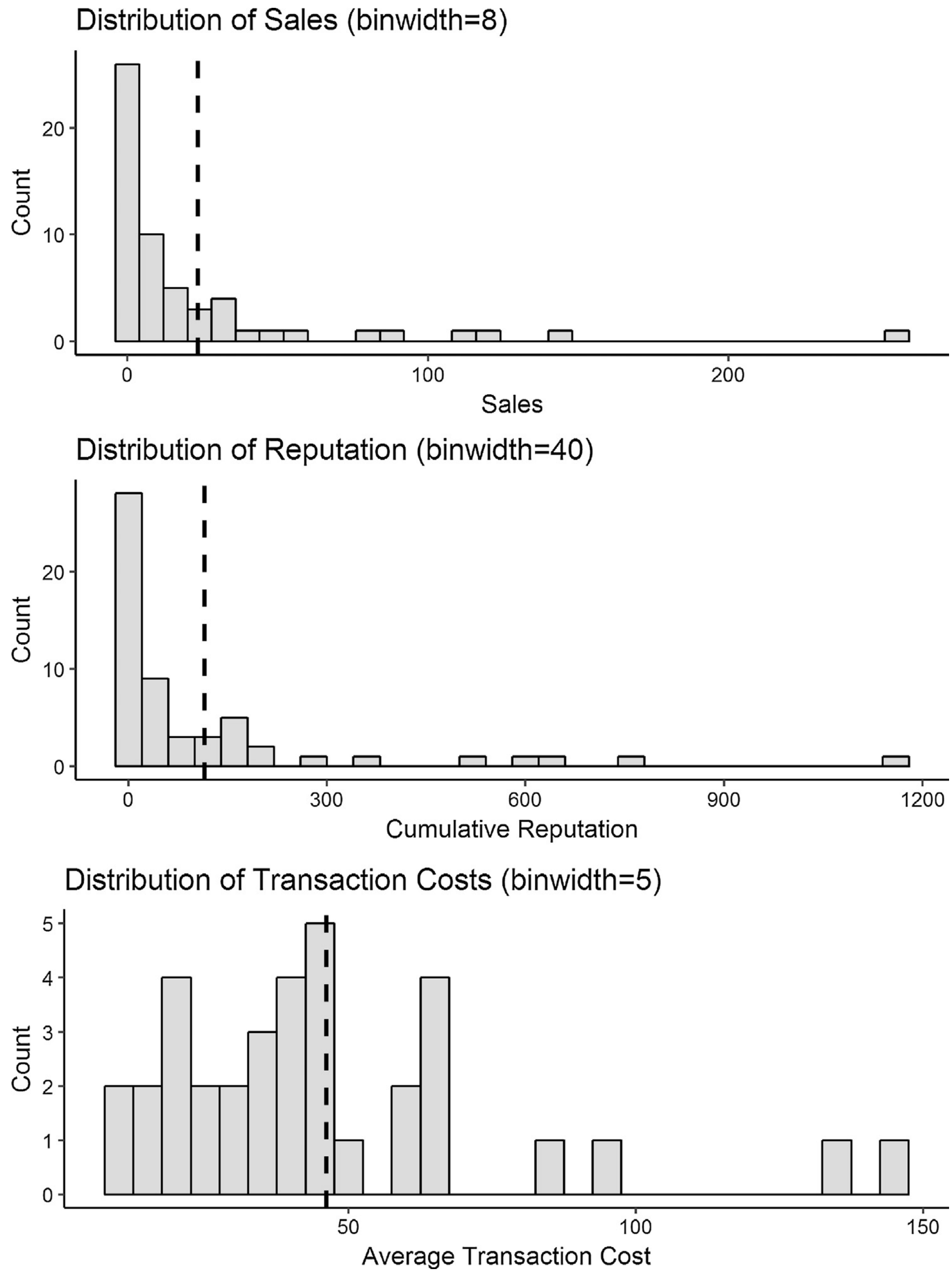

Fig. 1. Univariate distribution for sales, vendor reputation, and average transaction cost. Dashed line is the mean of the distribution.

or if a power-law distribution forms simply because high k vendors span broad consumer bases (e.g. Stephen and Toubia, 2009).[16]

One relevant control variable to consider is buyers' concern with the apparent legitimacy of vendors (Van Hout and Bingham, 2013). The capacity for vendors to provide professional services and to cultivate legitimacy likely increases depending on how many individuals are involved in distribution. Group organization allows for a division of labor and more consistent services (DellaPosta, 2017). Our group distribution variable—taken as a proxy for professionalism and efficient service—is a binary variable indicating whether vendors advertise themselves as operating independently or as part of a coalition. Each vendor provides a summary of their services on their webpage. If the vendor describes their services using second person (e.g. 'we', 'us'), it is coded '1'; if they used first person, it is coded '0'. We also control for geographic location, as tastes for certain drugs may be affected by regional availability, local preferences, or lower shipping costs for proximal regions. Unfortunately, the geographic region of buyers is unavailable. We include the geographic location of each vendor as a control for potential regional variation in purchasing patterns, treating the United States as the reference category. Table 2 shares descriptive statistics for actor-level variables.

Network effects: Bernoulli ERGM

The main concern of our Bernoulli ERGM is to evaluate why buyers connect to vendors from whom they have never purchased

able based on the actual chemical classification of drug, rather than how a vendor listed the drug.

[16] We note here that outliers are not a statistical problem in ERGM. Instead, outliers should be interpreted as highly influential and structurally embedded actors (Koskinen et al., 2008).

Table 2
Descriptive Attributional Variables.

	% or Mean(SD)	Range
Geographic Region		
USA	60.9	
France	9.7	
Netherlands	7.3	
UK	12.2	
Germany	2.4	
Canada	9.7	
Distribution Variables		
Group distribution	38.6	
Sells > 1 product	82.4	
Average transaction cost (mean)	46.29 (13.80)	17–149
Vendor Trust		
Scam to sale ratio (mean)	0.174 (0.32)	0–1
Reputation score (mean)	114.58 (219.29)	1–1158
Number of buyers	706	
Number of vendors	57	
Total	763	

before. We include three network controls: buyers' k, vendors' k,[17] and whether the buyer has made more than one purchase.[18] Lusher and Ackland (2011) note that the omission of k statistics may over emphasize the effects of actor level variables. This may be especially true in power-law distributions, where a few actors account for most connections. Additionally, including a vendor's k score allows us to control for the independent effects of a vendor's cumulative reputation and how many sales a vendor has made. Similarly, controlling for buyers who make more than one purchase allows us to account for those buyers who may purchase once and never return to the market.

Network effects: Poisson ERGM

Poisson ERGMs model weighted edge outcomes. In our model, this is the frequency with which buyers purchase from specific vendors (ranging from 1 to 11). Since the model evaluates count outcomes, the intercept is the sum of edge values instead of the count of edges in the network (Krivitsky, 2012). We parameterize our Poisson ERGM with a non-zero constant, which measures the count of non-zero dyads in the network. This parameterization is recommended for networks in which the count of zeroes is especially high, but those interactions which do occur are relatively frequent (Krivitsky, 2012). Since the Poisson ERGM explicitly models edge values, degree parameters are not a meaningful control. Instead, we control for dyads whose edge value is <2—transactions between a vendor and a buyer which are never repeated.[19] This allows us to focus on the effects of preferential attachment in repeat purchases. We provide evaluations of model fit in the Appendix A.

Robustness to disruption

Degree mixing

We measure the structural capacity of the network to be resilient to key actor removal by evaluating degree mixing between actors in the network. Newman (2002) provides a method to evaluate assortative and dissortative degree mixing by calculating a degree mixing coefficient r that is mathematically akin to Pearson's correlation coefficient. The value of r ranges from -1 to 1, where positive values indicate increasing assortativity, and negative values indicate increasing dissortativity. Newman (2003) also proposes a jack-knifing method—a variant of bootstrapping—to generate the standard error of the mixing coefficient. This will provide a basis to evaluate the structural capacity of the network to be robust against key actor removal.

Vertex removal simulations

Following successful methods in prior research (Albert et al., 2004; Newman, 2002; Wood, 2017), we utilize a k based removal process. Vendors are removed in order of decreasing k. Decreasing k is ideal for examining drug market disruption because most enforcement agencies seek to prosecute high profile offenders. We assess the impact of each vendor removal as the number of components remaining in the graph, the size of the largest component, and the number of remaining isolates. This captures the number of components that are split from the largest component, the extent to which each removal impacts the size of the largest component, and the count of buyers who are rendered isolates with each split. Since most buyers in our network never make more than one purchase, we run additional simulations with only buyers with a $k > 1$. This allows us to target active members of the drug market, rather than peripheral members who may never make a second purchase.

We advance this method further to evaluate the impact of focused deterrence on the network structure (e.g. Kennedy, 2008). To do so, we identify all those vendors with $k > 50$ in our weighted network (7 total). We then remove these actors in all possible triadic combinations (35 unique combinations total) and evaluate the average impact of the removals on the network. This gives insight to the extent that a coordinated enforcement effort on high profile distributors disrupts online drug market activity. To evaluate how vendors situated over structural holes impact the network, we compare the results of these calculations to triadic removal of vendors that broker structural holes.[20] Since most brokerage measurements have been developed for one-mode networks (e.g. Burt, 2004), and because one-mode projections tend to over-estimate local clustering (Opsahl, 2013), we use Jasny and Lubell's (2015) measure of brokerage for two-mode networks.

Results

Topology

Fig. 2 shows the fitted cumulative degree distribution in log–log space. The results from our Kolmogorov-Smirnov yield a KS-stat of 0.09 and a p of 0.95. These results indicate that the data can be comfortably fit to a power-law. The resulting γ is equal to 2.24. This is consistent with prior empirical research on power law distributions, where this value tends to fall between 2 and 3 (Barabasi and Albert, 1999; Stephen and Toubia, 2009).

Since our degree distribution is continuous, we compared the power-law fit to the exponential distribution—which has been observed in other drug distribution networks (Wood, 2017)—and the log-normal distribution, which is also heavy tailed. The comparison of power-law to the exponential distribution yields a highly significant fit (LLR = 6.47; $p < 0.001$), indicating that the data fits the power-law distribution better than the exponential distribution. The comparison of the power-law to the log-normal distribution, however, indicates no discernible difference (LLR = 0.36; $p = 0.64$). This is not surprising, as both distributions are heavily left-skewed and may form through preferential attachment. Though we cannot determine whether the degree distribution of the network is

[17] We parameterize both degree scores with the geometrically weighted degree parameter. The decay parameter for both variables is fixed at 0.5.

[18] We measure this as b1mindeg(2) in the *statnet ergm* package, which adds a parameter to the model for buyers who have a minimum degree score of 2.

[19] Measured as the atmost(2) specification in *statnet's ergm.count* suite. This term indicates whether an edge has a value above or below 2.

[20] In the aggregate network, leading k vendors were also those vendors who brokered structural holes. Thus, we did not repeat the analysis for the entire network.

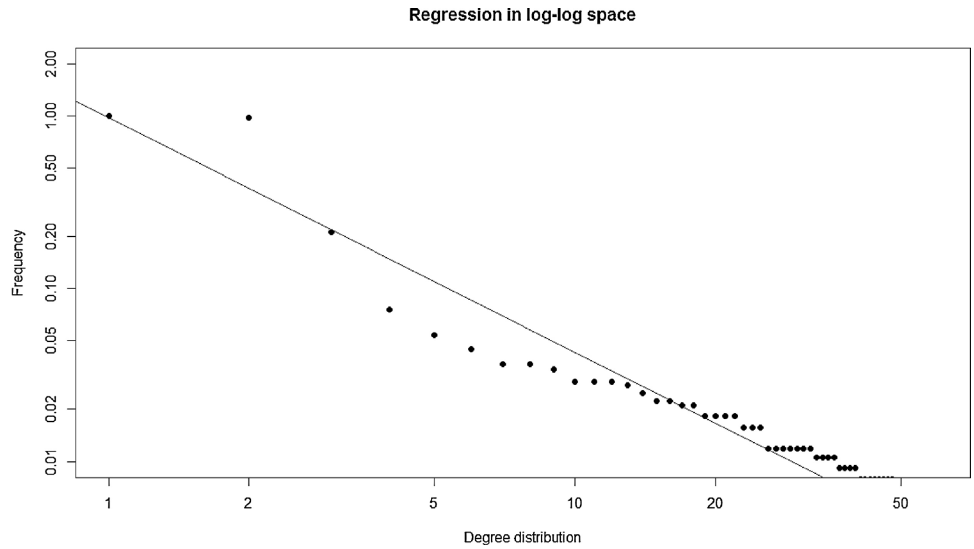

Fig. 2. Power-Law Distribution in Log–Log Space.

better fit to a power-law or a log-normal distribution, the results indicate that the network exhibits key features of scale-free networks, such as highly connected hubs and a left-skewed degree distribution (Hypothesis 1).

Testing preferential attachment

Some researchers note that degree scaling may emerge without preferential attachment (Vazquez, 2003), especially in commerce networks (Stephen and Toubia, 2009). Table 3 introduces the results for the Bernoulli ERGM predicting initial vendor attachment. Model 1 specifies distribution variables—product diversity and average transaction cost—along with controls. Significant controls include group distribution, geographic region, degree statistics, and buyers' purchasing habits. The infrequency of repeat transactions is reflected in this last coefficient, which shows that it is extremely rare for buyers to make a second purchase. Further, controls indicate that France and the Netherlands are more desirable than the US for vendor location, while Canada is less desirable. Vendors who operate as a group are more likely to attract initial connections than vendors who operate independently. Interestingly, neither product diversity or average transaction cost are statistically significant.

Model 2 includes trust variables and removes distribution variables. Only the cumulative reputation score is statistically significant; the scam-to-sale ratio is not statistically significant. The inclusion of the trust parameters mediates the relative desirability of vendors in the Netherlands and the relative undesirability of vendors in Canada. This suggests that there may be an abundance of high reputation vendors in the Netherlands and a paucity of high reputation vendors in Canada. Indeed, the bivariate correlation for vendors in Netherland and reputation is 0.89; alternatively, the bivariate correlation for vendors in Canada and reputation is −0.19.

In the full model (Model 3), both trust variables are statistically significant. The significant effect of the scam-to-sale ratio indicates that as accusations of fraud increase relative to the number of sales a vendor has made, the odds of being selected for purchasing decrease. The suppressed effect of scamming is uncovered by the inclusion of distribution variables (average transaction cost and selling multiple products). While we find support for preferential attachment regarding both distribution and trust, we direct more attention to the trust parameters in Model 3. This is because 1) both trust parameters reflect the hypothesized effects in the full model, and 2) reputation scores cover a wide range of values. While a one unit increase in reputation is correlated with a mere 0.2% increase in the odds of attachment ($\exp(0.002) = 1.002$), the range of potential reputation scores stretches from 1 to 1158—indicating a large amount of variation in vendor appeal.

Table 4 introduces the Poisson ERGM for the frequency of transactions between a vendor and a buyer. Model 1 includes vendors' reputation score, the scam-to-sale ratio, and controls. The significant effect of the nonzero constant indicates that the affiliation matrix of the network has a high count of zero dyads and that the inflated specification is the correct modelling choice (Krivitsky, 2012). Results show that transactions between a buyer and a vendor which are never repeated are much more likely to occur than those which are repeated. Further, vendors in France and Germany are more desirable than those in the US, while those in the Netherlands and Canada are less desirable. Group distribution is associated with an increase in the log-odds of vendor selection. In terms of main effects, results show that increasing reputation score is associated with increasing desirability, whereas increasing scam-to-sale ratio is associated with decreasing desirability.

Model 2 adds distribution variables to the Poisson ERGM. The effects of vendor trustworthiness persist in size and strength. Interestingly, the inclusion of distribution parameters changes the direction of the coefficient for the Netherlands. This is likely because vendors in the Netherlands may offer higher prices or sell fewer products compared to US vendors. In contrast to the Bernoulli model, all distribution parameters are significant. Increasing cost is associated with a decrease in the log-odds of tie formation and vendors who sell more than one type of drug attract more transactions than those who sell only one type of drug. These results are consistent with research in social commerce networks and online drug markets (Barratt et al., 2016b; Stephen and Toubia, 2009; Van Hout and Bingham, 2014).

Contrasting with the results from the Bernoulli model, the Poisson ERGM suggests that trust may be less dominant in the frequency of transactions when compared to initial selection since many distribution parameters are only significant in the Poisson model. It is also worth noting that the strength of the coefficients is relatively low for the distribution variables compared to the trust variables in the Poisson ERGM. The average transaction cost parameter operates over a range of 17–149 ($US), whereas the reputation parameter operates over a range of 1–1158. Similarly, vendors who sell more than one chemical class of drug are

Table 3
Bernoulli ERGM Testing Preferential Attachment Mechanisms in Initial Transactions.

	Model 1	Model 2	Model 3
Distribution variables			
Sells > 1 product	0.097 (0.083)		0.159 (0.104)
Average transaction cost	0.000 (0.000)		−0.002 (0.001)
Vendor trust			
Scam to sale ratio		−0.231 (0.157)	−0.369* (0.153)
Reputation score		0.002*** (0.000)	0.002*** (0.000)
Controls			
Edges (Constant)	−5.360*** (0.246)	−5.442*** (0.171)	−5.636*** (0.200)
Vendors' GWDEGREE (decay = 0.5)	−6.662*** (0.523)	−5.782*** (0.427)	−5.059*** (0.484)
Buyers' GWDEGREE (decay = 0.5)	7.057*** (1.054)	6.995*** (0.037)	7.006*** (0.039)
Buyer has made >1 purchase	−2.935*** (0.333)	−2.937*** (0.227)	−2.950*** (0.229)
Group distribution	0.569*** (0.087)	0.267*** (0.076)	0.369*** (0.092)
Location of vendor			
France	0.708*** (0.118)	0.534*** (0.107)	0.801*** (0.131)
Netherlands	1.464*** (0.089)	0.161 (0.126)	0.165 (0.128)
UK	−0.086 (0.100)	0.061 (0.113)	0.096 (0.123)
Germany	0.006 (0.227)	0.337 (0.231)	0.13 (0.234)
Canada	−0.623*** (0.158)	−0.072 (0.134)	−0.310 (0.193)
AIC	6568	6222	6201
BIC	6679	6336	6330

N = 763; *N* of vendors = 57; *N* of buyers = 706.
**p* < 0.05; ****p* < 0.001.

Table 4
Poisson ERGM Testing Preferential Attachment Mechanisms in Valued Transactions.[a]

	Model 1	Model 2
Distribution variables		
Sells > 1 product		0.008* (0.003)
Average transaction cost		−0.001*** (0.000)
Vendor trust		
Scam to sale ratio	−1.700*** (0.008)	−1.558*** (0.002)
Reputation score	0.001*** (0.000)	0.001*** (0.000)
Controls		
Sum (Constant)	−0.452*** (0.048)	1.036*** (0.027)
Nonzero (Constant)	−3.801*** (0.054)	−5.297*** (0.043)
Single transaction between buyer and vendor	1.311*** (0.061)	4.911*** (0.229)
Group distribution	0.350*** (0.062)	0.543***(0.248)
Location of vendor		
France	0.447*** (0.069)	0.722*** (0.003)
Netherlands	−0.542*** (0.075)	0.269*** (0.004)
UK	0.088 (0.106)	0.064 (0.005)
Germany	0.438** (0.149)	0.019 (0.016)
Canada	−0.671*** (0.016)	−0.889*** (0.015)
AIC	−70,388	−63,718
BIC	−70,302	−63,597

N = 763; *N* of vendors = 57; *N* of buyers = 706.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.
[a] We could not estimate a model with only distribution variables and controls due to graph degeneracy.

only 0.8% more likely to attract buyers than those who do not. This indicates that, while there is evidence of audience spanning (e.g. Stephen and Toubia, 2009), the effect is negligible. Further, a one unit increase in the scam-to-sale ratio is associated with a 79% decrease (exp(−1.558) = 0.21) in the incidence rate of vendor attachment. Thus, while distribution variables yield a more pronounced effect in repeat purchases compared to initial purchases, trust continues to play the strongest role in preferential attachment on digital drug markets.

Still, results also suggest that there is a marginal decrease in the role of trust after a buyer has made their initial purchase. While the average transaction cost parameter is not statistically significant in the Bernoulli ERGM, the Poisson ERGM focusing on repeat transaction shows a negative effect. This suggests that buyers may be more inclined to evaluate vendors based on the quality of prior transactions after an initial purchase. A second possibility is that buyers may only consider affordability when choosing between a pool of trustworthy vendors. Fig. 3 plots the bivariate relationship between average transaction cost and vendors' number of sales and vendors' cumulative reputation score. It shows that without controlling for relevant confounders, high reputation vendors tend to have higher average transaction costs than low reputation vendors. In light of the negative correlation between transaction costs and the frequency of purchases in the Poisson ERGM, this suggests that affordability may help buyers choose between trustworthy vendors.

These results lend support to our hypotheses. We find evidence of preferential attachment towards trustworthy vendors (Hypotheses 2 and 3). We also find evidence of preferential attachment towards low prices (refute Hypothesis 4), but the effect size is very weak and contingent on buyers' previous purchasing habits and the pool of trustworthy vendors.

Robustness to disruption

Since many criminal networks are particularly concerned with the robustness of their network structure (e.g. Raab and Milward, 2003; Morselli et al., 2007), the existence of a scale-free criminal network formed through preferential attachment is somewhat unintuitive. A scale-free network structure suggests that the network may be especially vulnerable to key actor removal (Albert et al., 2004). Results indicate a slight inclination towards dissortativity (highly connected actors tend to connect to low k actors) ($r = -0.04$). This inclination is much smaller than in comparable real-world drug distribution networks (Wood, 2017), suggesting that online drug distribution networks may be less vulnerable to disruption than their real-world counterparts, although they do not appear to be robust (Hypothesis 5). Notably, the standard error is relatively large compared to r, and thus interpretations of robustness based on degree-mixing must be taken with a grain of salt.

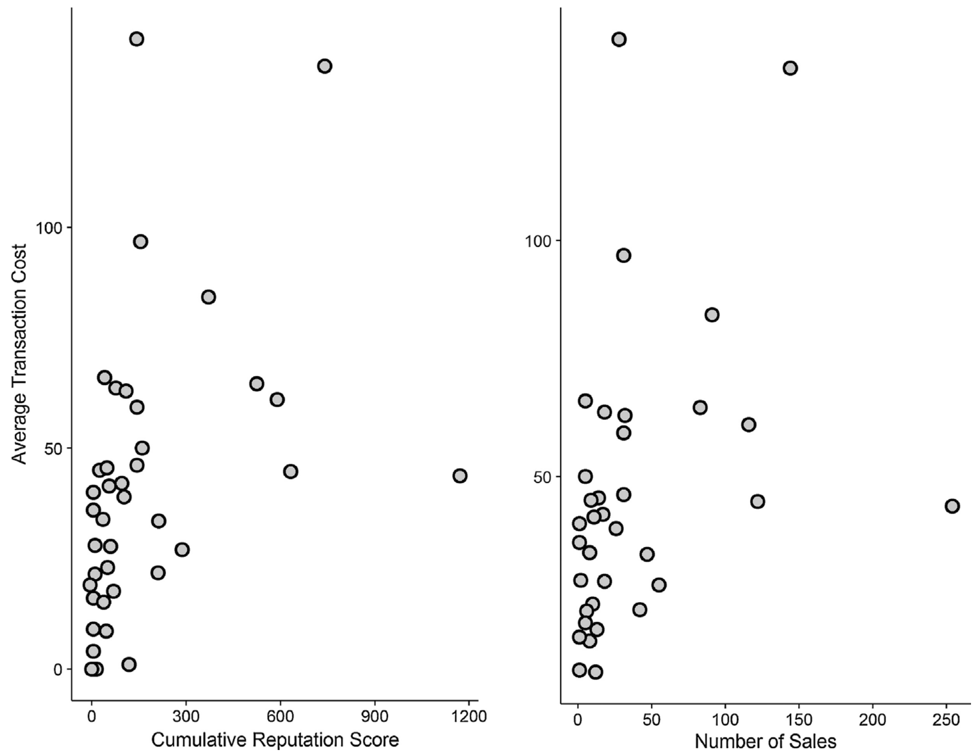

Fig. 3. Association between average transaction cost and vendors' reputation and amount of sales.

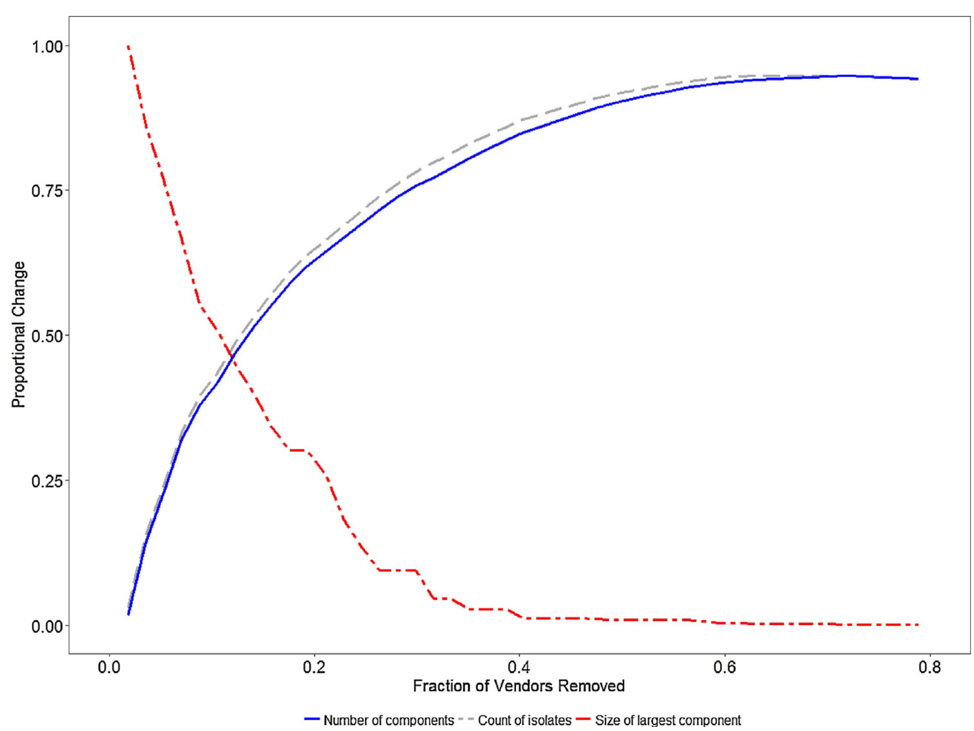

Fig. 4. Impact of Vendor Removal on Network.
The number of remaining components, size of the largest component, and count of isolates after a vendor is removed. Vendors are removed in descending k.

Fig. 4 shows vertex removal simulations in descending k for vendors. It shows the size of the largest component plummets as the fraction of vendors removed increases. Similarly, the proportion of isolates in the network and the proportion of potential components in the network increases as more vendors are removed. These values plateau as the network becomes completely fragmented, and then begin to decline as network size decreases due to vertex deletion.

Since most buyers in the network only make a single purchase, examining the robustness of the entire network may paint a different picture than the network of active customers. The subgraph of the network with only buyers who have made more than one pur-

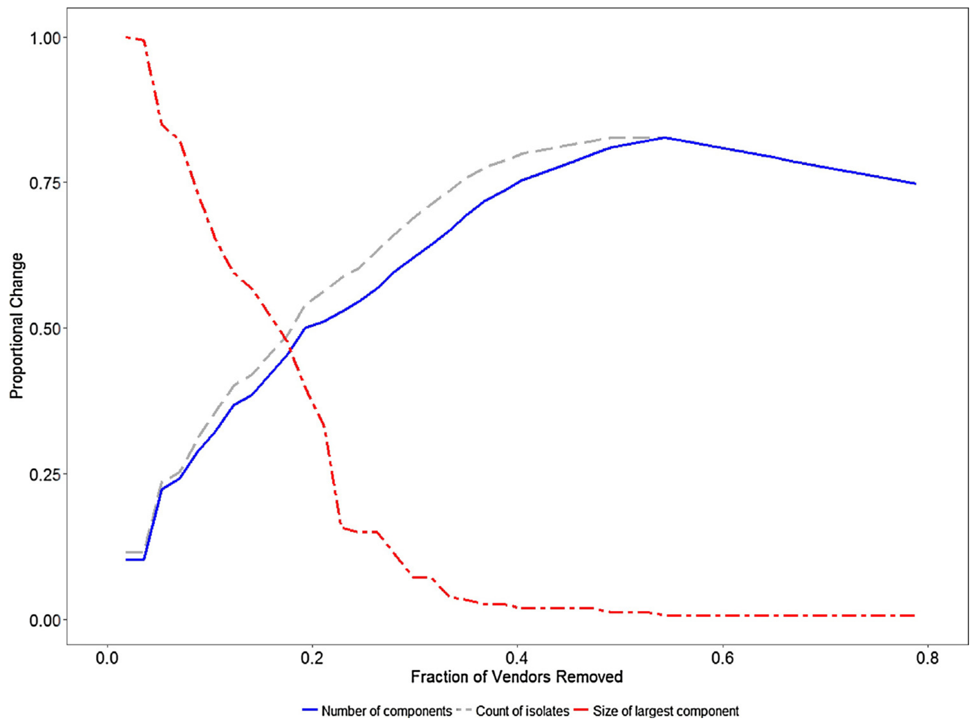

Fig. 5. Impact of Vendor Removal on Repeat Transactions Network.
The number of remaining components, size of the largest component, and count of isolates after a vendor is removed. Vendors are removed in descending *k*.

chase is a 174-vertex network with 284 edges.[21] The *r* coefficient for this network is 0.04 with a standard error of 0.05. This indicates a slight, but non-significant, inclination to assortative degree mixing (highly connected actors connect to other highly connected actors). Fig. 5 shows a slight increase in robustness in this subgraph. Vertex removal simulations for the repeat transactions network show a steep decline in the size of the largest component, while the increase in proportion of isolates and proportion of potential components is slightly more gradual than the overall network. This indicates that the most active segments of digital drug markets may be harder to disrupt than the aggregate network.

Table 5 shows the impact of triadic vendor removal on the network structure. Each subnetwork removes three of the seven most high prolific vendors—all vendors with $k > 50$. There are 35 ways to remove three of the seven vendors, so we present the average count of isolates, number of components, and size of the largest component in each subnetwork. Results indicate that, on average, a random triadic removal of high profile vendors increases the count of components in the total network by a factor of roughly 7. Similarly, while the impact of triadic removal on the size of the largest component is relatively slight, triadic removal of high profile vendors increases the count of isolates in the network by a factor of 10. For the sake of comparison, removing the three highest *k* vendors in the total network yields 244 isolates, 254 components, and the largest component contains 466 actors.

The repeat transactions subgraph is much more robust to triadic vendor removal than the aggregate network. On average, triadic removal only increases the number of components by 30% ($20^*1.3 = 26$), the count of isolates by roughly the same amount, and decreases the size of the largest component by roughly 7%. To compare, the removal of the three highest *k* vendors in the repeat transactions network yielded a largest component of 126 actors, 42 isolates, and 44 components. From a policy perspective, these results suggest that targeting any available combination of high profile distributors may be an alternative strategy to leading distributor removal when leading distributors are difficult to isolate or identify.

Table 6 presents the results for additional calculations removing vendors who broker structural holes in the high activity subgraph. Triadic removal of vendors who broker structural holes have a greater effect than average random triadic removal of leading vendors or triadic removal of vendors with leading *k* scores. Notably, of all triadic combinations, brokerage based removal has the *greatest* effect on the count of isolates, number of components, and size of the largest component. This indicates that focusing disruption on brokers will have a greater effect on highly active regions of drug markets than lead *k* distributors alone. Not to be taken as mutually exclusive, these results suggest that deterrence efforts aiming to disrupt drug markets should consider the structural position and non-redundancy of high profile vendors as well as their overall activity to disrupt both active segments of the market as well as infrequent buyers.

Discussion

Results support the existence of preferential attachment in a scale-free online drug market and distribution network. In contrast to some social commerce networks (e.g. Stephen and Toubia, 2009), the power-law distribution is not an artifact of appealing to broad audiences, but rather forms through buyers' desire for trustworthy and affordable vendors. These results are consistent with prior research that highlights the role of trust in drug exchange (Bouchard and Nyugen, 2010; Cox, 2016; Tremblay, 1993; Weerman, 2003).

The topology of the network offers some interesting insight to research in criminal networks. Many scholars highlight a security/efficiency trade off in the social structure of criminal networks (Morselli et al., 2007; Raab and Milward, 2003). When compared to

[21] Repeat purchasing may be rare because we are only capturing a six-month time period.

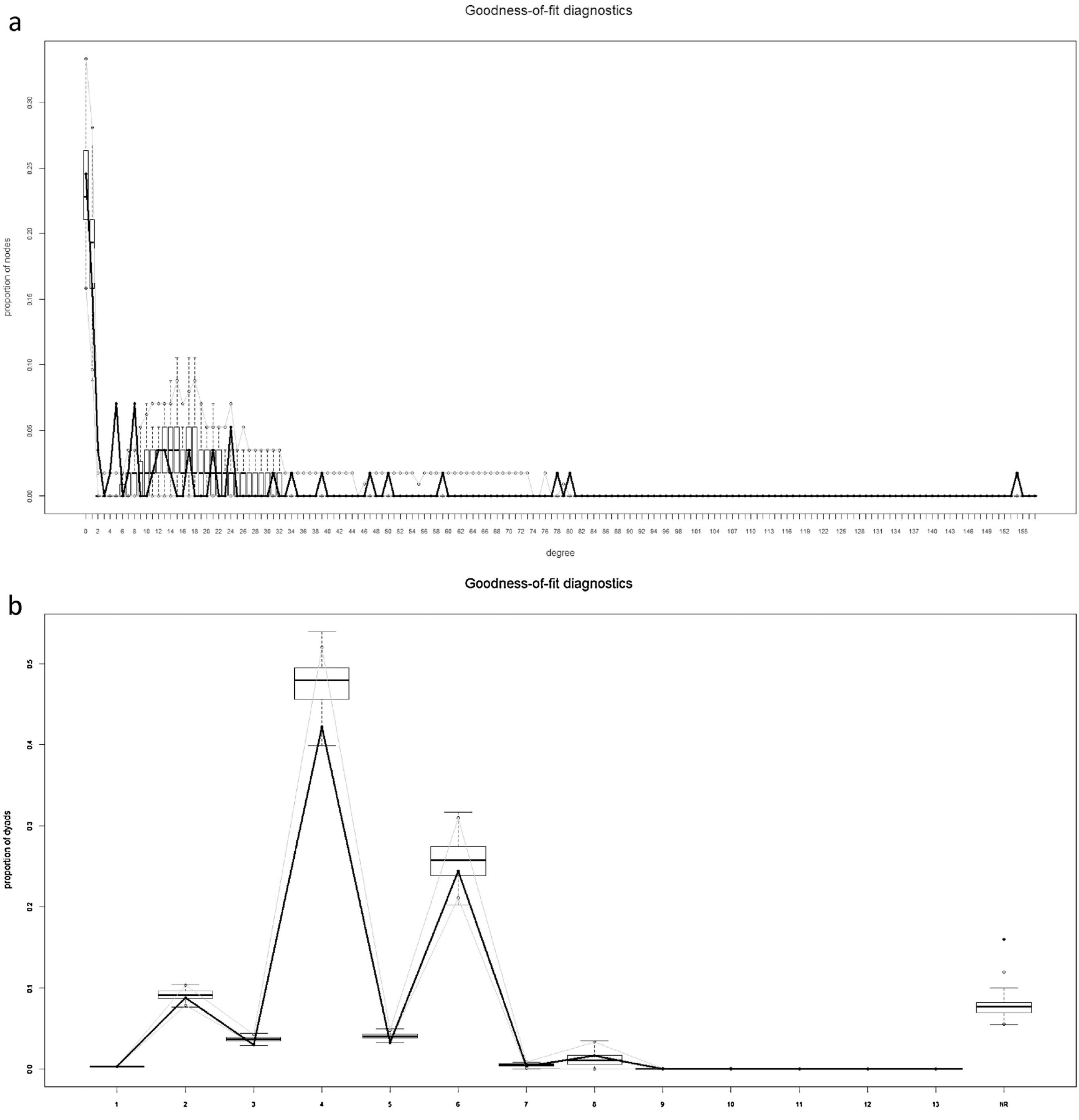

Fig. 6. a. Goodness of fit for degree distribution. b. Goodness of fit for geodesic distances.

Table 5
Impact of Triadic Vendor Removal.

Measures	Full network				Repeat transactions network			
	Initial value	Mean	SD	Range	Initial value	Mean	SD	Range
Components	24	168.86	41.09	101–254	20	26	7.91	20–51
Isolates	14	158.43	40.68	91–244	18	23.71	7.64	18–47
Largest component	699	546.86	46.35	454–619	153	143.57	8.41	116–150
Network size	763				174			

Vendors with $k > 50$ in the weighted network removed in random triads across 35 possible unique combinations.

Table 6
Triadic Removal of Brokers.

Measures	Repeat transactions network		
	Random (mean)	Lead k	Brokers
Components	26	44	51
Isolates	23.71	39	47
Largest component	143.57	126	116

offline drug networks (e.g. Wood, 2017), we find relative robustness (structural security) in the degree mixing of the network alongside a highly efficient network structure (scale-free). This suggests that online offending may facilitate much more efficient network structures than real-world offending. Indeed, some research suggests that criminal groups use social media to co-ordinate over a much larger distance, draw on more resources, and engage in more crime than their offline counterparts (Patton et al., 2013, 2016). A promising future avenue of inquiry is to compare offline criminal network structures to digital criminal network structures to evaluate how the efficiency of offending is facilitated by inter-connective technologies.

Our examination of preferential attachment mechanisms lends greater support to the influence of trust than the effect of product differentiation or affordability. We find strong preferential attachment towards trustworthy vendors and somewhat weaker preferential attachment towards affordable vendors, group vending, and vendors who offer many products.

As a drug distribution network, the *Cryptomarket* opioid transaction network may also give some insight to dynamics of online co-offending. First, as Tremblay (1993) suggests, trust may become increasingly important as the size of potential co-offenders grows. In our case study of 763 drug buyers and vendors, trust appears to play the greatest role in vendor selection. Future research can examine this directly using longitudinal methods to determine if the role of trust increases in tandem with network size. Second, trust may be *more* important in online co-offending when compared to offline co-offending because uncertainty about the characteristics of co-offenders is especially high online. This suggests that while online co-offending networks may be much larger, they may also be far less stable, as co-offenders drop out of the network or incriminate one another more frequently. Consequently, lead offender detection may be easier in online networks as only a relatively small portion of the network will remain active across time. However, such trends are beyond the scope of this study and will have to be confirmed by future research.

Consistent with research in drug distribution networks (e.g. Wood, 2017), we find that removing the most prolific vendors in sequential order fragments the network in relatively little time. However, when focusing on the most active subgraph of buyers in the network, we find much higher robustness to vertex removal. This is a unique result, and may indicate that the active components of online drug markets are harder to disrupt than the aggregate market.

The effects of triadic removal in the aggregate network are comparable to the effects of decreasing k removal. Consistent with prior research (McGloin, 2005; Morselli and Roy, 2008), removing vendors with the fewest redundant connections disrupts high-activity segments of the market more than either decreasing k or random triadic removal. This offers unique insight to disrupting high-activity segments of drug-markets, which may exhibit unusual levels of resilience. Rather than targeting the most prolific vendors, removing high profile vendors who broker structural holes may fragment relatively dense regions of an active drug market more so than focusing on vendors' activity alone. Combining these approaches, law enforcement may find the greatest disruptive effect when targeting the most active drug dealers in tandem with those with the fewest redundant connections.

Future research faces a few tasks. Online drug trade and trafficking is a burgeoning trend. Networks research in this area is necessary to understand how criminal organizations recruit offenders, carry out offending, and how co-offenders select into digital crime networks. Similarly, research into illicit materials markets will help examine how black markets operate via online venues by testing hypotheses from commerce research and criminology. Results from such studies will shed light on online drug trafficking and offers the potential to test long-standing criminological theory against the effects of inter-connective technology on criminal network composition, evolution, and stability (Fig. 6).

Appendix A.

In line with Hunter et al. (2008), we evaluate the goodness of fit of ERGM by comparing a distribution of degree statistics and geodesic distance from networks simulated from ERGM parameters to the network statistics of the empirical network.

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