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Network embeddedness in illegal online markets: endogenous sources of prices and profit in anonymous criminal drug trade

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Abstract

Although economic sociology emphasizes the role of social networks for shaping economic action, little research has examined how network governance structures affect prices in the unregulated and high-risk social context of online criminal trade. We consider how overembeddedness—a state of excessive interconnectedness among market actors—arises from endogenous trade relations to shape prices in illegal online markets with aggregate consequences for short-term gross illegal revenue. Drawing on transaction-level data on 16 847 illegal drug transactions over 14 months of trade in a 'darknet' drug market, we assess how repeated exchanges and closure in buyer–vendor trade networks nonlinearly influence prices and short-term gross revenue from illegal drug trade. Using a series of panel models, we find that increases in closure and repeated exchange raise prices until a threshold is reached upon which prices and gross monthly revenue begin to decline as networks become overembedded. Findings provide insight into the network determinants of prices and gross monthly revenue in illegal online drug trade and illustrate how network structure shapes prices in criminal markets, even in anonymous trade environments.

Key words: illegal markets, markets, networks, technology, prices, trust

JEL classification: K42 Illegal Behavior and Enforcement of Law

1. Introduction

Illegal markets have long captured the imagination of the public and social scientists. From the 19th-century British–Chinese opium wars to the French heroin crisis of the 1970s, historical efforts to combat and control drug distribution have shaped contemporary international drug regulation and relations among countries caught in the crossfire of the illegal drug trade (UNODC, 2008, p. 175). Today, drugs continue to demand international concern. Drug consumption is on the rise globally, with an estimated 271 million drug users worldwide—up 30% from 2010 (UNODC, 2017). Increases in mortality have underscored these trends in consumption. Drug overdose claimed the lives of roughly 510 000 people worldwide in 2017 (UNODC, 2017), and mortality rates from drug overdose quadrupled in the USA between 2000 and 2016 (Hedegaard *et al.*, 2017). In 2010 alone, 1% of the US gross domestic product was spent on illegal drugs, totaling $109 billion (Kilmer *et al.*, 2014).

Despite the importance of illegal drug markets for public health and political economy, sociological research on illegal markets is limited. While economic sociologists have recently turned attention to illegal markets (Beckert and Wehinger, 2013; Beckert and Dewey, 2017), severe data limitations have hindered research into their operations. Illegal market actors are unlikely to share information with researchers, and those data that exist are only available for market segments. We lack knowledge regarding how illegal markets ensure co-operation, foster competition and assign value to illegal goods. In particular, little sociological research has examined the determinants of illegal prices. Nevertheless, price is arguably the most central concept in economic analysis. Prices influence competition, competitive efficiency and purchasing behavior among market agents. Prices also set the standards for profits in illegal exchange, influencing the viability of organized crime as a source of income. Because consumption is heavily shaped by the price of illegal goods (Becker, 1968; Bushway and Reuter, 2008), inattention to the determinants of illegal prices is a critical sociological research omission.

In this study, we overcome the data limitations that have hampered prior research on illegal prices by using novel transaction-level data on one large 'darknet' drug market. Darknet drug markets function much like other online markets (i.e. *eBay*), but the products for sale are clandestine (Barratt, 2012). Buyers access darknet web sites, convert currency to cryptocurrency and peruse illegal drug listings for sale that are subsequently delivered to their doorstep through a postal service. The darknet is also distinct in that it is increasingly acting as a primary medium for drug trade. In 2010, darknet drug trade was non-existent, as the first darknet drug markets had yet to be established (Barratt, 2012). Yet, by 2015, the largest darknet markets generated as much as $180 million USD in annual revenue (Soska and Christin, 2015). Recent drug surveys report that as many as 9% of all surveyed users purchased drugs from the darknet and that as much as 10% of all drug trafficking is now conducted online (UNODC, 2017; Global Drug Survey, 2018). Our analysis of darknet data is thus methodologically advantageous and provides insight into a rapidly growing type of illegal market.

Our uniquely comprehensive transaction-level data on 16 847 drug exchanges between 7196 actors over 14 months of market activity allow us to reconstruct dynamic trade networks from the web of illegal exchanges that accrue over time. While past sociological research on illegal markets emphasizes how social networks act as a precursor to economic exchange (e.g. Gambetta, 2009; Beckert and Wehinger, 2013), we consider whether the structure of endogenous trade networks—the network of *economic* relations that develop from histories of trade—affect illegal prices by building trust between market actors with aggregate consequences for illegal gross revenue.[1]

1 We use the following definition of gross revenue: $Prices \times Numberofsales$.

One of the most consistent findings in the 'new economic sociology' is that social networks constrain market operations (Granovetter, 1985; Uzzi, 1996; Kranton and Minehart, 2001; Fligstein and Dauter, 2007). However, this conclusion has been contested in research on online markets where traders are anonymous (Diekmann *et al.*, 2014; Przepiorka *et al.*, 2017). Our findings reveal that economic exchange networks emerge to nonlinearly influence prices and gross monthly revenue in anonymous illegal online markets. These results show that endogenous trade networks connecting market actors can emerge to affect prices even in anonymous environments where preexisting social ties are absent.

Further, while past research examines illegal prices, these findings have been restricted by an absence of comprehensive data on criminal transaction records. Consequently, the current understanding of illegal prices is primarily descriptive and qualitative in nature (Caulkins *et al.*, 1999; Levitt and Venkatesh, 2000; Arkes *et al.*, 2004; Moeller and Sandberg, 2019). We advance this literature by importing economic sociological insights on embedded networks to present endogenous trade network structure as a determinant of illegal prices with aggregate consequences for monthly revenue. Thus, we show the importance of accounting for trade network structure in research on illegal prices and illegal earnings.

2. Pricing in illegal drug markets

Governments play a crucial role in price setting. Governments lay out the rules of competition and enforce contracts (Fligstein, 2001). In contrast to legitimate markets, illegal markets violate legal stipulations and must actively work against the state (Caulkins and Reuter, 2006; Beckert and Wehinger, 2013) . Illegal markets face much higher risk, and the valuation of illegal goods is far more volatile than in legitimate markets (Becker *et al.*, 2006; Bushway and Reuter, 2008; Bouchard and Wilkins, 2009). Consequently, illegal prices have proven notoriously difficult to predict (Horowitz, 2001; Moeller and Sandberg, 2019).

Among the many types of illegal markets, street-level drug markets are the most widely studied (Bushway and Reuter, 2008), in part because of their political and social importance and because they are among the most lucrative and well-developed illegal markets. Hampered by incomplete and often cross-sectional data, prior research on street-level drug markets has produced significant insight into illegal prices but is mainly descriptive in nature. For instance, Levitt and Venkatesh (2000) examine the monthly financial records of one drug-selling gang in Chicago. They find that immediate returns to drug selling are small and that most members participate in drug selling under the promise of future riches. Studies using the DEA STRIDE data, which reports the prices paid for drug transactions with undercover federal agents in the USA, characterize the geographic dispersion of drug prices (Caulkins, 1995), the quantity of drug transactions (Caulkins, 1994) and the consequences of supply-side policing for prices (DeSimone and Farrelly, 2003). These studies characterize drug prices as highly variable across time and space and costly compared with legitimate goods (Caulkins and Reuter, 1998). Other analyses are conceptual, providing theoretical insight into drug market elasticity and resiliency concerning risk and the threat of policing (Becker *et al.*, 2006; Bouchard 2007).

While economic and criminological studies provide important insight into the risks faced by illegal market actors and their consequences for illegal prices, little sociological work has examined illegal prices. Sociologists regard prices as the 'outcome of struggles between market actors taking place within market fields' (Beckert, 2011, p. 759). Prices are affected by the status of market actors (Podolny, 2010), the cultural meaning assigned to goods (Fligstein, 2001), institutional influences that set the rules for competition (Beckert, 2011, pp. 766–771) and networks of social relations that build trust (Granovetter and Swedberg, 1992; Uzzi, 1999; Uzzi and Lancaster, 2004) . Qualitative work on illegal markets, for instance, consistently emphasizes the importance of network dependency for market operations, including price setting (Gambetta, 2009; Beckert and Wehinger, 2013). Actors in illegal markets use third-party network referrals to endorse one-another and multiplex social ties (i.e. ethnicity, kinship) as signals of dependability (Gambetta, 2009; Smith and Papachristos, 2016; Bright *et al.*, 2019). In these regards, the structural dynamics of illegal markets mirror pre-modern trade (Beckert and Wehinger, 2013, p. 17), where actors rely on social networks to build trust, surveil one another and circulate reputational information (Greif, 2006; Hillmann and Aven, 2011; Riberio, 2015).

Like other forms of risky trade (Kollock, 1994; Greif, 2006; Hillmann and Aven, 2011), the central concern among illegal market actors is establishing the trustworthiness of trade partners (Gambetta, 2009; Beckert and Wehinger, 2013). However, unlike offline illegal markets where interpersonal relationships inform prices based on the perceived risks of associating with an untrustworthy exchange partner and the prospect of future trade (Moeller and Sandberg, 2019, pp. 301–303), online market actors are unable to rely on personal networks to solve valuation problems. Traders are anonymous in online markets and unable to rely on social knowledge to inform prices and assess transaction costs (Diekmann *et al.*, 2014, p. 66). The standard strategies for establishing trustworthiness in offline illegal markets, such as personal friendships, kinship and shared ethnicity (Gambetta, 2009), are therefore unavailable online.

Although sociological research on illegal prices is uncommon, the rare studies that have examined prices on illegal online markets reach a similar conclusion regarding network effects. Przepiorka *et al.* (2017, p. 753) argue that formal reputation systems enable cooperative behavior in illegal online trade even in the absence of social networks. Illegal online markets incorporate sales rating systems that help vendors construct publicly visible formal reputations that buyers use to evaluate trustworthiness. Indeed, Przepiorka *et al.* (2017) find that buyers are willing to pay higher prices to drug vendors with histories of good sales ratings. A similar conclusion is reached in works examining the network structure of illegal online markets (Duxbury and Haynie, 2018a,*b*; Norbutas *et al.*, 2020). These studies find that illegal online trade structures are primarily formed by buyers seeking out vendors with histories of positive sales reviews, rather than network structure influencing market actors' trading behavior.[2]

These conclusions on the relative unimportance of network dynamics for prices in illegal online markets are surprising, as research on risky trade and offline illegal markets consistently emphasizes network dependency. Furthermore, evidence suggests that the

2 Note here that discussions of reputation-based systems differ in online markets from offline markets. In offline markets, such as medieval trade networks (Greif, 2006; Hillmann and Aven, 2011), network-based governance structures are regarded as those that rely on reputational arrangements to navigate trade. In online markets, reputational systems are given a formal character through sales ratings systems (Resnick and Zeckhauser, 2002; Diekmann *et al.*, 2014; Przepiorka *et al.*, 2017). Hence, reputational arrangements in online markets are distinct from offline markets in that they subvert, rather than depend on, networks.

effectiveness of formal reputational systems is limited in illegal online markets. The prevalence of highly positive reviews is far greater than in legal online markets, leading buyers to be somewhat skeptical of formal sales evaluations (Van Hout and Bingham, 2013; 2014a; Cox, 2016) . Nevertheless, no study has measured and empirically assessed the effect of trade network structure on illegal prices to our knowledge. Our goal is to re-evaluate conclusions on network effects by examining whether and how network embeddedness emerges to shape prices in illegal online trade. In the next section, we elaborate on our argument that the network structure of illegal trade relations may effectively promote trust in illegal online markets. Then, in Section 4, we discuss how the illegal trade network structure's trust-building function also carries nonlinear consequences for illegal prices and short-term gross revenue.

3. Endogenous trade structure as a source of trust

While prior work on illegal markets emphasizes reliance on preexisting personal networks (Gambetta, 2009; Beckert and Wehinger, 2013; Smith and Papachristos, 2016; Bright *et al.*, 2019), it is also possible that social relations are forged through economic trade. By relying on endogenous trade structures, market actors subvert online anonymity to build trust and reduce uncertainty in illegal online trade. Kollock (1994, p. 314), for instance, reasons that repeated trade relations allowed Thai rubber traders to escape the 'Prisoner's Dilemma' of anonymous exchange by 'abandon[ing] the anonymous exchange of the market for personal, long-term exchange relationships between particular buyers and sellers'. Uzzi (1996, p. 679) similarly finds that 'arms-length' impersonal economic relations in an interfirm network in the apparel industry are recast into embedded ties when the 'iterative process [of repeated exchange] becomes independent of initial economic goals'. While neither of these studies focuses on the illicit context, their findings suggest that trust may develop in even anonymous exchange environments with consequences for illegal prices. Below, we consider two trade network mechanisms: repeated exchange and closure.

3.1 Repeated exchange

Several prior studies emphasize the importance of repeated exchange for increasing trust in uncertain trade environments (Kollock, 1994; Podolny, 1994; Granovetter, 2005), particularly offline illegal trade (Steffensmeier, 1986; Moeller and Sandberg, 2019). Patterns of successful exchange can produce feelings of trust that are carried forward into future trade (Uzzi, 1996). Repeated exchange increases familiarity with an illegal product of interest, reducing the uncertainty about whether an illegal purchase will yield a product of sufficient quality, and ongoing trade relationships can reduce the cognitive cost of seeking out new illegal vendors. Furthermore, repeated exchange can facilitate information transmission. Although actors in online markets are anonymous, exchange relations provide an impetus for information transmission through communication between buyers and vendors, including the logistics of delivery, product quality and conflict resolution in disputes, each of which can enhance interpersonal trust.

3.2 Bipartite closure

Our second network mechanism is *closure*. Closure in endogenous trade structure occurs when multiple actors have all exchanged with one another. In this respect, closure provides an endorsement or referral that conveys to a buyer that a vendor is trustworthy. Most research examining closure examines exchange networks among producers (Uzzi, 1996; Uzzi and Lancaster, 2004; Fligstein and Dauter, 2007, p. 108). In such markets, the exchange network is unipartite, where each producer can sell and purchase goods from one another. In these contexts, closure takes the form of triangles that manifest through third-party network referrals (Uzzi, 1996; Hillmann and Aven, 2011) and are commonly discussed in qualitative work on illegal markets (Gambetta, 2009, pp. 10–11). However, buyer–vendor markets take a distinct bipartite network structure (Kranton and Minehart, 2001), where ties are only possible between two distinct sets of actors, buyers and vendors.[3] In bipartite networks, triadic closure is impossible because ties between buyers and ties between vendors do not exist.

In bipartite trade networks, closure occurs when two buyers purchase from the same two vendors, forming a 'four-cycle' (Figure 1; Latapy *et al.*, 2008; Lusher et al., 2013, pp. 122–124).[4] Four-cycle closure acts as an indirect referral. A focal buyer is more likely to perceive a vendor in question to be trustworthy when the focal buyer recognizes other buyers in the vendor's sales history. When two buyers have purchased from the same vendor in the past, a shared purchasing history conveys to the focal buyers that a new vendor in question is trustworthy and sells products comparable to or better in quality than the vendor with whom the two buyers have previously purchased. Hence, four-cycle closure in buyer–vendor networks can perform a similar function as third-party referrals in one-mode networks, where shared purchasing history acts as an *indirect* referral or endorsement that helps establish the trustworthiness of embedded vendors. Buyer–vendor closure thus differs from closure in producer networks, where the referral is not deliberate or intentional but rather arises from the shared purchasing history of two buyers.

To be clear, we do not assume that buyers and vendors have perfect information on network structure or on the stable of buyers and vendors on the market at any given time point. Rather, we contend that actors are aware of high-profile market actors' connectivity and incorporate such connectivity into their selection of exchange partners.[5] Our expectation is in

3 To be sure, it is possible to cast buyer–vendor markets as *multilevel* networks. Multilevel networks allow for buyer–vendor exchanges as well as vendor–vendor exchanges. However, in the context of our study, the vast majority of drug exchanges are between vendors and buyers (99.8%), meaning that very little insight is gained from treating the network as multilevel. Treating buyer–vendor markets as bipartite networks also keeps with prior research on online drug markets (Duxbury and Haynie, 2018a,b, 74; Norbutas, 2018) and economic theory on buyer–vendor markets (Kranton and Minehart, 2001), both of which regard buyer–vendor markets as bipartite networks.

4 Note here that 'four-cycles' in bipartite networks do not imply the same structure as 'four-cycles' in unipartite networks. In unipartite networks, four-cycles refer to sets of four actors where each actor is connected *only* to one other actor. In bipartite networks, four-cycles refer to a closed structure where two buyers purchase from the same two vendors (see Figure 1). Bipartite four-cycle configurations are sometimes referred to as 'bowties' or 'bicliques' in fields outside of the social sciences.

5 Two factors may influence how closure operates to influence trade. First, negative sales evaluations may have the opposite deterrent effect by conveying that a vendor in question is untrustworthy or sells poor-quality drugs. As we detail in our descriptive results below, negative sales evaluations are in the empirical minority in our data, and prior work similarly reports disproportionately positive sales ratings (Cox, 2016; Przepiorka *et al.*, 2017). Secondly, closure is likely to be influenced by the timing of purchasing behavior, where more recent transactions are likely more influential. We account for this in our analytic section by incorporating time weights into our measurement of network mechanisms.

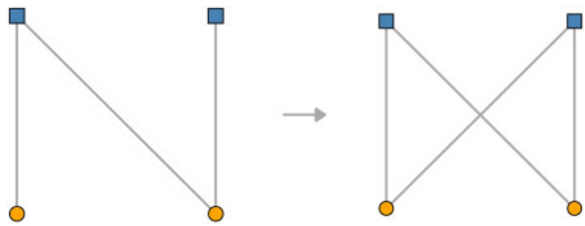

Figure 1. Example of four-cycle closure between buyers (yellow nodes) and vendors (blue squares).

line with prior qualitative research interviewing online drug market actors. In contrast to offline drug markets where product availability is limited and geographic constraints stunt buyers' bargaining power, online markets open-up a 'candy store' for buyers to shop to an extent that would otherwise be impossible (Barratt *et al.*, 2016). For instance, one buyer in Van Hout and Bingham's (2014*a*, 526) study reports that they use darknet markets because of the wide range of options to choose from and sale reviews to evaluate. In another study, a different respondent advocates for a systematic review of sales histories before making a drug purchase: 'Doing intelligence investigations and weighing things up beforehand is very important . . .If you're going to purchase from someone, you need to do your research first, just don't go in blindly because the vendor has a 5-star review, the last 5 people who bought from them might be saying 'hey this guy is selling funked products" (Van Hout and Bingham, 2013, p. 390). Barratt *et al.* (2016) similarly report that buyers spend a disproportionate amount of time on darknet markets 'window shopping' for new products, distributors and discounts.

4. Illegal prices, online markets and the paradox of embeddedness

Our reasoning that endogenous trade networks help build trust among otherwise anonymous market actors allows us to derive hypotheses on the effects of embeddedness on prices and gross revenue in illegal online markets. We depart from prior research on criminal earnings, which has emphasized criminal skillsets (Loughran *et al.*, 2013), opportunity structures (Steffensmeier and Ulmer, 2005) and mentorship (Morselli *et al.*, 2006), as well as research on online illegal markets, which emphasizes formal reputation systems, technical innovation and geographic propinquity (Décary-Hétu *et al.*, 2016; Przepiorka *et al.*, 2017; Norbutas, 2018; Ladegaard, 2020) . Instead, we emphasize the role of embeddedness and overembeddedness—a state of excessive network connectedness that can derail economic performance (Uzzi, 1997, p. 35)—as determinants of prices in illegal online markets.

Our core hypothesis is that there is a nonlinear functional form on the relationship between embeddedness and prices in illegal online markets because of the 'doubly' risky nature of illegal online trade. While risk and uncertainty exist in all markets (Beckert, 2009), these problems are exacerbated in illegal online trade. First, the absence of state supervision in illegal markets undermines most forms of third-party oversight. There are no credentialing agencies, formal contracts or property rights to enforce the rules of an exchange. Furthermore, illegal goods (drugs) intended for consumption can cause severe health consequences if contaminated, and careless behavior can lead to incarceration. Secondly, trade's online context increases information asymmetry and insulates actors from standard enforcement mechanisms (Kollock, 1999). In offline illegal markets, market actors can use violence and intimidation to enforce cooperation (Jacques and Wright, 2008; Reuter, 2009), and goods are often branded to be immediately recognizable by consumers (Gambetta, 2009, pp. 199–201). In online markets, actors are insulated from violent retaliation by physical distance, and 'brands' cannot be guaranteed until after illegal goods are delivered.

Therefore, the online and illegal contexts of these criminal markets create a level of risk and uncertainty that is uncommon in most other markets. We expect that this critical mass of risk and uncertainty in illegal online markets places a purchasing premium on trust, where actors are willing to pay higher prices to trustworthy vendors to ensure that high-quality illegal goods are delivered in a timely manner—and indeed, delivered at all—in good condition, and in a discrete manner that does not draw the attention of law enforcement. Because vendors on markets are typically aware of their relative standing compared with their competition, low-to-moderate amounts of embeddedness should also enable vendors to increase illegal prices.

While low-to-moderate levels of embeddedness should increase prices in illegal online markets by imposing a trust premium on illegal exchanges, excessive embeddedness can lead vendors to reduce prices. Uzzi (1997) first introduced the concept of overembeddedness to describe a nonlinear relationship between social ties and market performance. While Uzzi (1997) develops his case focusing on organizational efficiency in competitive markets, we expect similar principles to apply to prices in illegal online markets.

High levels of repeated exchange, for instance, can embed exchange relations with feelings of obligation and loyalty that lead distributors to offer services at-cost as the 'anonymous exchange of the market' gives way to long-term interpersonal trade (Uzzi, 1996, 1997). Repeated trade relationships can also incentivize vendors to discount illegal goods to retain customers and promote future trade. High levels of four-cycle closure, too, can decrease illegal prices. Highly embedded vendors may reduce prices to consolidate market shares and undercut competitors who cannot afford to decrease prices. Alternatively, four-cycle closure can increase the likelihood of direct communication lines because relatively savvy, highly embedded buyers are more likely to message vendors before purchasing and barter for reduced prices.[6] Therefore, we expect that after a threshold, the positive effect of repeated exchange and closure will invert, yielding an upside-down U-shaped relationship between network variables and prices in illegal online drug markets.

Several studies report findings consistent with our expected relationship between network embeddedness and illegal prices. Although Przepiorka *et al.* (2017) and Diekmann *et al.* (2014) challenge the necessity of network dependency for online trade, their finding that high-reputation vendors charge higher prices for both legal and illegal goods in online settings is consistent with our reasoning that there is a trust premium on the prices of illegal goods in illegal online markets. In a sample of 68 Norwegian (offline) drug dealers, Moeller and Sandberg (2019) find that drug dealers report reducing prices for regular clients to

6 One vendor in our data, for instance, encouraged such behavior, writing: 'PRICES ARE NOT SET IN STONE. Message me if another seller offers a lower price with the listing'. One of the largest vendors in our study, too, referred buyers to open up communication channels to 'Get in touch direct [via direct messages] for pricing'. This evidence is consistent with prior interview data showing that communication between buyers and vendors is prevalent in darknet drug markets (Van Hout and Bingham, 2014*a*,*b*).

maintain ongoing exchange relations (also see Uzzi and Lancaster, 2004). Consistent with the hypothesized nonlinear relationship, Hillmann and Aven (2011) examine social networks in the context of emerging markets in Late Imperial Russia, where state oversight was limited. They find that closure in personal networks increased short-term capital investments but ultimately reduced overall capital investments by discouraging risky ventures developed through expansive bridging ties in favor of long-term relationships within close-knit social networks. While Hillmann and Aven (2011) do not examine illegal trade or prices, their findings on capital investments in emerging markets are consistent with our reasoning on embeddedness and prices in unsupervised and risk-laden trade environments.[7]

5. Data and methods

Data were collected from one darknet illicit drug market, the *Silk Road 3.1*. We chose this market for several reasons. First, many darknet drug markets encrypt buyers' and vendors' usernames. For instance, instead of 'adrugbuyer', many darknet drug markets report 'a****r'. Generating network data require the ability to match unique identifiers between participants. The *Silk Road 3.1* is one of the rare darknet drug markets which reports full usernames for both buyers and vendors, allowing us to recreate the entire illegal drug transaction network based upon trade relationships connecting buyers and vendors. Secondly, the *Silk Road 3.1* is one of the longest running and most popular darknet drug markets, with a lifespan of over 6 years (under various monikers). This longevity suggests that pricing on the *Silk Road 3.1* is not idiosyncratic but reflective of broader drug trade patterns on the darknet.[8]

We collected data from the *Silk Road 3.1* at routine intervals over a week using a web crawler implemented in Python. It accessed *Silk Road 3.1* using a Tor web browser—the most common software for accessing darknet web sites—and downloaded every webpage

7 A reviewer pointed out that an alternative explanation for the type of clustering and recurrent trade that we observe is that vendors seek to consolidate market shares. We do not see this possibility as inconsistent with our reasoning on trust and illegal prices. Vendors are only able to consolidate market shares if buyers purchase illegal goods at the established prices. While vendors certainly seek to push out competition by promoting repeated exchange and clustering within illegal online markets, their efforts are only successful if they can convince buyers that they are trustworthy enough for ongoing exchange. Hence, while the endogenous trade dynamics that we study may indeed give rise to market coalitions, they are only likely to do so by effectively establishing the kinds of trust and feelings of loyalty that permit price negotiation among anonymous actors on illegal online markets.

8 *Silk Road 3.1* sold not only drugs, but also contraband information, such as stolen credit cards and hacked account information for online streaming services (e.g. Netflix). In our data collection, such contraband accounted for a small minority of all exchanges on *Silk Road 3.1*. Furthermore, none of the identified vendors sold both drugs and contraband. As such, the *Silk Road 3.1* drug market and contraband market operated largely independently. We focused our data collection only on drug exchange because it accounts for the vast majority of trade on *Silk Road 3.1* and because a focus on online drug trade provides a case comparison to the well-researched context of offline drug trade, which is the most well-studied type of illegal market (Bushway and Reuter, 2008).

for each vendor. These webpages were stored as HTML files. We then programmed a data scraper to comb through the HTML files and compile the website information into a unique dataset of every drug transaction that occurred on the market.[9]

To construct our network data, we established the presence of transactions by reviewing vendors' transaction histories. Most darknet drug markets, including *Silk Road 3.1*, enforce mandatory sales reviews, which are required to finalize a transaction (though buyers can return and edit them at any point in the future). Since these reviews are mandatory, researchers have found success in recreating darknet drug transaction networks from sales reviews (Duxbury and Haynie, 2018*a*,*b*; Norbutas, 2018).[10] We identified the population of 169 vendors on *Silk Road 3.1* by downloading the webpages for all vendors who had sold drugs on the market between January 2017 (the first month of market operation) and February 2018. We reviewed all sales evaluations with each of these vendors, identifying drug exchanges with 7047 unique buyers, yielding a total of 7196 market actors, and 16 847 drug transactions in the bipartite drug exchange network.[11]

We recorded information on the timing of each drug transaction. More recent purchases frequently had more precise information on the timing of transactions, down to the hour or day. However, older transactions were typically only available at the level of months. Thus, we recorded the timing of transactions occurring each month. With coverage between January 2017 and February 2018, this yielded 14 time points. The *Silk Road 3.1* was shut down in July 2017 for approximately one month to undergo routine maintenance. No transaction histories were reset, and user accounts were otherwise unaffected, but drug exchange did not occur in this period. Thus, we exclude July 2017 from our data, yielding 13 time periods.

In addition to the timing of events and data on transaction occurrence, users' sales evaluations also provide attributional information for each transaction. For each sales evaluation, we recorded how the buyer rated the transaction (a scale of –5 to 5 with higher scores indicating more positive reviews), the type of drug a buyer purchased (e.g. heroin, cocaine) and the amount of money a buyer paid for the drug in USD. We supplemented our transaction-level data with data on vendor characteristics retrieved from vendors' webpages and pages of vendors' drug listings, including the types of drugs a vendor sells, vendors' country of origin, and whether the vendor was willing to ship drugs across international borders.

9 We assessed the coverage of the data by comparing vendors' reputations listed on the *Silk Road 3.1*, which are the sum of all sales ratings, to the reputations scores created by summing the transaction-level sales ratings in our data. The mean difference between the two measures was 2.48—an average difference of 0.2%. The summation of all differences between the two measures was 387 'missing' reputation points out of a total 73 540 reputation points (0.5%). At an average sales rating of 4.8, this suggests the existence of roughly 80 drug exchanges unaccounted for in our data, compared with the 16 847 recorded drug exchanges. Thus, while our data do not encompass the *entire* history of market exchanges, our estimates suggest that we do account for roughly 99.5% of it.

10 Criminologists and drug policy researchers also widely rely on these reviews to understand the scope of darknet drug trafficking (Soska and Christin, 2015; Aldridge and Decary-Hetu, 2016).

11 Only buyers who actually purchased drugs from a vendor are included in our network. In other words, we do not have information on individuals who browsed the market without making a purchase.

5.1 Dependent variable

We conduct a transaction-level analysis of illegal drug exchange on the *Silk Road 3.1*. The dependent variable is the price paid in a drug exchange, measured in USD. Although drug purchases on *Silk Road 3.1* are typically completed using cryptocurrency like Bitcoin, sales ratings also list the purchase cost in USD based on the conversion rate at the time of sale. Due to the impressive amount of information in digital trace data, we were able to obtain the prices paid for every drug transaction accompanied by a sale's review. The price variable is positively skewed, reflecting high variability in drug prices. We, therefore, log-transform the variable for statistical analyses.

An important consideration is the size of a drug purchase. We constructed this variable in our data collection by measuring the number of drug purchases in grams (Przepiorka *et al.*, 2017). We present supplementary models treating the (logged) price per gram as the dependent variable, rather than the unweighted price. Because results from these models are consistent with primary results, and because data on the size of drug purchases were missing for a large number of drug transaction records (38%), we treat the unweighted price as our primary outcome of interest.

5.2 Network measures

To obtain network structural measures, we must consider the set of all possible transactions between active buyers and vendors on the marketplace. We construct network measures following methods proposed by Brandenberger (2018) for bipartite relational event data. We first reconstructed the network at each month of observation based on the set of all buyers and vendors who have been active on the market up until that time point. We then calculated endogenous graph statistics on the network for each period. Finally, we stored the measures and excluded all dyads that did not engage in a drug exchange. This procedure yields the endogenous graph statistics for each transaction based on the network of all possible transactions when the transaction occurred.

We construct four network variables using measures introduced by Brandenberger (2018). Because each measure is calculated on prior drug exchanges, we assign a weight function that prioritizes more recent drug exchanges. Formulae and descriptions of each variable are presented in Table 1.

Our theoretical variables of interest are recurrent exchange partnerships and closure in exchange structure. Our measure of repeated drug exchange is *sales inertia*,[12] which measures the weighted number of drug exchanges between a buyer and vendor before a given time point. A transaction obtains a higher value when it repeats a greater number of prior transactions. Our measure of clustering is *four-cycle closure*, indicating the number of four cycles that is closed by a given transaction. A transaction obtains a higher value of the four-cycle statistic when the transaction in question closes a greater number of *preexisting* open four cycles (Brandenberger, 2018). We hypothesize that both sales inertia and four-cycle closure will be nonlinearly related to drug transaction pricing. Thus, we also include quadratic terms for each variable.

12 The term 'inertia' is widely used in the literature on relational event modeling to refer to measurements of ties that persist across time (Butts, 2008; Brandenberger, 2018). Because relational events (i.e. drug exchanges) only exist in ephemeral temporal moments, ties that do 'persist' across time are those that are repeated frequently.

Table 1. Structural measures and description

Variable	Measurement	Interpretation
Vendor market activity	$\sum w_t(i,b)$	Higher values indicate that a focal vendor b has made more sales, with greater weight assigned to recent sales
Buyer market activity	$\sum w_t(a,j)$	Higher values indicate that a focal buyer a has made more purchases, with greater weight assigned to recent purchases
Sales inertia	$w_t(a,b)$	Higher values indicate that a greater number of transactions between a and b have occurred in the past, with greater weight assigned to more recent transactions
Four-cycle closure	$\sqrt[3]{\sum w_t(a,j)\cdot w_t(i,b)\cdot w_t(i,j)}$	Higher values indicate that a potential transaction would close a greater number of four cycles, with greater weight assigned to more recent transactions
Recency weight (w_t)	$\sum e^{-(t-t_e)\cdot\frac{ln(2)}{\alpha}}\cdot\frac{ln(2)}{\alpha}$	Weighting function, where more recent transactional ties are assigned greater weight

where (w_t) is a weight function assigning greater weight to more recent transactional ties, t is the current event time, t_e is a past event time, a is a focal buyer, b is a focal vendor, i is one member of a set of all buyers who have purchased drugs from a focal vendor b, j is one member of a set of all vendors who have sold drugs to a focal buyer a and α is a decay parameter assigned by the researcher. Measurements are developed by Brandenberger (2018).

We also control for vendors' and buyers' market activity. These variables measure the number of drug exchanges in which a vendor and buyer have been involved. Including these controls allows us to consider a cumulative advantage, where buyers and vendors who have engaged in high volumes of drug exchange in the past engage in more drug exchange in the future.

Network variables are endogenous in that they are calculated on the network state defined by transactions. While this poses a dilemma for cross-sectional network analysis (Robins *et al.*, 2007), dynamic network models account for endogeneity by lagging network variables (Snijders, 2001; Butts, 2008; Brandenberger, 2018). Lagging network variables ensure conditional independence on the network state, and thus, conventional methods for statistical analysis can be used. Therefore, we lag all network variables by 1 month to ensure the sequential exogeneity of our network variables.[13] After lagging, our analysis makes use of $T-1=12$ time periods, yielding 14 713 illegal drug transactions for analysis.

5.3 Controls

In addition to network variables, we account for vendor- and transaction-level controls that could shape prices. Past research concludes that formal reputation systems largely account

13 While lagging reputation and network variables does not 'fix' endogeneity problems in the sense that other possible sources of endogeneity like omitted variables may affect the model, lagging variables on the right-hand side of the equation does ensure the sequential exogeneity of reputation measures and network variables, each of which vary as a function of drug transactions.

for pricing in online markets (Kollock, 1999; Resnick and Zeckhauser, 2002; Diekmann *et al.*, 2014; Przepiorka *et al.*, 2017). We control for formal reputations using two measures. The first is a cumulative reputation score equal to the number of positive and negative sales ratings a vendor has received until a given time point. The measure is cumulative as it includes all sales ratings before a given time point and thus reflects vendors' entire transaction histories. The second is negative sales ratings, which is the sum of negative sales evaluations a vendor has received in a given month. The measure resets at each month, capturing periodicity or exogenous shocks to vendors' reputations in the form of strings of negative sales reviews. We lag both measures by one month to ensure the correct temporal order of variables.

To account for location, we control for vendors' country of origin. The countries observed in our dataset are the UK, the USA, France, Germany, Australia and 'unknown'. We also include a variable measuring whether vendors are willing to ship across international borders, as vendors may be able to charge higher prices for taking on the risk of international shipping (Décary-Hétu *et al.*, 2016). At the transaction level, we control for the type of drug exchanged: marijuana, prescription opioids (including fentanyl), heroin, methamphetamine, disassociatives and benzodiazepines, MDMA/ecstasy, psychedelics, crack or powder cocaine and novelty psychoactive substances (e.g. synthetic cannabinoids, cathinones).

It is also possible that unmeasured or unmeasurable characteristics may shape pricing on drug markets. We take several steps to account for unobserved heterogeneity. First, we provide models, including vendor fixed effects. These models eliminate all possible confounding from vendor characteristics that may not be reflected in the measured variables. Secondly, we provide models with time fixed effects. These models control for all possible period effects, such as seasonal drug pricing or market growth trends. Thirdly, we include buyer-level frailty terms in all models to correct our estimates for unobserved buyer-level heterogeneity.

5.4 Analysis plan

We use two sets of models to examine prices and gross monthly revenue in illegal online drug trade. Our primary analyses utilize random effects models with vendor and time fixed effects and buyer-level frailty terms. These models allow us to assess the effect of network variables on illegal drug prices. Including vendor and time fixed effects allow us to account for unmeasurable vendor and period effects, while the buyer-level frailty term accounts for heterogeneity in buyer purchasing patterns. We then provide a secondary set of analyses using generalized estimating equations (GEEs) to evaluate network variables' aggregate effects on gross monthly revenue. GEE allows us to estimate population average effects at the vendor level, providing insight into the aggregate effects of repeated exchange and buyer–vendor closure on vendors' gross monthly revenue. GEE results provide insight into how endogenous trade networks have aggregate consequences for gross monthly revenue from illegal drug trade.

6. Results

We begin by describing the properties of our transaction network data. The lion's share of drug trade is accounted for by a handful of highly connected vendors. Table 2 shows that

Table 2. Descriptive statistics

Measure	Mean (SD) or %	Range
Network properties		
Density	0.014	
Number of drug transactions	16 847	
Number of one-time transactions	8690	
Number of repeat transactions	5213	
Proportion of transactions that close a previously open four-cycle	0.210	
Degree centrality (vendors)	99.69 (195.93)	0–1623
Degree centrality (buyers)	2.39 (2.65)	1–53
Number of vendors	119	
Number of buyers	7047	
Number of market actors	7156	
Number of time periods	12	
Univariate Statistics for Transaction Data		
Price (USD) (logged)	4.597 (1.373)	0.693–9.893
Price per gram (USD) (logged)	4.799 (2.268)	−2.758 to 14.708
Sales inertia $_{\alpha=.7,\ t-1}$	.933 (.877)	0–12.778
Four-cycle closure $_{\alpha=.7,\ t-1}$	1.214 (1.284)	0–9.223
Vendor cumulative reputation $_{t-1}$ (logged)	6.016 (1.500)	0–8.843
Vendor negative sales ratings $_{t-1}$ (logged)	1.565 (1.541)	0–5.165
Vendor market activity $_{\alpha=1.2,\ t-1}$	240.571 (195.525)	1.564–780.179
Buyer market activity $_{\alpha=1.2,\ t-1}$	2.585 (2.339)	0.291–18.695
International shipping	21.89	0–1
Drug exchanged		
Cocaine/Crack cocaine	16.65	0–1
Dissociative/Benzodiazepine	4.07	0–1
Heroin	5.44	0–1
Prescription opioid	4.18	0–1
Marijuana	23.58	0–1
MDMA/Ecstasy	11.43	0–1
Psychedelic	0.07	0–1
Methamphetamine	9.62	0–1
Novelty psychoactive	2.92	0–1
Unknown/Other	23.4	0–1
Vendor location		
USA	39.05	0–1
UK	8.28	0–1
Germany	1.78	0–1
Canada	2.34	0–1
France	5.33	0–1
Australia	0.06	0–1
Unknown	43.16	0–1

Market observed from January 1, 2017 to February 1, 2018.

the range of vendors' drug exchanges is highly skewed, with some vendors engaging in over 1600 drug exchanges, while others struggle to attract any customers at all. This skewness is also reflected in prices, where the most expensive drug exchange cost roughly $20 000, while the cheapest cost only $5. Consistent with expectations, roughly 31% of drug exchanges are repetitions of earlier exchanges, indicating that repeated exchange is relatively common. Also consistent with the reasoning that vendor loyalty is likely high, the bipartite network density is 0.014, meaning that of all possible buyer–vendor economic ties, only 1.4% actually occur.

Despite low network density, four-cycle closure is common (Figure 2). Approximately 21% of all drug transactions close at least one open four cycle. Of those transactions that close at least one four cycle, 86% connect at least three unique vendors, and 52% connect at least four unique vendors. In fact, roughly 14% of all drug transactions close a four cycle involving three or four unique vendors. This result is broadly consistent with the reasoning that the indirect referral mechanism is most likely to be enacted when a buyer recognizes other buyers from the purchasing histories of multiple embedded vendors.

Descriptive results conform to prior research on street-level drug markets, demonstrating high variability in drug prices on the *Silk Road 3.1* and four-cycle closure and recurrent exchange levels consistent with our reasoning on the importance of embeddedness. The next step is to assess the sources of illegal drug prices. Model 1 in Table 3 regresses (logged) drug prices on network variables in a multilevel model with a buyer-level frailty term. The variance component for the buyer-level frailty term is 0.997, reflecting relatively little unmeasured buyer-level heterogeneity. Consistent with expectations, both the four-cycle and sales inertia measures are positively associated with price, meaning that repeated exchange and closure in buyer–vendor network structure increase the prices paid for illegal drugs. For instance, a 1-U increase in the sales inertia measure correlates with a 12.9% increase in the illegal drug price, while a one-unit increase in the four-cycle measure correlates with an

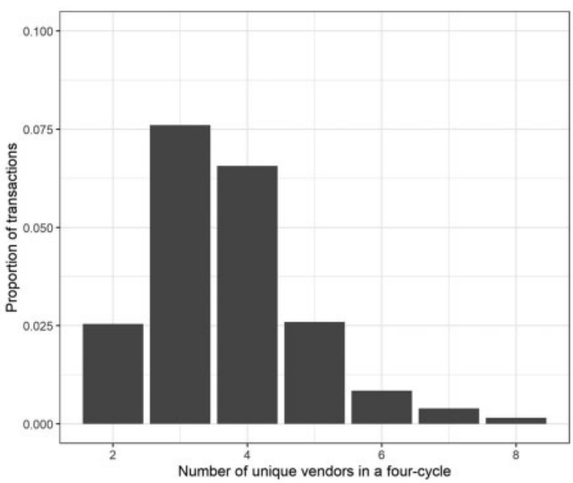

Figure 2. Proportion of drug transactions that close an open four cycle.
X axis reports the number of unique vendors connected by each four cycle.

Table 3. Random effects models of illegal drug prices

Variable	Price (logged)						Price per gram (logged)
	1	2	3	4	5	6	7
Sales inertia $_{\alpha=.7,\ t\text{–}1}$	0.129***	0.495***	0.285***		0.207***	0.179***	0.149***
	(0.018)	(0.033)	(0.050)		(0.027)	(0.027)	(0.042)
Sales inertia $_{\alpha=.7,\ t\text{–}1}$ squared		–0.064***	–0.048***		–0.026***	–0.031***	–0.040**
		(0.005)	(0.013)		(0.004)	(0.003)	(0.011)
Four-cycle closure $_{\alpha=.7,\ t\text{–}1}$	0.118***	0.292***	0.152***		0.142***	0.088***	0.079**
	(0.012)	(0.017)	(0.029)		(0.024)	(0.019)	(0.025)
Four-cycle closure $_{\alpha=.7,\ t\text{–}1}$ squared		–0.049***	–0.051***		–0.042***	–0.021***	–0.024***
		(0.006)	(0.008)		(0.007)	(0.004)	(007)
Negative sales ratings $_{t\text{–}1}$ (logged)			–0.051***	–0.051***	0.002	–0.006	0.000
			(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
Vendors' cumulative reputation $_{t\text{–}1}$ (logged)			–0.208***	–0.200***	–0.222***	0.053*	0.078**
			(0.008)	(0.008)	(0.011)	(0.023)	(0.021)
Vendor market activity $_{\alpha=1.2,\ t\text{–}1}$			0.001***	0.008***	0.004***	0.001***	0.001*
			(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Buyer market activity $_{\alpha=1.2,\ t\text{–}1}$			0.092***	0.111***	0.075***	0.080***	0.027*
			(0.012)	(0.008)	(0.010)	(0.010)	(0.011)
Drug exchanged (cocaine is referent)							
Dissociative			–0.374***	–0.388***	–0.467***	–0.493***	–0.364***
			(0.071)	(0.071)	(0.091)	(0.090)	(0.089)
Heroin			–0.330***	–0.336***	–0.513***	–0.532***	–0.565***
			(0.067)	(0.067)	(0.084)	(0.083)	(0.084)
Prescription opioid			–0.301***	–0.304***	–0.468***	–0.477***	–0.637***
			(0.069)	(0.069)	(0.086)	(0.084)	(0.085)
Marijuana			–0.005	–0.018	–0.161*	–0.187*	–0.057
			(0.061)	(0.061)	(0.084)	(0.083)	(0.085)
MDMA/Ecstasy			–0.525***	–0.542***	–0.659***	–0.700***	–0.623***
			(0.063)	(0.063)	(0.084)	(0.083)	(0.084)
Psychedelic			–0.237	–0.213	–0.338	–0.203	–0.581*
			(0.288)	(0.289)	(0.277)	(0.273)	(0.026)
Methamphetamine			–0.561***	–0.590***	–0.663***	–0.661***	–0.724***
			(0.062)	(0.062)	(0.090)	(0.088)	(0.093)
Novelty Psychoactive			–0.625***	–0.641***	–0.721***	–0.740***	–0.536***
			(0.060)	(0.060)	(0.081)	(0.080)	(0.084)
Unknown			–1.205***	–1.217***	–0.758***	–0.786***	–0.899***
			(0.063)	(0.063)	(0.078)	(0.077)	(0.127)
Vendor ships internationally			0.099***	0.101***			
			(0.026)	(0.026)			

continued

Table 3. *Continued*

Variable	Price (logged)						Price per gram (logged)
	1	2	3	4	5	6	7
Vendor location (USA is referent)							
France			−0.298***	−0.296***			
			(0.049)	(0.050)			
UK			−0.284***	−0.283***			
			(0.050)	(0.033)			
Germany			0.137	0.100			
			(0.147)	(0.148)			
Canada			−0.515***	−0.511***			
			(0.045)	(0.045)			
Australia			−1.199***	−1.206***			
			(0.189)	(0.191)			
Unknown			−0.559***	−0.552***			
			(0.029)	(0.029)			
Constant	4.198***	3.916***	6.011***	5.550***	6.253***	6.384***	7.268***
	(0.023)	(0.029)	(0.077)	(0.054)	(0.177)	(0.235)	(0.021)
Variance component (buyers)	0.997	0.943	0.408	0.417	0.201	0.188	0.310
Vendor fixed effects?	No	No	No	No	Yes	Yes	Yes
Time fixed effects?	No	No	No	No	No	Yes	Yes
R^2	0.22	0.23	0.41	0.41	0.53	0.55	0.72
χ^2	3989***	4258***	7916***	7785***	11 572***	12 180***	34 378***
AIC	39 840	39 790	38 498	38 531	26 306	26 064	46 904
BIC	39 863	39 828	38 531	38 690	27 188	27 019	47 858
N	14 713	14 713	14 713	14 713	14 713	14 713	10 459

$^{*}P < 0.05$; $^{**}P < 0.01$; $^{***}P < 0.001$. Two-tailed tests.

11.8% increase in price. Based on the mean price of \$96.54 (mean log price = 4.57, exp(4.57)=96.54), a 1-U increase in sales inertia would increase the price of a drug exchange to \$174.16 (1.13 × 4.57 = 5.16, exp(5.16) = 174.16), while a 1-U increase in the four-cycle measure would increase the price of a drug exchange to \$167 (1.12 × 4.57 = 5.12, exp(5.12)= 167.00). This change in pricing is consistent with buyers 'doubling up' on drug purchase size once they have found a trustworthy vendor.

In Model 2, we include quadratic specifications to account for the hypothesized nonlinear relationships. The linear specifications for both sales' inertia and four cycles are positive, while the quadratic coefficients are negative. Consistent with expectations, both network variables are nonlinearly related to illegal drug prices. Network variables increase the prices of illegal goods until a threshold before the relationship inverts and turns negative. Also consistent with expectations, both variables' quadratic terms are more informative than the linear terms, yielding improvements in both Akaike information criteria (AIC) and Bayesian Information Criteria (BIC) and significantly better model fit (χ^2 = 368.17, P <0.001). The

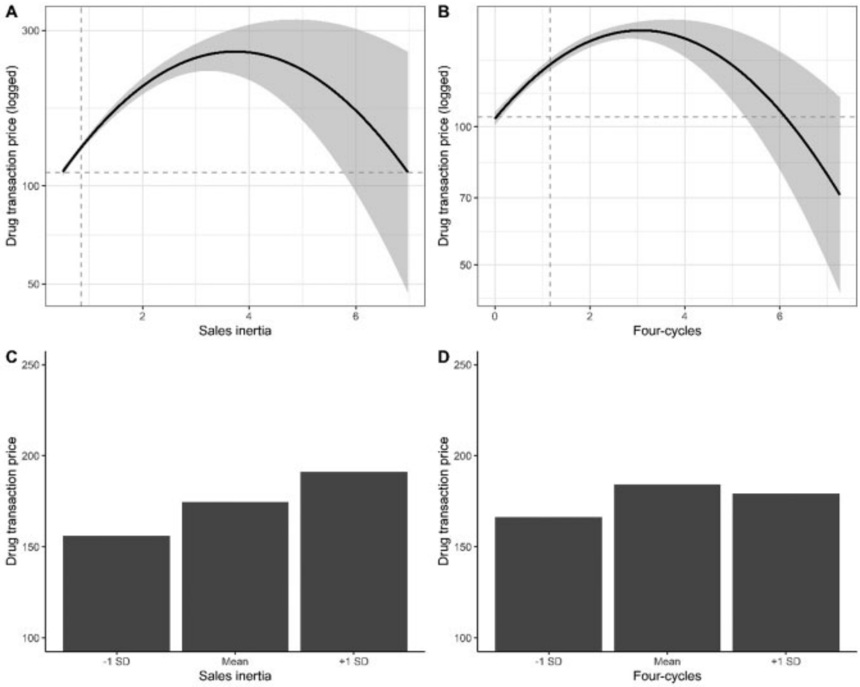

Figure 3. Relationship between embeddedness and illegal drug prices.
Vertical lines in panels A and B mark mean of *X* axis. Horizontal lines in panels A and B mark the predicted price when a network variable has a value of 0.

R^2 is 0.23, meaning that 23% of the variation in illegal drug prices are explained with non-linear network variables alone.

Models 1 and 2 reveal strong network effects consistent with the expectations. Model 3 includes control variables. Consistent with Przepiorka *et al.* (2017), negative sales ratings have a deleterious effect on illegal drug prices. Also consistent with Décary-Hétu *et al.* (2016), international shipping increases drug prices, as vendors are forced to assume a greater risk by shipping across international borders. The coefficients for the drug being exchanged indicate that cocaine and crack cocaine purchases tend to have the highest prices. Although including controls attenuate the coefficients' size for network variables, the linear and quadratic coefficients for both sales inertia and four-cycle closure are robust in terms of direction and significance. In Model 4, we exclude network variables to assess goodness of fit. The increases in AIC and BIC indicate that including sales inertia and four-cycle measures are more informative than the controls-only model ($\chi^2 = 130.58$, $P < 0.001$).

Figure 3 plots the relationship between four cycles, sales inertia and drug prices to facilitate interpretation of effect size. On average, increasing sales inertia by 1 SD above its mean increases the price of a drug exchange from $172.73 to $193.05, holding all other variables at their mean (Panel C). However, the relationship is nonlinear, and at higher values, increases in sales inertia reduce drug prices. In fact, at high values, the prices of repeated exchanges are equal to those of non-repeated exchanges (Panel A). Similarly, decreasing the four-cycle measure 1 SD below its mean reduces prices by \$18 per transaction while increasing it 1 SD above its mean reduces prices by \$5 (Panel D). Once the four-cycle measure reaches high values, the benefits to network closure disappear, and additional increases reduce prices below the price of transactions that occur outside of four cycles (Panel B). These results illustrate that both sales inertia and four cycles have nonlinear effects on drug prices. Also, of note is the variability in the point estimates in panels A and B. At high values of four-cycle closure and sales inertia, the confidence intervals of are wide such that the effect of network embeddedness on prices is rendered insignificant at the highest levels of embeddedness.

Consistent with expectations, our results reveal strong, nonlinear effects of four-cycle closure and sales inertia on illicit drug prices net of reputation effects from formal rating systems. The next step is to assess these findings' robustness to unobserved heterogeneity, such as unmeasurable vendor effects (informal reputations for high-quality products or good communication) and period effects (stage of market growth or seasonal purchasing). Model 5 includes vendor fixed effects that control for all vendor-level variation. Results illustrate that coefficients in Model 3 are robust to vendor fixed effects in terms of network coefficient size, direction and significance. Model 6 includes time fixed effects in addition to vendor fixed effects that control for vendor and period effects simultaneously. While the coefficients for four-cycle closure are attenuated, the terms remain robust in direction and significance. Model 6 also uncovers evidence of cumulative reputational effects consistent with prior work. Here, vendors' cumulative reputations are positively related to illegal drug prices. These findings collectively illustrate that unmeasured vendor or period effects cannot account for the influence of network variables on illegal drug prices.

Finally, Model 7 evaluates whether the size of drug purchases influences our results by treating the (logged) price per gram as the dependent variable in a restricted sample of 10 459 transactions with data on purchase size. Results are consistent with those in previous models, where sales inertia and four-cycle closure are both nonlinearly related to the price per gram. The R^2 is 0.72, indicating strong model fit. Moreover, excluding the network variables from Model 7 increases both AIC and BIC, meaning that the nonlinear effects of four-cycle closure and sales inertia significantly improve the model's ability to explain drug price per gram when compared with models where network variables are excluded ($\chi^2 = 171.7$, $P < 0.001$). These results are consistent with expectations, as buyers' willingness to purchase large drug quantities is likely influenced by trust considerations, which are in turn likely shaped by embeddedness (see Moeller and Sandberg, 2019, pp. 301–303).

Results thus far provide strong support for nonlinear network effects on illegal online drug prices. We now turn to GEE to assess how the effect of network variables on prices shapes vendors' gross monthly revenue from illegal drug trade by calculating population average effects. Models 8 and 9 present GEE results before and after including control variables and time fixed effects (Table 4). Results replicate primary results, where both sales inertia and four-cycle closure are nonlinearly related to vendors' gross monthly revenue. Decreasing the four-cycle measure 1 SD below its mean while holding all other covariates constant yields a decrease of \$245.76 in vendors' average gross monthly revenue. Similarly, decreasing the sales inertia 1 SD below its mean yields a \$135.73 decrease in vendors' average gross monthly revenue. To contextualize these effects, vendors-expected gross monthly revenue when all variables are held at their mean is \$1824.26. Results in Model 9 also

Table 4. Generalized estimating equations of vendor-level population average effects on illegal drug prices (logged) ($N = 14\,713$)

Variable	Model 8		Model 9	
	Vendor average effect	Standard error	Vendor average effect	Standard error
Sales inertia $_{\alpha=.7,\ t-1}$	0.394***	(0.071)	0.205**	(0.081)
Sales inertia $_{\alpha=.7,\ t-1}$ squared	–0.057***	(0.006)	–0.041***	(0.004)
Four-cycle closure $_{\alpha=.7,\ t-1}$	0.386***	(0.074)	0.126**	(0.047)
Four-cycle closure $_{\alpha=.7,\ t-1}$ squared	–0.079***	(0.021)	–0.034*	(0.015)
Negative sales ratings $_{t-1}$ (logged)			–0.091***	(0.027)
Vendors' cumulative reputation $_{t-1}$ (logged)			0.043*	(0.021)
Vendor market activity $_{\alpha=1.2,\ t-1}$			0.000	(0.000)
Buyer market activity $_{\alpha=1.2,\ t-1}$			0.087***	(0.013)
Drug exchanged (cocaine is referent)				
Dissociative			–0.521***	(0.151)
Heroin			–0.623***	(0.147)
Prescription opioid			–0.469***	(0.106)
Marijuana			–0.111	(0.119)
MDMA/Ecstasy			–0.742***	(0.137)
Psychedelic			–0.167	(0.107)
Methamphetamine			–0.691***	(0.089)
Novelty Psychoactive			–0.817***	(0.108)
Unknown			–1.60***	(0.167)
Vendor ships internationally			0.049***	(0.013)
Vendor location (USA is referent)				
France			–0.148	(0.217)
UK			–0.312*	(0.145)
Germany			–0.099	(0.159)
Canada			–0.664***	(0.103)
Australia			–0.445***	(0.144)
Unknown			–0.349*	(0.167)
Constant	3.902***	(0.073)	6.035***	(0.969)
Time fixed effects?	Yes.		Yes.	
R^2	0.17		0.43	

*$P < 0.05$; **$P < 0.01$; ***$P < 0.001$. Two-tailed tests. Vendor average effects are population average effects from GEE. Robust standard errors are reported. GEEs are estimated using an independent correlation structure, as the time fixed effects control for autocorrelation. Recall, also, that GEE is a consistent estimator even when the covariance structure is mis-specified.

demonstrate that vendors with fewer negative sales evaluations and higher cumulative reputations tend to accrue greater gross monthly revenue, consistent with prior work.

In sum, results lend support to the endogenous trade network explanation of illegal drug prices in darknet markets. Four-cycle closure and sales inertia are nonlinearly related to illegal drug prices and drug vendors' gross monthly revenue. Further, sensitivity analyses considering alternative modeling specifications, measurement strategies and unmeasurable heterogeneity sources illustrate that findings on network effects are robust. These results illustrate that network embeddedness can emerge to affect prices and gross monthly revenue in online drug trade.

7. Discussion

Recent research on illegal markets has concluded that ‘exchanges within illegal markets must take place within social networks to a much greater extent [than in legitimate markets]’ (Beckert and Wehinger, 2013, p. 18). However, this argument has been contested by research on online markets, where actors are anonymous and not connected through personal ties (Diekmann *et al.*, 2014; Przepiorka *et al.*, 2017). In this study, we considered how network embeddedness influences prices and gross monthly revenue in illegal online drug markets. Results indicate that while moderate levels of repeated exchange and four-cycle closure increase illegal drug prices and gross monthly revenue, high levels of embeddedness decrease prices and, in some cases, can reduce prices below those of non-embedded transactions. To be sure, while we also find evidence of formal reputational effects on prices consistent with earlier work on online markets (Diekmann *et al.*, 2014; Przepiorka *et al.*, 2017), our findings also present new evidence on nonlinear network effects in illegal online drug trade.

The finding that embeddedness impacts drug prices sheds light on illegal market operations. While sociologists have hypothesized that network structures influence illegal trade, the lack of comprehensive transaction-level data has thwarted prior examination into the network determinants of illegal prices. Our results reveal that network mechanisms are salient forces shaping the price of illegal goods. Trade networks help to build trust among market actors and impose a payment premium at low values. However, overembeddedness in transaction network structures can have the opposite effect. These findings are consistent with the hypothesized ‘embeddedness paradox’ in illegal online drug trade.

While past research has examined pricing and elasticity in illegal drug markets using descriptive analyses, interviews and theoretical models (Caulkins *et al.*, 1999; Levitt and Venkatesh, 2000; Becker *et al.*, 2006; Bushway and Reuter, 2008; Moeller and Sandberg, 2019), the lack of data on illegal trade has hampered analyses into the sociological aspects of illegal market operations. Our results thus advance prior research focusing on the role of violence and intimidation (Jacques and Wright, 2008), geographic monopolies (Papachristos, Braga, and Hureau, 2013), risk (Becker *et al.*, 2006) and reputational incentives (Przepiorka *et al.*, 2017), by showing that the structure of trade networks themselves influences the price of illegal goods .

Our results further elucidate the relational determinants of illegal income. While past research on criminal earnings highlights the roles of experience, mentorship and skillsets (Morselli *et al.*, 2006; Loughran *et al.*, 2013), our findings demonstrate that endogenous trade networks are related to gross monthly revenue from criminal trade. These findings suggest that future research on criminal earnings must look beyond personal histories and opportunity structures and consider the vital role of exchange networks to better understand profit accrued from illegal trade. In particular, our results focus on *monthly* gross revenue. Qualitative interviews suggest that while drug dealers may charge lower prices to regular customers, part of their motivation is the belief that return customers increase long-term revenue by generating loyalty (Moeller and Sandberg, 2019). Future work should consider the possibility that network embeddedness increases long-term revenue even at high values and that overembeddedness in illegal online markets may primarily affect short-term economic gains.

Findings on the nonlinear effects of embeddedness also provide insight into network effects on illegal market competition. While endogenous network structures help vendors increase prices at low-to-moderate levels of embeddedness, overembeddedness negatively affects vendor prices. This finding is consistent with Moeller and Sandberg's (2019) qualitative results showing that embedded social ties can place drug dealers at competitive disadvantages by promoting cost cutting. In these regards, while endogenous trade networks help to resolve coordination problems in illegal online markets by helping to assign value and set prices for illegal goods (e.g. Beckert and Wehinger, 2013), endogenous trade networks may sometimes do so at the cost of competitive efficiency, where discounted goods limit vendors' ability to reinvest in drug distribution in the short run.

Our findings also suggest that networks can emerge to influence prices in anonymous markets for legitimate goods. While past research on online trade concludes that 'it is unlikely that network governance structures will emerge to resolve potential exchange problems' (Diekmann *et al.*, 2014, p. 67), we show that endogenous patterns of transactions indeed affect prices in some illegal online markets. Future work should explore the possibility of endogenous network effects in legitimate online trade.

While our results provide unique insight into how trade networks shape prices in illegal online markets, it remains an open question as to how these findings play out in the offline context. Although our analyses show that trade networks have substantial effects in anonymous exchange, we cannot determine whether endogenous trade structures are more or less impactful than personal social relations that develop between drug dealers and buyers in street-level markets. In offline markets, trade and personal relations likely evolve in tandem to contribute to embedded networks. A fruitful avenue for future research is to collect data on illegal drug transaction records and to assess the co-evolution of personal and economic networks and their impact on illegal pricing. While data on this type of exchange are difficult to obtain, recent analyses suggest that captured criminal organizations' administrative records may prove useful for this type of inquiry (Morselli *et al.*, 2017). Furthermore, we note that many darknet drug markets do not report actors' usernames, and so indirect referrals via four-cycle closure are not possible on some markets. Hence, while our study provides evidence of strong network effects from repeated exchange and closure, we note that this latter effect of closure is likely limited in markets where usernames are not publicly viewable.

While we have developed our study in the context of illegal online trade, our core arguments regarding endogenous network effects hinge on the notion of riskiness. In this respect, the differences between illegal online trade and other forms of trade are not a matter of type but of degree. Offline trade environments can be similarly high stakes, as can legal online trade. For instance, the current COVID-19 pandemic has increased the prevalence of online purchasing for costly legitimate goods, such as houses and cars. We expect that the nonlinear relationship between embeddedness in economic networks and prices should be prevalent in any sufficiently risky trade environment. We encourage further work examining endogenous trade network effects in other types of risky—and indeed, less risky—forms of trade to gauge how the risk and uncertainty implicit in illegal online markets gives rise to the identified nonlinear relationship between prices and network variables.

In sum, our study examined prices in illegal online drug markets. Results indicate that embedded networks develop through endogenous trade relations to shape illegal drug prices. Findings are consistent with the hypothesized existence of nonlinear network effects: at low-to-moderate values of embeddedness, network structures increase trust among market actors, and thus pricing rises; however, high levels of embeddedness reduce prices and gross monthly revenue. These findings demonstrate the substantial impact of trade network structure in anonymous exchange environments and endogenous trade networks' capacity to influence prices in illegal online markets.

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