Shining a Light on the Shadows: Endogenous Trade Structure and the Growth of an Online Illegal Market[1]

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How do illegal markets grow and develop? Using unique transaction-level data on 7,205 market actors and 16,847 illegal drug exchanges on a "darknet" drug market, the authors evaluate the network processes that shape online illegal drug trade and promote the growth of online illegal drug markets. Contrary to past research on online markets, the authors argue that the high-risk context of illegal trade enhances market actors' reliance on social relationships that emerge endogenously from transaction networks. The findings reveal a highly structured trade network characterized by dense clustering and frequent recurrent drug exchange. Dynamic network models reveal that both embeddedness and closure in exchange structure increase the hazard rate of illegal drug trade, with effect sizes comparable to formal reputations. These effects are pronounced in the early stages of market development but wane once the market reaches maturity. These findings demonstrate the powerful, temporally contingent, influence of transaction networks on illegal trade in online markets and reveal how endogenous networks of economic relations can promote risky exchange under conditions of relative anonymity and illegality.

Governments play a key role in market development. States define the type of products for sale as well as the rules governing exchange. Markets also rely on

[1] We are indebted to Srinivasan Parthasarathy and Mohit Jangid for coding assistance. We also thank David Melamed for helpful comments on an earlier draft of this article. This research was supported two National Science Foundation grants (00046370 and 1949037). Direct correspondence to Scott W. Duxbury, Department of Sociology, University of North Carolina, Chapel Hill, 163 Pauli Murray Hall, 102 Emerson Drive, Chapel Hill, North Carolina 27514. Email: duxbury@email.unc.edu

 https://doi.org/10.1086/718197

governmental backing to enforce contracts and ensure property rights. While the sociology of markets has been at the heart of much economic sociology (White 1981; Granovetter 1985), research and theory have focused almost exclusively on legal markets, where governmental oversight can be assumed. Illegal markets, however, involve the exchange of products that violate legal stipulations. Illegal market actors not only forfeit state protection but also act against the law. Market actors must conceal activities to avoid detection, and failure to do so can result in legal sanctioning and loss of profit. Thus, the illegality of exchange exacerbates coordination problems related to ensuring cooperation and promoting trade in illegal markets (Beckert and Wehlinger 2013).

Despite long-standing criminological and sociological research on organizational and economic offending (e.g., Sutherland 1949; Cloward and Ohlin 1960; Baker and Faulkner 1993; Venkatesh 1997; Simpson 2002; Baumer et al. 2017), studies have overwhelmingly focused on the structure and behaviors of criminal organizations, rather than exchange within illegal markets. Consequently, we know little about how illegal markets grow and develop. However, illegal markets are a growing social and political problem. In 2010, 1% of the U.S. gross domestic product was spent on illegal drugs, totaling $109 billion (Kilmer et al. 2014), and rates of death from drug overdose tripled between 2000 and 2016 alone (Hedegaard, Warner, and Minino 2017). Since profitable markets require "stable worlds" to mitigate uncertainty (Fligstein 2001), inattention to illegal market development is an important research omission.

In large part, methodological difficulties explain why illegal markets remain "in the shadows" of sociological research (Beckert and Wehlinger 2013). Data on illegal transactions are rare, and the few studies that have gained access to illegal trade records have only obtained aggregated information for market segments (Levitt and Venkatesh 2000). Illegal market actors typically do not keep detailed accounts of their involvement in illegal trade, and those that do are unlikely to share those records with researchers. However, to understand illegal market development, it is necessary to obtain longitudinal transaction-level network data encompassing the early stages of market operations, which, to date, has proved to be a herculean task.[2]

[2] Two primary sources of exchange data have been used in prior research. First, economists and policy researchers have examined the U.S. Drug Enforcement Agency's System to Retrieve Information from Drug Evidence data or, in some cases, administrative records provided by gang bookkeepers (e.g., Caulkins et al. 1999; Levitt and Venkatesh 2000). These data are limited because they do not constitute an entire market and are not longitudinal. Second, more recently scholars have leveraged digital trace data from online drug markets to examine transaction patterns (e.g., Soska and Christin 2015; Aldridge and Decary-Hetu 2016; Martin et al. 2018; Ladegaard 2019, 2020). However, few prior studies have collected network data, and those studies that have do not consider market growth trajectories or trade in emerging markets.

To overcome the data limitations that have hampered prior research into illegal market development, we examine novel transaction-level digital trace data on illegal trade. Unlike conventional data sources, digital trace data are not biased by self-report, and rich information is available on the timing of illegal transactions (see Lazer et al. 2009). Data can also be obtained from an entire market, allowing dynamic transaction networks to be constructed from the web of illicit transactions that accrue over time.

Beyond providing unobtrusive measures of criminal trade, digital trace data offer insight into an increasingly prevalent form of crime. Technological advances in encryption software along with the now-widespread availability of internet technologies have provided people around the globe with the access and anonymity necessary to participate in illegal trade at a scale and level of coordination that has historically been impossible. Black markets have now blossomed in secluded ("deep web") and encrypted ("darknet") regions of cyberspace.[3] These markets specialize in various illegal products, including stolen credit cards, child pornography, and illicit drugs (Barratt and Aldridge 2017). Current surveys report that 11% of surveyed drug users worldwide have purchased drugs from the darknet (Global Drug Survey 2018). In fact, some larger darknet drug markets generate as much as $180 million in annual revenue (Soska and Christin 2015). Online drug trade also contributes to contemporary drug epidemics. Following increased hydrocodone (a prescription opioid) regulation in 2014, for instance, rates of oxycodone and fentanyl sales on the darknet doubled as opioid users turned to online drug markets to procure cheaper and more potent alternatives (Martin et al. 2018). A focus on how darknet drug markets grow and develop is thus not only theoretically informative but relevant to policy makers seeking to curtail the recent explosion of online illicit drug trade.

Our central goal is to assess how online illegal markets grow and how market actors conduct trade in the absence of state supervision. To do so, we examine a new data set of 16,847 illicit drug exchanges between 7,205 users (7,047 buyers, 169 vendors) on one darknet drug market observed over the first 14 months of market activity.[4] The unique temporal and network coverage of our data allows us to trace the formation of illegal trade networks in the early stages of market development and assess how they shape trajectories of market growth. In doing so, we make several contributions to research on illegal markets, networks, and risky social exchange.

[3] The "Clearnet" refers to all websites that can be accessed through a mainstream search engine (e.g., Google, Bing). The "deep web" refers to all nonencrypted websites that are not indexed by mainstream search engines. The "darknet" or "dark web" is a colloquialism referring to encrypted websites, typically hosted on the Tor network, which can only be accessed with specialized web browsers, like Tor (see Barratt and Aldridge 2017).

[4] Eleven vendors also initiated drug purchases at some point and are listed as buyers as well as vendors.

One of the most consistent findings in the "new economic sociology" has been that market actors rely on social networks for information exchange and to build trust (Granovetter 1985; Coleman 1990; Burt 1992; Kollock 1999). However, while social networks have proved to be a robust determinant of exchange under conditions of uncertainty and limited governmental oversight (e.g., Kollock 1994; Greif 2006), research on online markets has suggested that networks matter little for online trade as "traders are anonymous and not connected through a social network" (Diekmann et al. 2014, p. 66). However, little empirical evidence has been brought to bear on online illegal markets' structural network properties. Thus, we first evaluate whether complex transaction networks emerge in online illegal markets.

Second, we examine how transaction networks in illegal markets pattern and promote online illegal drug trade. Prior research has focused primarily on how exogenous social networks influence economic relations (Granovetter 1985; Uzzi 1996; Kranton and Minehart 2001) and how networks of economic relations provide a conduit for reputational information transmission (Greif 1989; Hillmann 2013). Less research has theorized whether and how the structure of endogenous trade networks can influence illegal trade in online settings, where there are few preexisting social relations and information transmission is easily achieved in the absence of network relations (Diekmann et al. 2014; Przepiorka, Norbutas, and Corten 2017; Bakken, Moeller, and Sandberg 2018; Ladegaard 2020). Here, we develop an account that considers how closure and embeddedness in transaction networks build social relationships among online illegal market actors by establishing feelings of trust, loyalty, social obligation, and familiarity. As such, we show that endogenous transaction networks of economic relations can promote risky exchange among actors in illegal online markets, net of preexisting social ties and reputation effects.

Third, we consider how the stage of online illegal market development conditions the direct and indirect effects of network mechanisms on illegal trade relationships. When markets are young, actors have little reputational information, and risk is high. Therefore, the assurance provided by closure and dyadic embeddedness is greatest in the early stages of online illegal market development but can be detrimental to trade once markets mature and actors establish their reputations. We thus provide new evidence on how the effects of endogenous trade network structure on risky illegal exchange vary over a market's life course.

Analytically, we test our hypotheses using relational event models for longitudinal network data (Butts 2008). Relational event models are a relatively underutilized method for analyzing dyadic event data when fine-grained information on the timing of network ties is available. This unique analytic strategy allows us to evaluate complex interdependencies between endogenous network dynamics, actor attributes, and the hazard rate of illegal drug trade. In doing so, we show how methods for dyadic event data can be leveraged to gain new insight on temporal and network interdependencies in social interaction.

ONLINE ILLEGAL MARKETS

Illegal markets have long captured the imagination of the public and social scientists. Almost 40 years ago, at the dawn of the War on Drugs, President Reagan (1986, p. 1) called "drug abuse the repudiation of everything America is." Today, drugs continue to demand national concern. Current estimates suggest that online drug trafficking accounts for roughly 10% of all drug trafficking worldwide (World Drug Report 2016). Drug buyers purchase drugs on the internet, sometimes from overseas pharmacies where drugs are less regulated and other times from illegal drug websites on the darknet. These websites function akin to familiar online markets like eBay and Amazon. Buyers download specialized software, convert their currency to cryptocurrency (e.g., Bitcoin), peruse listings of drugs for sale, and select drugs to purchase that are subsequently delivered to their doorsteps through a postal service.[5]

The ease of accessing and using online drug markets has had numerous social and health consequences. Online drug buyers report increases in drug consumption, polydrug experimentation, and the use of more potent substances (Barratt et al. 2016; Martin et al. 2018). Research has begun to analyze the patterning of drug trade in online illegal markets. A consistent finding in this literature is that formal reputation systems promote online drug trade (Cox 2016; Przepiorka et al. 2017; Duxbury and Haynie 2018*b*; Norbutas, Ruiter, and Corten 2020). In these regards, online illegal markets function much the same as their legal counterparts, relying on reciprocation (Diekmann et al. 2014), sales ratings (Resnick and Zeckhauser 2002; Przepiorka et al. 2017), and public discourse to promote trade (Kollock 1999; Ladegaard 2020).

An assumption that has undergirded much research on online markets is that networks are relatively unimportant (Diekmann et al. 2014, p. 66; Przepiorka et al. 2017, p. 753; Bakken et al. 2018, p. 457; Ladegaard 2020, p. 532). Diekmann et al. (2014, p. 67) write that "[online] markets are not characterized by customized and complex exchanges, and . . . repeated interactions between the same two traders are infrequent. Under these conditions, it is unlikely that network governance structures will emerge to solve potential exchange problems." The reasoning goes that because online market actors are relatively anonymous, they cannot rely on social knowledge or information flow through social relationships to make purchasing decisions. Similarly, because repeated exchange is empirically rare, it is unlikely that transaction networks can be used to inform future purchasing on online illegal markets.

[5] More information on the details of online drug markets can be found in Barratt and Aldridge's (2017) review.

Research on online illegal drug markets has reached a similar conclusion regarding the role of networks. While offline illegal markets depend on personal networks to conduct trade (Beckert and Wehlinger 2013, pp. 18–20), some have concluded that anonymizing encryption software has fundamentally reconfigured illegal drug trade, such that "drug dealing is no longer limited to shadowy personal networks" (Ladegaard 2020, p. 532). For instance, Ladegaard (2020) examines how online illegal drug markets react to law enforcement interventions. He finds that rather than relying on network structure for protection, as in offline illegal markets (Morselli, Petit, and Giguere 2007; Malm and Bichler 2011; Wood 2017), online illegal market actors use discourse on online message boards to overcome state pressures that would otherwise inhibit illegal trade.

Other scholars reason that networks are ultimately unnecessary in online illegal markets because market actors have alternative strategies for building trust. Bakken et al. (2018, p. 457), for instance, write that "[in online drug markets] the investments in trust that characterize distribution in social networks can be transferred to the review system." Przepiorka et al. (2017, p. 753) similarly suggest that reputational information on online illegal markets is sufficient to conduct trade despite the absence of personal networks. Hence, while few studies have examined network effects in online illegal markets, the expectation provided by prior literature is that networks are relatively unimportant, as sales rating systems and online discussion serve the reputation-building and surveillance functions of networks.

Because online trade increases information asymmetry, the finding that complex networks are uncommon in online markets contradicts research on risky exchange. Theory and research on social exchange find that actors rely on networks to establish trust when uncertainty is high (Kollock 1994; Podolny 2001; Greif 2006). In online markets, buyers cannot inspect products before purchasing and have limited recourse if products are not delivered as promised. These risks are increased in illegal markets. Actors in illegal markets run the risk of apprehension by law enforcement, and illegal goods designed for consumption (drugs) may pose health consequences if contaminated. Qualitative research suggests that buyers factor such risk assessments into their purchasing behavior, expressing concerns about product contamination, arrest, and scamming when making purchasing decisions (Van Hout and Bingham 2014; Barratt et al. 2016; Cox 2016). Prior findings on the relative unimportance of networks are puzzling as the riskiness and high uncertainty of online illegal exchange imply that networks should be more influential in online illegal markets than in most other markets.

Kollock (1999) first detailed a similar dilemma in the early years of the online market eBay. At the turn of the millennium, online trade was a new frontier, and so the ability for traders to build reputations and participate in online trade in the presence of pronounced information asymmetry was questionable.

Kollock (1999) found that early eBay traders reduced uncertainty by building social capital through open discourse. Discourse on online auctions and message boards helped eBay users to develop informal reputations and social relations that were later transferred into formal reputations through sales reviews. Kollock's (1999) study provides an important insight for our analysis: although actors in online illegal markets are anonymous at the time of market entry, the presence of website-specific pseudonyms (user names) allows users to develop interpersonal relationships despite the relative anonymity of the exchange environment. In the context of early stage eBay, such social ties were developed through dialogue on message boards. Here, we consider whether the structure of endogenous illegal transaction networks that accrues through trade relationships serves a similar function by building social capital among market actors that can be mobilized to mitigate uncertainty in illegal online drug trade.

Several studies have examined the network properties of illegal online markets, reporting strong community structure, preferential attachment, robustness to disruption, and reliance on formal reputation systems and geographic propinquity (Duxbury and Haynie 2018*a*, 2018*b*; Norbutas 2018). However, each of these studies relies on cross-sectional data, and, as such, they cannot comment on the dynamics of illegal market growth. Moreover, none of the studies examine the determinative influence of transaction network structure. What is missing from current research is understanding how endogenous trade network structures pattern trade in online illegal markets and how network dynamics influence market growth over time.

In the study most similar to ours, Norbutas et al. (2020) examine network-reputational effects in online illegal markets. They find that prior positive exchange relationships influence whom buyers choose to trust and are particularly more influential than third-party reputational information. While Norbutas et al. (2020) provide important insight into reputation conferences in online environments, their study was not designed to examine the network structure of illegal trade or whether endogenous trade network structures influence illegal economic relations. Further, because the study cannot examine early stage market growth, it is unclear from their results whether and how endogenous trade structures influence exchange in an online illegal market's formative years.

The heightened uncertainty of illegal online trade implies a greater need for well-formed networks to govern exchange than in legitimate markets, yet the apparent absence of complex interactions in online markets implies that trade network structures are underdeveloped. Our empirical inquiry of darknet drug trade seeks to address this dilemma with the following questions: Do online illegal markets exhibit significant network structure? Are endogenous illegal trade networks merely a product of trade relations, or are they a determinative mechanism? Moreover, how do the effects of trade networks vary across the life course of online illegal markets? We depart from prior work on the sociology of illegal markets that emphasizes exogenous social ties (Gambetta 2009; Beckert and Wehlinger 2013) to consider instead how endogenous network structures of economic trade relations build trust and social capital among actors in illegal online markets.

TRADE NETWORKS AND ILLEGAL MARKETS

While economic sociologists regard network dependency as a defining feature of illegal markets (Gambetta 2009; Beckert and Wehlinger 2013), a stream of criminological research suggests that the social ties among illegal market actors may be too unstable to be responsible for market growth.[6] Indicative of this perspective, Gottfredson and Hirschi (1990) argue that "the idea of crime is incompatible with the pursuit of long-term cooperative relationships, and the people who tend toward criminality are unlikely to be reliable, trustworthy, or cooperative" (p. 213). Although a wealth of research has examined criminal organizations' network properties (Morselli 2009; Faust and Tita 2019), evidence on the durability of social ties among illegal market actors remains contested. On the one hand, case studies on illegal markets argue that kinship and friendship networks facilitate entry into criminal organizations (Gambetta 2009; Smith and Papachristos 2016), and network structure helps to subvert state surveillance and insulate key actors from law enforcement (Bouchard 2007; Morselli et al. 2007).

On the other hand, ties among actors in criminal organizations tend to be relatively short-lived (Shover 1996; Wright and Decker 1997; McGloin et al. 2008; Morselli 2009). While studies show that embedded social ties increase the lifespan of criminal organizations when such ties do exist (Pyrooz, Sweeten, and Piquero 2013; Smith and Papachristos 2016; Ouellet, Bouchard, and Charette 2019), networks connecting offenders tend to be composed of loosely organized, fleeting, and opportunistic relationships (Sarnecki 1990; Shover 1996; Wright and Decker 1997; McGloin et al. 2008). For instance, Pyrooz et al. (2013) report that although embeddedness increases the length of gang membership, most gang members are not deeply embedded, and hence persistent gang membership is uncommon (also see Ouellet et al. 2019). Given this inconsistent evidence on the durability of social ties among actors in criminal organizations, it is unclear whether networks connecting online illegal market actors are stable and interconnected enough to generate the type of recurrent, frequent, and long-term trade relationships required for illegal market growth

[6] A sizable literature exists on illegal markets and supply- and demand-side policing (Becker, Murphy, and Grossman 2006; Bouchard 2007; Bushway and Reuter 2008; Caulkins and Reuter 2010). Much of this research has been carried out by economists and criminologists using formal theory or qualitative case studies to anticipate how illegal markets weather law enforcement interventions or to theorize on illegal price setting (Bouchard and Wilkins 2009).

and that mitigate uncertainty in the high-risk early stages of illegal market development.

We argue that the network structure of illegal exchanges that develops endogenously from successful trade patterns is an important patterning force contributing to illegal trade and online illegal market development. Economic sociological approaches to market exchanges typically emphasize two possibilities for how network relations influence market operations. First, economic relations become embedded in social relations, where preexisting social ties provide the basis for economic trade (Granovetter 1985; Kranton and Minehart 2001; Uzzi and Lancaster 2004). Uzzi (1996), for instance, concludes that "[trade] network structures develop primarily from . . . personal relations" (p. 679) and that "a 'primed' relationship develops into ongoing, embedded ties that develop with a stock of trust appropriated from a pre-existing social relationship" (p. 680). Second, networks of economic relations can provide the basis for information transmission, circulating the types of reputational information that promotes cooperation in unregulated trade (Greif 2006; Hillmann and Aven 2011; Hillmann 2013).

The problem in isolating the influence of endogenous trade structure in online markets is that neither of these traditional network functions is available in online settings. Because actors are pseudonymous, they have few preexisting social relations to translate into economic outcomes (Diekmann et al. 2014; Przepiorka et al. 2017). Similarly, actors are provided with review comments and message boards, which enable them to share reputational information without network dependence (Bakken et al. 2018; Ladegaard 2020).

We consider a third possibility: economic relations can "become overlaid with social content that carries strong expectations of trust and abstention from opportunism" (Granovetter 1985, p. 490), net of embeddedness in preexisting social relations. Embeddedness in transaction networks can help establish trust, familiarity, social obligation, and loyalty that facilitate more frequent exchange with established clientele while also attracting new customers. In these regards, embedded trade relations do not necessarily emerge from preexisting social relationships but rather generate the very social relationships that promote illegal trade. As we describe below, several studies have considered this network function in the context of repeated exchange in experimental settings and offline legal markets (Kollock 1994; Podolny 1994, 2001). We build on these studies by generalizing the reasoning to online illicit trade and introducing bipartite closure as a new mechanism.

A relatively small but rich vein of qualitative case studies reveals findings consistent with our expectation that transaction networks can emerge endogenously to promote feelings of trust and attachment and influence trade in online illegal markets. In pioneering work, Steffensmeier (1986) describes the importance of social relations for criminal success. In particular, he details how a dealer of stolen goods (i.e., a fence) maintains ties between thieves and legitimate business people to sell illegal goods for profit and avoid police detection (also see Steffensmeier and Ulmer 2005). Jacques, Allen, and Wright (2014) examined drug dealers' networks in St. Louis, Missouri, finding that drug dealers are most likely to "rip off" irregular customers yet carefully maintain social ties with regular customers. Hoffer (2006) replicates this finding in an ethnography of a Colorado heroin dealing network. Similarly, in recent studies, Moeller and Sandberg (2015, 2019) interview Norwegian drug dealers, finding that exchange histories affect drug dealers' reports of drug pricing and exchange frequency.

NETWORK MECHANISMS

A substantial literature examines how networks influence legitimate markets (e.g., Granovetter 1985; Uzzi 1996, 1997; Burt 2005; Manea 2011). Two mechanisms are commonly proposed: dyadic embeddedness and closure. Because research on offline legitimate markets has focused primarily on these two mechanisms, we discuss how dyadic embeddedness and closure in buyer-vendor transaction networks can influence trade in online illegal markets.[7]

Dyadic Embeddedness

First proposed by Granovetter (1985) as an important property of markets, *dyadic embeddedness* refers to reliance on multiplex social ties to conduct trade. Preexisting social relationships promote trust between market actors, helping to penetrate uncertainty in economic transactions (Uzzi 1996; Uzzi and Lancaster 2004). This focus on embeddedness is echoed in economic theory on buyer-vendor networks, which argues that buyer-vendor exchanges are constrained by exogenous social ties (Kranton and Minehart 2001; Corominas-Bosch 2004). While dyadic embeddedness usually relates to preexisting social relationships, market actors can also come to form feelings of familiarity, loyalty, social obligation, and trust via histories of successful economic exchange. Kollock (1994), for instance, argues that buyers and vendors in the Thai rubber trade escaped the "Prisoner's Dilemma" of uncertain rubber quality by "abandoning the anonymous exchange of the market for personal, long-term exchange relationships between buyers and sellers" (p. 314). Consistent with our reasoning on the salience of risk for network reliance, Podolny (1994) finds that market actors depend more on repeated exchange partners when uncertainty is high.

[7] A third network property that is often discussed is brokerage, where actors span otherwise disjointed network components (Granovetter 1973; Burt 1992; Hillmann and Aven 2011). Brokers gain access to diverse sources of information and resources that increase their relative position and "power" in exchange relations. The brunt of research examining brokerage focuses on how brokerage positions increase actors' individual utility (although, see Clement, Shipilov, and Galunic 2018). Because our focus is on overall market growth, rather than actors' utility within markets, we do not examine brokerage in the current analysis.

Although scholars have observed that economic relations can act as a source of embeddedness (Geertz 1978; Okun 1981; Kollock 1994; Podolny 1994, 2001), this mechanism is overlooked in most research on online trade (although, see Norbutas et al. 2020). First, few comprehensive data sets on buyer-vendor relations exist (Granovetter 2005, p. 39), and as a result, researchers have had few opportunities to examine the prevalence of repeated exchange across the entire lifespan of a market. Second, most data on buyer-vendor relations come from legitimate online markets, where repeated exchanges are rare. For instance, Diekmann et al. (2014) examine the frequency of repeated exchange in the electronics trade on eBay, finding that only 3%–5% of transactions are repetitions of past transactions.

Our reasoning that online drug trade's illegality substantially increases risk suggests that dyadic embeddedness will be an important mechanism contributing to market growth. Ongoing, repeated exchanges assuage concerns about market actors' trustworthiness and establish trust between specific traders in a high-risk environment. Patterns of successful trade can also imbue economic relations with feelings of loyalty and familiarity that discourage actors from, or increase the marginal cognitive cost of, seeking out new vendors. The risk associated with purchasing from new vendors is further enhanced in online illegal drug markets because purchasing poor quality or contaminated drugs can potentially lead to severe health consequences, such as overdose and death. Therefore, we expect dyadic embeddedness to be common in online illegal markets and increase the frequency of illegal online trade.

Bipartite Closure

A second network mechanism is *closure* or clustering, where the majority of illegal exchanges occur within relatively small market subgroups (see Watts and Strogatz 1998). Closure in networks implies that exchange partners are all linked, such that trade partners have endorsed one another (Burt 2005). Closure in one-mode exchange networks takes a familiar form: it emerges from third-party network referrals or "triangles." In the context of illegal trade relations between buyers and vendors, the influence of closure requires theoretical elaboration. Buyer-vendor relations take the form of a bipartite network, where exchanges only occur between actors who occupy distinct roles.[8] In bipartite networks, closure manifests in "four-cycles" that link a pair of two

[8] It is possible in many online markets for vendors to trade with one another. That is, vendors can act as buyers, creating a multilevel network of buyer-vendor and vendor-vendor transactions. In our analysis, fewer than 50 (0.3%) transactions occurred between vendors. Thus, for practical purposes, the transaction network can be appropriately regarded as bipartite. This is also consistent with prior economic theory on buyer-vendor networks (Kranton and Minehart 2001; Granovetter 2005), which regards buyers and vendors as occupying distinct roles.

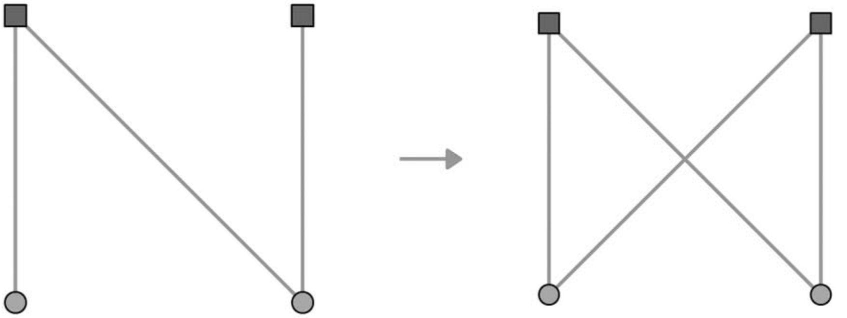

FIG. 1.—Example of four-cycle closure. Squares are drug vendors; circles are drug buyers; ties are drug exchanges. *Left*, open four-cycle; *right*, closed four-cycle.

buyers to the same two vendors (see fig. 1). Four-cycles are an important determinant structure in many bipartite networks (e.g., Bearman, Moody, and Stovel 2004; Latapy, Magnien, and Del Vecchio 2008; Brandenberger 2018). In transaction networks, the level of four-cycle closure reflects the extent to which two buyers purchase from two or more of the same vendors. A greater number of four-cycles suggests more frequent mutual-purchasing patterns, reflecting localized closeness (Robins and Alexander 2004).

Proximity in social space can influence buyers' purchasing decisions by shaping their choice set. While formal reputations and vendors' degree (number of sales) influence from whom buyers choose to purchase, closure can also convey trust by conferring reputation. Consider the hypothetical buyer-vendor network in figure 2. We expect that when buyer A chooses to purchase from a new vendor, A is more likely to purchase from T as opposed to V. Because both B and A have shared experience purchasing from U, B's endorsement of T conveys to A that T is trustworthy and sells products comparable in quality to, or better than, U's.[9] This closure mechanism is thus one of indirect referrals. Even though V is more connected than T in overall sales, the closure mechanism enacted by a shared purchasing history with B increases the appeal of purchasing from T, net of overall connectivity. Closure in buyer-vendor markets thus operates in much the same way as closure in one-mode exchange networks via indirect referrals that establish trust and increase past exchanges' visibility (e.g., Buskens and Raub 2002; Bohnet and Huck 2004).

[9] Two factors may influence how closure operates to increase trade. First, negative sales evaluations may have the opposite deterrent effect by conveying to A the T 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, indicating that the net effect of closure is positive. Second, 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 and by examining interactions between time and network mechanisms.

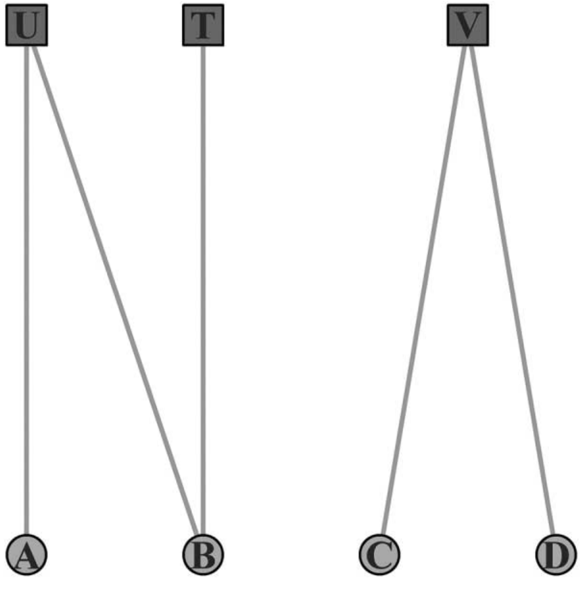

FIG. 2.—Hypothetical bipartite buyer-vendor trade network

We expect that four-cycle closure will contribute to online illegal market growth by increasing illegal trade frequency. To our knowledge, past research has not examined bipartite closure in online markets, legal or illegal.[10] Thus, in the analyses to follow, we evaluate the scope of four-cycle closure in our darknet drug market data and assess its influence on illegal drug trade. Prior studies have provided results consistent with our expectations. Small-group experiments reveal that cooperation is contagious in dynamic networks, where clusters form from cooperative relationships as noncooperative actors are excluded from further participation (Jordan et al. 2013). Other work has shown that such endogenous clustering promotes cooperation in economic games, net of reputation effects (Melamed, Harrell, and Simpson 2018).

Networks in Emerging Criminal Markets

Our reasoning thus far has been that the high risk and uncertainty implicit in digitally mediated illegal trade renders transaction networks especially

[10] Duxbury and Haynie (2018*b*) calculate the one-mode global clustering coefficient in their study of an online opioid submarket. Their goal was to evaluate the extent of vendor-vendor transactions, or the number of triangles (one-mode clustering), in the network, reporting no clustering. In contrast, our goal is to capture clustering between vendors and buyers (bipartite clustering), which, to our knowledge, has not been measured before. Consistent with our hypothesis of high clustering, Duxbury and Haynie (2018*b*) report strong subgroup formation in their network.

influential. The unique temporal coverage of our darknet drug exchange data allows us to consider how the direct and indirect effects of transaction networks are moderated by the stage of market development. New online illegal markets face a salient coordination dilemma. Reputational information is scarce, and information asymmetry is pronounced. The absence of reputational information reduces trust among market actors, so that in addition to the absence of state oversight, standard mechanisms for reducing uncertainty in online trade (i.e., reputations) are absent. This absence implies that uncertainty is greatest in young online illegal markets and thus that transaction networks are likely most impactful in the early stages of market development.

At the same time, evidence suggests that overly structured networks may discourage trade. Uzzi (1997) finds that excessive dyadic embeddedness decreases competitive efficiency in interfirm networks, while Hillmann and Aven (2011) find similar consequences for closure in the context of emerging markets in late imperial Russia, where excessive clustering reduces capital investments. In these circumstances, overembeddedness increases the redundancy of new information and reduces opportunities for profitable exchange.

While studies have generally been supportive of the concept of overembeddedness (Uzzi 1997; Uzzi and Lancaster 2004; Burt 2005), research has relied primarily on cross-sectional one-mode data, treating networks as static structures. In practice, transaction networks are dynamically evolving and may have a detrimental effect once illegal markets reach maturity. As illegal online markets mature, we expect that transaction networks grow increasingly interdependent, characterized by high frequencies of repeated buyer-vendor transactions and high levels of clustering, producing problems stemming from overembeddedness. Once online illegal markets reach maturity, networks can become irrelevant to trade or even damaging. They are irrelevant because reputational information is well established and circulated, rendering trade easy to navigate net of network dynamics. And they are damaging, because overembedded networks undermine competition by dissuading buyers from seeking out new vendors who offer cheaper or better products, leading to more frequent purchasing in the long run. We, therefore, expect that closure and dyadic embeddedness will be moderated by the stage of market development, so that the positive effects of closure and dyadic embeddedness will decline as online illegal markets age and eventually become negative or insignificant.

Our reasoning further suggests that one mechanism through which transaction networks contribute to trade in the early stages of market development is reputation formation. Because reputations are unestablished in early stage online illegal markets, closure and dyadic embeddedness help vendors attract new buyers and retain old ones, both of which help vendors construct reputations through formal sales evaluations. As markets age, reputations crystallize. Once reputations are well formed, they can become a sufficient condition for promoting trade and may even become self-perpetuating, where high-reputation vendors attract the lion's share of buyers and thus accrue greater reputations (e.g., Przepiorka et al. 2017). Consequently, transaction networks no longer increase vendors' reputations in well-formed markets and may decrease vendors' reputations by reducing the number of new buyers vendors can attract. We thus expect that the indirect effect of transaction networks, where closure and dyadic embeddedness promote illegal online trade by helping vendors to establish reputations, will be nonlinear: positive in the early stages of illegal market development, when reputations are contested and transaction networks are mobilized to conduct the bulk of trade, but insignificant once illegal online markets reach maturity and reputations are sufficient for promoting illegal exchange.

DATA

To evaluate our hypotheses, we collected network data from one currently active darknet illicit drug market, the Silk Road 3.1. We chose this market for several reasons. First, the Silk Road 3.1 is one of the longest-running and most popular darknet drug markets, with a lifespan of over six years (under various monikers). This longevity suggests that the customer base on the Silk Road 3.1 is not idiosyncratic but reflects broader patterns of drug trade on the darknet. Further, although Silk Road 3.1 was relatively small at the time of data collection by the standards of contemporary darknet markets, it has since grown into a relatively large market. Thus, our analysis provides insight into the generative properties that contributed to the growth of one of the larger darknet drug markets.

The second benefit of examining the Silk Road 3.1 is that we can collect complete network data covering the first 14 months of market activity, from its nascent stages in January 2017 to February 2018. Before January 2017, the Silk Road 3.1—previously called Silk Road 3.0—shut down for two months and underwent substantial website maintenance. Although the market's administrators did not change, buyers' and vendors' transaction histories were completely reset, providing a fresh start for the market. This unique temporal coverage allows us to ask and answer questions related to the social processes contributing to illegal trade relations during the market's formative years. We address the possibility that some vendors carry over informal reputations from the earlier Silk Road 3.0 in the analytic section below. Third, most darknet drug markets encrypt buyers' and vendors' user names. For instance, instead of "adrugbuyer," most darknet drug markets report "a****r." To create network data, a researcher must be able to match unique identifiers between participants. The Silk Road 3.1 is one of the rare darknet drug markets that reports full user names for both buyers and vendors, allowing us to re-create the entire illegal drug transaction network on the basis of trade relationships connecting buyers and vendors.

We programmed a web crawler that downloaded webpages from the Silk Road 3.1 at routine intervals over a week to collect our data. It accessed Silk Road 3.1 using a Tor web browser—the most common software for accessing darknet websites—and downloaded every webpage for each vendor, including the drugs they listed, buyers' evaluations of vendors' drug sales, and vendors' webpages that described the services they provide. 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 data set of every drug transaction that occurred on the market.[11]

To construct our network data, we established the presence of transactions by reviewing vendors' transaction histories. Most darknet drug markets enforce mandatory sales reviews, which are required to finalize a transaction (although buyers can return and edit them at any point in the future). Since these reviews are mandatory, researchers have found success in re-creating darknet drug transaction networks from sales reviews (Duxbury and Haynie 2018*a*, 2018*b*; Norbutas 2018). 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; Martin et al. 2018). 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 and February 2018. We then reviewed all sales evaluations with each of these vendors, identifying drug exchanges with 7,047 unique buyers, yielding a total of 7,205 market actors and 16,847 drug transactions in the bipartite drug exchange network. Ties are weighted, equal in value to the number of drug exchanges between a focal buyer and a focal vendor and equal to 0 if a buyer and vendor have not engaged in drug exchange. We also include vendors who had active accounts at some point during the market history but who had not made a sale.[12]

[11] Both the web crawler and data scraper were programmed in Python. The Ohio State University Human Subjects institutional review board determined that our study did not qualify for review because the Silk Road 3.1 is publicly accessible. 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 reputation 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 .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 to 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.

[12] 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.

We recorded information on the timing of each drug transaction. More recent purchases frequently had precise information on the timing of events, down to the hour or day. However, older transactions were typically only available at the level of months. Thus, we recorded the frequency of transactions between specific buyers and vendors 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 U.S. dollars. 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. We discuss these data in detail in the descriptive results below.

RELATIONAL EVENT MODELS

An interesting property of social networks is that, at once, they can be aggregated to represent durable and time-persistent patterns of relationships (e.g., the outcome of a stochastic process) or a dynamical system of relationships (e.g., an ongoing stochastic process; Butts 2009). In the case of relational events, such as coparticipation in golf games or illicit drug transactions, ties exist in discrete and ephemeral temporal moments. However, the historical patterning of relational events may influence future relational events. Conventional methods of statistical network analysis, such as network panel models (Snijders 2001; Hanneke, Fu, and Xing 2010) and cross-sectional network models (Robins et al. 2007), necessarily sacrifice information on network behavior and development when fine-grained data on the timing of events are available, which can provide misleading results on the timing of changes in network structure and how those changes affect illegal drug trade.

Relational event models (REMs) were developed to represent dynamic and structural interdependencies in relational event data (Butts 2008). A REM can be conceptualized as an event-history model for network data. A REM treats the occurrence of a drug transaction connecting a buyer and a vendor as the "hazard" for analysis. To estimate a REM, a researcher first transforms the data into an event-history format, in which the occurrence of a relational event is equal to 1 when it occurred and equal to 0 otherwise. In contrast to alternative dynamic network models (e.g., Snijders 2001; Hanneke et al. 2010), a REM accounts for the possibility that more than one relational event can occur in a period, such as when a focal buyer purchases illegal drugs from a focal vendor more than once in a given month (Brandenberger 2018).

The crucial distinction between event-history data and relational event data is that relational event data contain information on the time-varying network state. Researchers must reconstruct the time-varying network state at each time period to identify the possible drug exchanges that could have occurred but did not. The set of all dyads on the market at a given time point constitutes the risk set. Once the time-varying network states have been constructed, structural characteristics can be computed and treated as lagged regressors in the model. Lagging structural regressors ensures the network state's conditional independence, resolving statistical issues stemming from network dependencies in cross-sectional network models (see Robins et al. 2007).

Each drug transaction's timing is assessed as a multiplicative function of dyad characteristics, actor attributes, and the cumulative network structure. The probability of n illegal drug exchanges taking place between a buyer i and vendor j at time t is

$$\Pr(n_{ij}(t)) = \frac{\lambda_{ij}(t)^{n_{ij}(t)} \cdot \exp(-\lambda_{ij}(t))}{n_{ij}(t)!},$$

where $\lambda_{ij}(t)$ is the hazard rate. The rate function increases or decreases according to the covariate effects provided by the researcher:

$$\lambda_{ij}(t) = \exp\left[\lambda_0 + \sum_k \beta_k X_{ijk}(t)\right],$$

where λ_0 is the baseline hazard, β_k contains the k parameters, and $X_{ijk}(t)$ is the k-dimensional data matrix containing the relevant covariates, including temporal effects, sender effects, receiver effects, and time-varying graph statistics computed on the network. Parameters can be interpreted as in an event-history model, where covariate effects either increase or decrease the hazard rate of illegal drug exchange.

Since the conditional likelihood principle holds for relational event data (Butts 2008), maximum likelihood estimation is used to identify the parameter set. In the case of ordinal-timing data, such as ours, the model can be estimated as a discrete-time event-history analysis.[13] Thus, the final version

[13] We treat the timing data as ordinal because we omit one month of coverage, and so the spacing between each time period is unequal. Results were robust when treating time as continuous using a Cox model.

of an ordinal-timing REM is estimated as logistic regression (Butts 2008; Brandenberger 2018). We cluster our standard errors on buyers to account for heterogeneity in buyers' purchasing patterns.

Model Specification

Specifying a REM requires consideration of the various sender effects, receiver effects, structural effects, and temporal effects that may affect the event hazard rate. We consider each of these below.

Endogenous effects.—We account for network structural effects using measures developed by Brandenberger (2018) for bipartite relational event data. Each structural effect is lagged by one time period to be temporally prior to the contemporary network state. Table 1 provides definitions of each measure.

We measure dyadic embeddedness as *sales inertia*, where higher values indicate that a buyer and vendor have exchanged a greater number of illegal drugs in the past. Formally, sales inertia is calculated as

TABLE 1
Structural Measures and Description

Variable	Measurement	Interpretation
Vendor market activity	$\Sigma w_t(i, b)$	Higher values indicate that a focal vendor b has made more sales, with greater weight assigned to recent sales
Buyer market activity	$\Sigma w_t(a, j)$	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	$\sqrt[3]{\Sigma w_t(a,j) \cdot w_t(i,b) \cdot w_t(i,j)}$	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)	$\Sigma e^{-(t-t_e)\frac{\ln(2)}{\alpha}} \cdot \frac{\ln(2)}{\alpha}$	Weighting function, where more recent transactional ties are assigned greater weight

Note.—Weight function (w_t) assigns 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).

$$w_t(a, b),$$

where a is a focal buyer and b is a focal vendor; w_t is a weighting function that assigns greater value to more recent drug transactions such that

$$w_t = \sum e^{-(t-t_e)\cdot\frac{\ln(2)}{\alpha}} \cdot \frac{\ln(2)}{\alpha},$$

where t is the current event time, t_e is a past event time, and α is a tuning parameter that determines whether more recent events should be assigned greater or lesser weight.[14] The sales inertia measure is equal to the number of drug exchanges occurring between a and b in the past, with greater weight assigned to more recent transactions. Positive coefficients indicate that future transactions are more likely to occur when they link buyers and vendors who have a history of economic exchange, prioritizing recent exchange.

Network closure is measured using *four-cycles* (Robins and Alexander 2004; Latapy et al. 2008), where two buyers purchase illegal drugs from the same two vendors. The number of four-cycles closed by a drug exchange is defined as

$$\sqrt[3]{\sum w_t(a, j) \cdot w_t(i, b) \cdot w_t(i, j)},$$

where i is one member of a set of all buyers who have purchased drugs from a focal vendor b, and j is one member of a set of all vendors who have sold drugs to a focal buyer a. The measure increases in value when a drug exchange closes an increasing number of four-cycles (see fig. 1), with greater weight assigned to more recent transactions. Coefficients can be interpreted as the increase or decrease in the probability that illegal drug transactions will occur when they close an increasing number of four-cycles.

In addition to these network effects, it is important to account for how connectivity (e.g., having made a large number of sales/purchases) affects illegal drug trade. We account for buyers' and vendors' connectivity by controlling for their market activity and the number of exchanges in which they have engaged. For vendors, this is

$$\sum w_t(i, b);$$

for buyers, it is

$$\sum w_t(a, j).$$

Higher values reflect that the vendor/buyer has engaged in a greater number of illegal drug exchanges, with more weight assigned to recent drug

[14] Values less than 1 assign greater weight to more recent drug exchanges; values greater than 1 increase the weight assigned to less recent drug exchanges. We assigned a value of $\alpha = .7$ to place priority on more recent drug exchanges, although results were robust to specifications that placed greater weight on less recent drug exchanges.

transactions. The measures control for connectivity by accounting for the number of prior drug exchanges in which a vendor has engaged and are equivalent to computing a weighted degree centrality for all vendors and buyers at each time period. Although we follow convention in the literature on REMs by referring to these measures as market "activity," it is worth noting that the measures are analogous to weighted metrics of ego-network size, which have been linked to exchange behavior in past research (Uzzi 1996). To account for the possibility that networks develop simply because early stage markets have a smaller stable of active vendors to choose from, we control for the number of active vendors on the market at each month of observation.[15]

Exogenous effects.—In addition to structural measures, we control for vendor attributes. We measure vendors' formal reputations by summing the numeric sales evaluations of all past drug exchanges with a vendor up to a focal time period (Diekmann et al. 2014; Przepiorka et al. 2017). The resulting reputation measure is time varying and cumulative, where higher values reflect that vendors have received a greater number of positive sales ratings in the past. We also control for negative reputations by summing all negative sales ratings a vendor has received in a given month. It obtains a maximum value of 0 when the vendor has not received any negative sales evaluations.

In contrast to the cumulative reputation measure, the negative sales rating measure resets each month and only reflects the negative sales evaluations a vendor has received in a given month. This measurement captures periodicity, where strings of negative sales ratings may cause episodic disruptions to illegal drug trade. Since sales ratings are provided when a drug exchange is finalized, we lag both reputation measures by one month to ensure the correct temporal order of variables (i.e., exogeneity).

To account for the pricing of illegal drugs, we compute the average price of all transactions with a given vendor (Duxbury and Haynie 2018*a*, 2018*b*). Higher values indicate that, on average, purchases from a vendor tend to cost more. We also construct a time-varying metric to evaluate whether periodic decreases in drug prices, such as seasonal sales, increase the likelihood of illegal drug purchases. We constructed this metric by subtracting a given drug transaction's price from the mean price of drug exchanges with a given vendor (i.e., group mean centering). Lower values indicate that a drug transaction's price is below the mean price for a given vendor, while higher values indicate that the price of a drug transaction is above the mean price for a given vendor.[16] In robustness checks, we also standardized these

[15] We thank an *AJS* reviewer for this recommendation.

[16] For our time-varying price variable, we fixed values at 0 for dyads where drug exchanges did not occur, reflecting no variation in the time-varying price variable after controlling for

measures by the size of the drug purchase (measured in grams). Results were substantively consistent with those reported below. We elected to use the simpler unstandardized measures because of large amounts of missing data on drug purchase size.

Vendors may also attract buyers because they span consumer bases (Stephen and Toubia 2009; Duxbury and Haynie 2018*a*). In drug markets, customers have tastes or preferences for specific drugs, and thus vendors who sell multiple types of drugs may engage in more trade by spanning taste clusters. To account for this, we control for the number of drug types that a vendor sells, ranging from 1 to 9.[17] Vendors can broaden their consumer base by also expanding into international markets (Decary-Hetu, Pacquet-Couston, and Aldridge 2017). We include a binary variable equal to 1 if vendors are willing to ship to a country other than their country of origin and equal to 0 otherwise. We also control for vendors' country of origin. We include indicator variables for whether vendors are located in France, the United Kingdom, Germany, Canada, or Australia, or their location is unknown.[18] The reference category is the United States.[19]

A final consideration is that some vendors may carry over their informal reputations from the earlier version of the market, Silk Road 3.0. We address this by providing a series of stratified models, with fixed effects for vendors and vendor time periods. These models eliminate all time-invariant and time-varying vendor-level variation (respectively) and thus any unobserved heterogeneity among vendors, including informal reputations or any other unobservable vendor characteristic. This approach allows us to rule out all possible confounding from unmeasurable vendor attributes. We also include models that stratify by dyads—stratifying by dyads controls for any possible social relationships imported from online message boards or prior market iterations, by holding constant preexisting ties between market actors.

vendors' mean transaction cost. We also examined robustness checks in which we discretized the time-varying price variable, we treated price as a categorical variable, and the "cost" of drug exchanges that did not occur had a separate category. The results are consistent with those reported below. We report the simpler continuous measure because the discretized variable has 1,411 categories, which is difficult to report.

[17] These categories were marijuana, heroin/opium, prescription opioids (e.g., oxycodone, fentanyl), prescription stimulants (e.g., Ritalin, Adderall), methamphetamine, cocaine/crack cocaine, MDMA/ecstasy, psychedelics (e.g., LSD, hallucinogenic mushrooms), disassociatives/benzodiazepines (e.g., Klonopin, ketamine), and designer drugs/novelty psychoactive substances (e.g., mephedrone, cathinones, synthetic cannabanoids).

[18] In cases in which vendors' country of origin was unknown, we constructed the international shipping variable as equal to 1 if the vendors shipped to at least two destination countries or if the vendors listed that they shipped "worldwide" and equal to 0 otherwise.

[19] Data on buyers' country of origin are unavailable on Silk Road 3.1.

Analysis Plan

We begin by describing the characteristics of the Silk Road 3.1 network. First, we calculate the number of repeated transactions and compare them to repeated trade reports in legitimate online markets. Second, we calculate the bipartite clustering coefficient on the network and compare the clustering coefficient to simulated networks with the same size, density, and number of buyers and vendors. We then turn to REMs, in which we estimate models controlling for confounders before building in vendor, vendor–time period, and dyad fixed effects to account for unmeasured heterogeneity. To interpret effect size, we compare the partial effect of sales inertia and four-cycles given a 1-SD increase or decrease to cumulative reputations' partial effect given a 1-SD change. Finally, to assess moderation and indirect effects, we compute each network measure's average marginal effect at each time period and then calculate the change in each marginal effect after controlling for the time-varying effect of reputations.

RESULTS

Descriptive Results

Figure 3 plots the aggregated Silk Road 3.1 illegal drug transaction network. The network is sparse, as most nodes are disconnected from the brunt of network activity. The bipartite network density is .014, indicating that 1.4% of all possible drug exchange relationships actually occur (table 2). There is high variability in vendors' degree centrality, where the most active vendors have engaged in 1,623 illegal drug transactions. In contrast, the most active buyers have purchased 53 times. The buyers' degree distribution is also right skewed, with a mean of 2.39, indicating that a small number of buyers account for much of the illegal drug activity on Silk Road 3.1. There is substantial variation in pricing, where the cheapest transaction costs $5, while the most expensive illegal drug transaction costs nearly $20,000. This variation in pricing is consistent with past research, which shows that over half of all darknet drug revenue comes from wholesale purchases over $1,000, most likely intended for resale (Aldridge and Decary-Hetu 2016).

In contrast to prior findings on online markets, repeated drug exchanges are quite common. There are 16,847 drug transactions total; 8,690 transactions only occur once, while 5,213 transactions are repeated. In other words, 31% of all illegal drug transactions are repetitions of prior exchanges, indicating that repeated online drug exchange frequency is 6–10 times more common than reported in other legal online markets (Diekmann et al. 2014). This result is consistent with our expectation that online illegal markets are characterized by far more complex interactions than their legitimate counterparts.

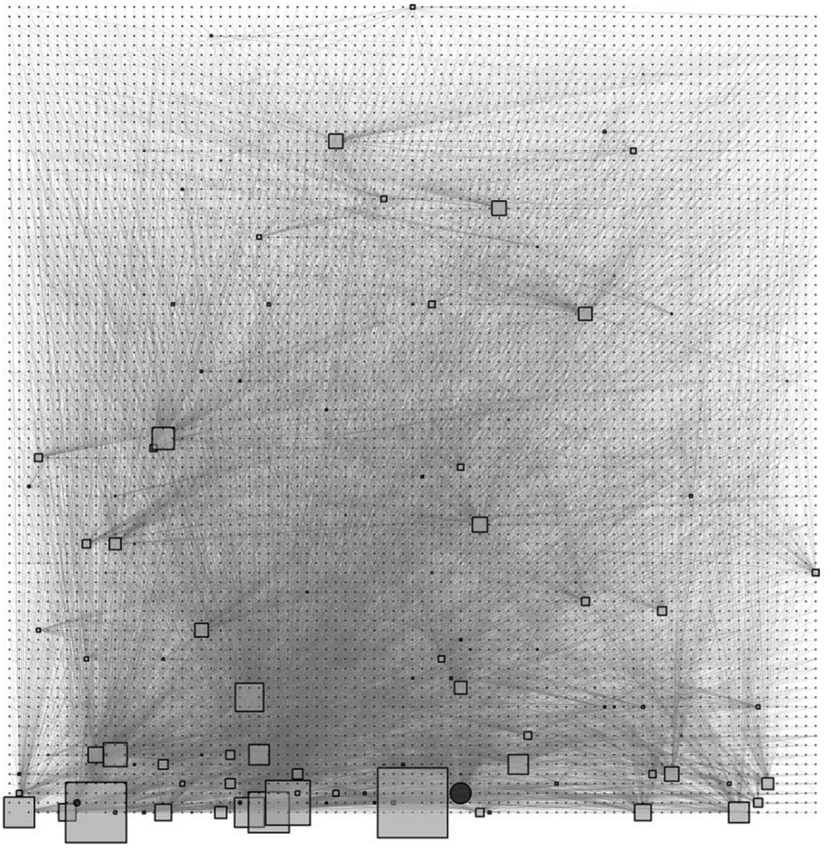

Fig. 3.—Silk Road 3.1 aggregate illegal drug trade network mapped to a grid layout. Squares are vendors; circles are buyers; ties are drug exchanges. Node size is proportional to degree centrality.

Also consistent with expectations, the dense concentration of illegal drug transactions at the bottom of figure 3 suggests that buyer-vendor closure is common. We measure closure in the aggregated drug transaction network with the bipartite clustering coefficient (Robins and Alexander 2004; Latapy et al. 2008), which is the ratio of closed four-cycles to open four-cycles (see fig. 1). The bipartite clustering coefficient is .05, reflecting that there is one closed four-cycle for every 20 open four-cycles. We simulated 100 bipartite networks with the same density and number of actors in each mode as in the Silk Road 3.1 but with random tie assignment to interpret this coefficient.[20] The

[20] Ideally, we would be able to compare the clustering coefficient to a legitimate online market. However, global structural measures like the clustering coefficient are highly sensitive to network size. Thus, to draw an adequate comparison, we would require a

TABLE 2
DESCRIPTIVE STATISTICS FOR SILK ROAD 3.1 ILLEGAL DRUG TRADE NETWORK

Measure	Mean or (%)	Range
Density	.014	
Bipartite clustering coefficient	.050	
Number of drug transactions	16,847	
Number of one-time transactions	8,690	
Number of repeat transactions	5,213	
Degree centrality (vendors)	99.69 [195.93]	0 to 1,623
Degree centrality (buyers)	2.39 [2.65]	1 to 53
Transaction costs (USD)	242.61 [585.10]	5 to 19,796
Vendor cumulative reputation	1,277.92 [1,557.54]	−5 to 8,058
Vendor negative sales ratings	−21.86 [49.73]	−406 to 0
Number of drug types sold	2.40 [1.65]	1 to 9
International shipping	21.89%	0 to 1
Vendor location:		
United States	(39.05)	0 to 1
United Kingdom	(8.28)	0 to 1
Germany	(1.78)	0 to 1
Canada	(2.34)	0 to 1
France	(5.33)	0 to 1
Australia	(.06)	0 to 1
Unknown	(43.16)	0 to 1
Number of vendors (monthly)	46.92 [30.48]	13 to 96
Number of vendors (total)	169	
Number of buyers	7,047	
Number of market actors	7,205	
Number of time periods	13	

NOTE.—Market observed from January 1, 2017, to February 1, 2018. Numbers in square brackets are SDs.

benefit of this simulation is it allows us to evaluate the counterfactual of no network effects, where illegal drug transactions are distributed without any influence from transaction networks. The mean bipartite clustering coefficient in the simulated networks is .0099, the smallest is .0093, and the largest is .0108, reflecting that the level of four-cycle closure in the Silk Road 3.1 illegal drug exchange network is five times as large as would be expected at random. With a Monte Carlo *P*-value of 0, this result is statistically significant.[21]

legitimate online market of buyer-vendor exchanges with approximately the same number of actors as the Silk Road 3.1. Because we know of no study that meets these criteria and measures bipartite clustering, we are unable to draw this comparison. An alternative strategy would be to simulate highly clustered small-world networks, rather than random networks, for the sake of comparison. But current methods for simulating small-world networks require a prespecified clustering coefficient, rendering this approach tautological and ultimately uninformative.

[21] We replicated this simulation a second time holding the degree distribution constant by using an exponential random graph model and offset parameters for the degree distribution of each mode. Consistent with primary results, the mean clustering coefficient in the simulated bipartite networks was .011, with a range of .008 to .027.

Descriptive findings are broadly consistent with our expectation that economic interactions are uniquely complex and transaction networks well formed in illegal online markets. The next step is to evaluate whether transaction networks influence online illegal drug trade and how the stage of market development conditions these effects. We now turn to REMs to examine the determinants of illicit drug market growth.

Relational Event Models

Table 3 presents REM results. Model 1 provides a baseline model with full control variables. Consistent with past research highlighting the importance of formal reputation systems for online trade, vendors' cumulative reputations increase the hazard rate of illegal drug trade, while negative sales ratings decrease it. The positive coefficient for buyers' market activity indicates that buyers who have engaged in frequent illegal drug trade in the past tend to engage in more drug trade in the future. Both the time-varying and time-invariant coefficients for vendors' transaction costs are positive, indicating that buyers are willing to pay a premium for high-quality drugs (e.g., Moeller and Sandberg 2019). The positive coefficient for the number of drugs sold reflects consumer taste spanning, where vendors who sell multiple types of drugs tend to engage in more frequent drug exchange.

Model 2 evaluates whether dyadic embeddedness and bipartite closure contribute to the hazard rate of online illegal drug trade, by including the sales inertia and four-cycle closure measures. Consistent with expectations, both the sales inertia and four-cycle closure coefficients are positive and significant, indicating that histories of successful trade and closure in illegal trade structure increase the hazard rate of illicit drug exchange. Including these covariates also renders buyers' market activity insignificant, suggesting that high-frequency buyers' propensity to engage in more frequent drug trade can be largely explained by high-frequency buyers' tendency to be integrated into transaction networks through closure and dyadic embeddedness.[22]

To interpret effect size, we compare the effects of sales inertia and four-cycle closure to the effect of vendors' cumulative reputations, as past research has attributed the success of online markets to formal reputation systems more than any other factor (Kollock 1999; Diekmann et al. 2014; Przepiorka et al. 2017). On average, a 1-SD increase above the sales inertia mean correlates with a .02 increase in the predicted probability of an illegal drug transaction (fig. 4). Likewise, when four-cycle closure increases one standard deviation above the mean, the predicted probability rises from .13 to .15. By comparison, a 1-SD increase in vendors' cumulative reputations increases the predicted

[22] A formal comparison of average marginal effects (Mize, Doan, and Long 2019) confirmed that this change in significance is itself statistically significant ($P < .001$).

probability of drug exchange by .02 from its mean. Put differently, the effects of closure and dyadic embeddedness are each comparable in size to the effect of vendors' cumulative reputations.

Another way to compare effect size is to consider the relative ease of moving one standard deviation for each metric. Vendors would have to finalize 311 illegal drug transactions and receive five-star ratings on each sale to increase their cumulative reputation by one standard deviation (SD = 1,558). By contrast, the standard deviations for sales inertia (SD = .598) and four-cycle closure (SD = 1.148) are far smaller. A potential illegal drug transaction increases the sales inertia measure by one standard deviation if it links a buyer and vendor who have traded drugs only twice in the prior month. Likewise, the four-cycle closure measure increases by one standard deviation if a potential illegal drug transaction closes three four-cycles constituted of illegal drug transactions that occurred in the prior month.[23] This evidence reveals that transaction networks explain substantial variation in online illegal drug trade and require fewer structurally well-poised economic ties to yield a comparable change in hazard rate as compared to reputations.

Findings in models 1 and 2 provide strong evidence that transaction networks promote illegal drug trade in online drug markets. Our next goal is to assess whether results are confounded by unobserved vendor-level heterogeneity. Model 3 considers the possibility of "spillover" reputations from an earlier version of the market. It presents results from REMs with vendors as strata, forcing all time-invariant vendor characteristics to zero. Results are consistent with model 2, revealing that vendors' reputations from an earlier version of the market are not responsible for the identified network effects. Model 4 includes vendor–time period interactions as strata, controlling for all time-invariant and time-varying vendor-level variation simultaneously. Results are, again, robust. These findings demonstrate that no observed or unobserved vendor characteristic—whether reputation, product quality, branding, or pricing—can account for the influence of network dynamics on illegal online drug trade.

In model 5, we stratify by dyads to account for the possibility of preexisting social or economic ties exogenous to market development. Findings are again robust in terms of direction, size, and significance. This result

[23] We calculated these estimates using the equations reported in table 1. For illegal drug transactions in the most recent time period, with a decay of .7, the weight function can be written $\Sigma e^{-(1)\cdot \ln(2)/7} \cdot \ln(2)/7$, which equals .36 for a single prior drug exchange. Assuming all drug transactions occur in the most recent time period, the value of each drug exchange increases the sales inertia measure by .36, and so a value of .72 ($2 \times .36$) moves the sales inertia measure more than one standard deviation. For open four-cycles constituted only of drug transactions in the prior month, the equation reduces to the cubic root of .36 cubed, which is .36. Closing three four-cycles thus increases the value of the four-cycle closure measure by 1.08, which is roughly a 1-SD increase.

TABLE 3

Relational Event Models of Illegal Drug Exchange on Silk Road 3.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sales inertia$_{\alpha=.7,\ t-1}$		.255***	.080***	.066***	.050**	.382***	.255***
		(.035)	(.022)	(.002)	(.014)	(.028)	(.060)
Four-cycle closure$_{\alpha=.7,\ t-1}$		.101***	.062***	.036***	1.479***	.166***	.116***
		(.027)	(.013)	(.007)	(.169)	(.022)	(.031)
Sales inertia$_{\alpha=.7,\ t-1}$ $\times$ time						−.045***	−.032***
						(.004)	(.007)
Four-cycle closure$_{\alpha=.7,\ t-1}$ $\times$ time						−.014**	−.010**
						(.003)	(.004)
Negative sales ratings$_{t-1}$ $\times$ time							.007***
							(.000)
Vendors' cumulative reputation$_{t-1}$ $\times$ time							−.025***
							(.001)
Negative sales ratings$_{t-1}$	−.046***	−.044***	−.232***		−.006***	−.012***	−.258***
	(.009)	(.009)	(.009)		(.001)	(.001)	(.009)
Vendors' cumulative reputation$_{t-1}$	.011**	.012***	.010***		.002***	.012***	.009***
	(.000)	(.000)	(.000)		(.000)	(.000)	(.000)
Vendor market activity$_{\alpha=1.2,\ t-1}$	.000	−.001	.018***		.012***	.012***	.016***
	(.000)	(.000)	(.000)		(.001)	(.000)	(.000)
Buyer market activity$_{\alpha=1.2,\ t-1}$	.055***	−.009	−.009	−.001	.406**	.000	.002
	(.015)	(.017)	(.009)	(.003)	(.057)	(.000)	(.007)
Transaction costs (centered on vendor mean)	.001***	.001***	.001***	.001***	.000*	.000***	.000***
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)
Transaction costs (vendor mean)	.002***	.002***					
	(.000)	(.000)					
Number of drugs sold	.031***	.036***					
	(.009)	(.009)					
Vendor ships internationally	.046	.043					
	(.033)	(.033)					

Vendor location:							
France	.303***	.306***					
	(.071)	(.072)					
United Kingdom	.022***	.212***					
	(.048)	(.048)					
Germany	1.879***	1.961***					
	(.092)	(.092)					
Canada	−.073	−.062					
	(.076)	(.069)					
Australia	−.794***	−.804***					
	(.206)	(.212)					
Unknown	.054	.039					
	(.043)	(.044)					
Number of vendors	.053***	.054***	.031***		.019***	.033***	.037***
	(.003)	(.003)	(.002)		(.003)	(.002)	(.002)
Time	5.433***	5.423***	1.397***		1.759***	1.644***	1.427***
	(.315)	(.319)	(.119)		(.179)	(.074)	(.155)
Time^2	−.770***	−.765***	−.180***		−.035	−.171***	−.185***
	(.044)	(.044)	(.011)		(.023)	(.010)	(.020)
Time^3	.036***	.036***	.009***		.002	.008***	.009***
	(.002)	(.002)	(.000)		(.001)	(.000)	(.000)
Constant	−15.126***	−15.285***					
	(.724)	(.730)					
Vendor fixed effects?	No	No	Yes	Yes	Yes	Yes	Yes
Vendor-time fixed effects?	No	No	No	Yes	No	No	No
Dyad fixed effects?	No	No	No	No	Yes	No	No
χ^2	21,986***	22,290***	14,001***	239***	1,570***	27,528***	30,689***
Akaike information criterion	371,867	371,551	224,064	165,551	32,344	227,617	224,461
Bayesian information criterion	372,006	371,705	224,188	165,582	32,422	227,710	224,569

NOTE.—Two-tailed significance tests. Standard errors (in parentheses) are clustered on buyers. Coefficients for vendors' cumulative reputations are multiplied by 10. Negative sales ratings are reverse coded to facilitate interpretation. Intercepts are not reported for models 3–7 because they are estimated as stratified Cox models, which have an equivalent likelihood to conditional logistic regression. $N = 119{,}047$.

* $P < .05$.

** $P < .01$.

*** $P < .001$.

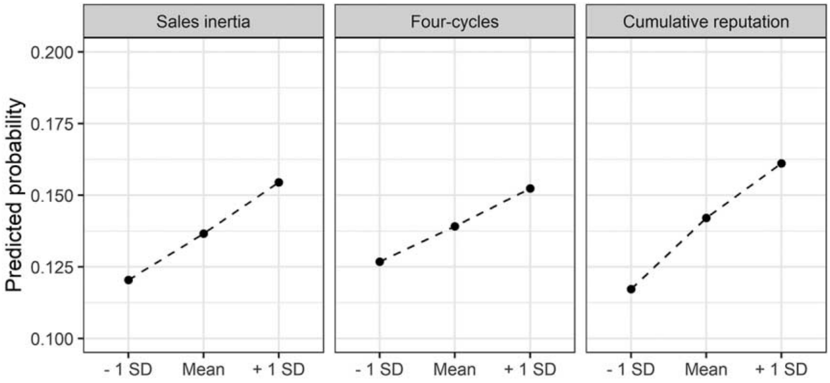

FIG. 4.—Predicted probability of illegal drug exchange given a 1-SD change in predictor variable.

demonstrates that the detected network effects do not merely reflect preexisting social or economic relations but develop endogenously from illegal trade network structures that form during online illegal market development.

Findings thus far reveal that transaction networks have a large, robust impact on online illegal drug trade. Transaction networks emerge to facilitate trust and eschew uncertainty in the digitally mediated criminal exchange between relatively anonymous actors. Our final goal is to evaluate whether the stage of market development, when risk and uncertainty are greatest in young online illegal markets, conditions the direct and indirect effects of bipartite closure and dyadic embeddedness. Because interaction coefficients are uninterpretable in nonlinear probability models (Allison 1999), we calculate the second difference in average marginal effects for the sales inertia and four-cycle closure measures between the market in its first month of operation and the final month of data collection to test and interpret direct and indirect interaction effects (Duxbury 2021; Long and Mustillo 2021).

Model 6 includes interactions between sales inertia, four-cycle closure, and time. The average marginal effect for sales inertia is .03 ($P < .001$) in the first month of market development but declines to $-.01$ ($P < .001$) in the final month of data collection (fig. 5*A*).[24] And the decline in average marginal effect is statistically significant (second difference $= -.04$, $P < .001$). Consistent with this finding, the average marginal effect for four-cycle closure declines from .01 ($P < .001$) to $-.001$ ($P > .05$) between the first and last month of market development (second difference $= -.015$, $P = .01$; fig. 5*B*). In line with expectations, these results indicate that while sales inertia and four-cycle closure are especially influential for promoting online illegal drug trade when markets are young, highly embedded and clustered transaction

[24] All average marginal effects are reported on the scale of probabilities.

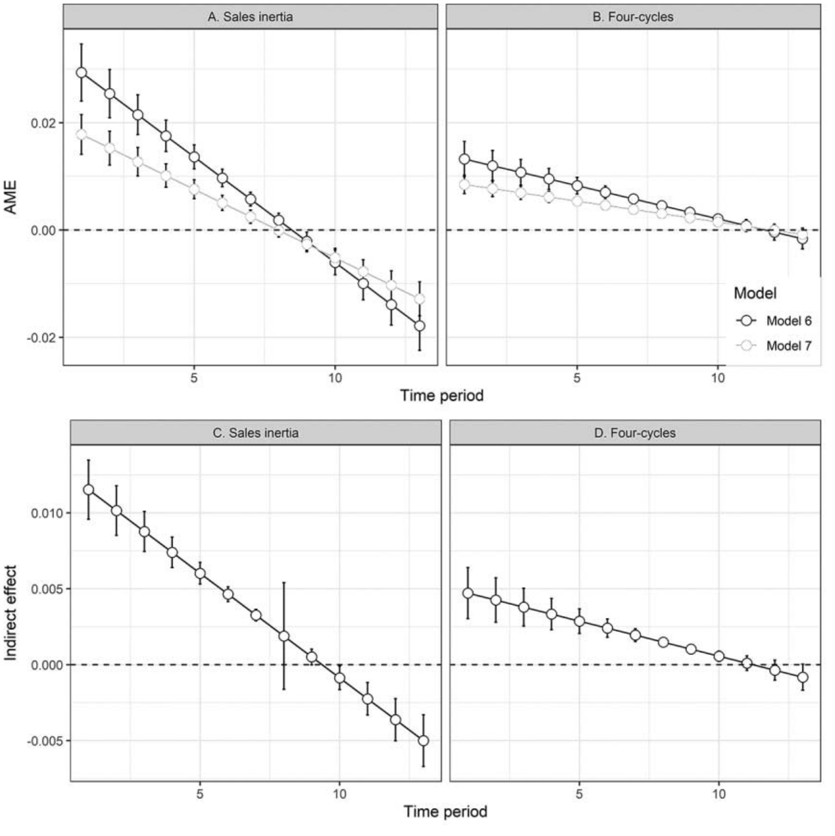

FIG. 5.—Average marginal effects (AME) and difference in average marginal effects (indirect effect) between models 6 and 7 for time-varying effects of sales inertia and four-cycle closure. Bands are 95% confidence intervals.

networks cease to increase illegal trade once markets reach maturity and, instead, in the case of dyadic embeddedness, reduce the frequency of illegal drug trade by discouraging buyers from seeking out new vendors who sell cheaper or higher-quality drugs.

Our final expectation is that transaction networks function to help online illegal drug market actors establish reputations in the high-risk nascent stages of market development. To test this, model 7 includes interactions between negative reputations, cumulative reputations, and time. Controlling for reputation interactions attenuates the second differences for sales inertia ($-.031$, $P < .001$) and four-cycle closure ($-.009$, $P = .01$) by 31% and 40%, respectively.[25] On average, the temporally contingent effect of reputations explains

[25] While coefficients cannot be compared between models in logistic regression, second differences can be compared (Mize et al. 2019).

37% of the average marginal effect of sales inertia and 39% of the average marginal effect of four-cycle closure (figs. 5*A* and 5*B*). To test these indirect effects, we calculate the difference in average marginal effects between models 6 and 7 (Mize et al. 2019; Duxbury 2021). The indirect effects of sales inertia and four-cycle closure decline in size over time and, in the case of four-cycle closure, become insignificant in the final month of observation (figs. 5*C* and 5*D*). These results demonstrate that transaction networks help actors construct reputations in the early stages of online illegal drug market development but are rendered redundant once vendors accrue a critical mass of reputations in the later stages of an illegal market's life course.

In sum, results demonstrate that market actors rely on transaction networks to conduct illegal drug trade and reduce risk and uncertainty, especially in the early stages of online illegal market development. Descriptive findings reveal a highly structured transaction network with far more prevalent repeated exchange than is observed in legitimate online markets and far greater closure than is observed in random networks of the same size and density. Results from REMs reveal that the average effects of closure and dyadic embeddedness are substantial, each comparable in size to reputations. Further mediation and moderation analyses show that transaction networks' effects are nonlinear, powerful, and positive when markets are young but negative or insignificant once markets mature. These findings demonstrate that transaction networks are an important, understudied determinant of online illegal market growth that operate to build trust and promote cooperation among anonymous actors in risky illegal exchange.

DISCUSSION

Theoretical work 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 Wehlinger 2013, p. 18). Yet, this argument is contradicted by the infrequency of recurrent exchange in online legal markets and the often short-lived nature of social ties among criminal offenders. Using novel digital trace data on darknet drug trade, we examined the prevalence and impact of complex transaction networks on online illegal drug trade during the first 14 months of market activity. Findings reveal a highly structured illegal trade network characterized by complex interactions, including frequent recurrent drug exchange and high levels of network closure. Statistical network analyses demonstrate that these network properties pattern illegal drug trade, carrying powerful direct and indirect effects in the early stages of market development. Collectively, these results demonstrate that endogenous illegal trade networks emerge to resolve coordination problems stemming from high risk and uncertainty implicit in the unregulated social context of online illegal drug trade.

Our findings provide insight into how networks develop to facilitate risky illegal exchange under conditions of relative anonymity. While research on both licit and illicit markets has focused primarily on how preexisting personal relationships are mobilized to conduct trade (e.g., Granovetter 1985; Coleman 1990; Uzzi 1996; Beckert and Wehlinger 2013), we demonstrate that transaction networks of illicit economic relations among pseudonymous market actors can emerge endogenously to form feelings of trust, familiarity, social obligation, and loyalty. Thus, although online market actors are anonymous at the time of market entry, they come to establish interpersonal social relations through histories of successful exchange and bipartite closure that confer trust to embedded market actors. This endogenous process explains how social capital develops in pseudonymous exchange environments and promotes illegal trade in online markets.

While past research has considered how illegal market actors enforce cooperation through geographic monopolies, violence, and intimidation (Jacques and Wright 2008; Reuter 2009; Papachristos, Hureau, and Braga 2013), less has examined cooperative exchange behavior within illegal markets. Our findings shed new light on how endogenous exchange structures influence illegal market development. Finding that transaction networks in online illegal markets facilitate illegal drug trade indicates that patterns of complex economic relations contribute to cooperation in criminal markets. As such, while prior studies have examined elasticity, price setting, vulnerability, and dominance hierarchies in illegal markets (Reuter 1985; Becker et al. 2006; Bouchard 2007; Bushway and Reuter 2008; Caulkins and Reuter 2010), we show that transaction networks play an important role in patterning the cooperative aspects of illegal market operations.

Sociological theory on economic action posits that exogenous social networks are a prerequisite for trade (Granovetter 1985; Uzzi 1996; Hillmann and Aven 2011). The development of online markets is typically viewed as an exception to the rule, where exogenous social relations are initially mobilized to develop formal reputations (Kollock 1999) but are later rendered irrelevant (Diekmann et al. 2014; Przepiorka et al. 2017; Ladegaard 2020). We advance this literature by highlighting endogenous trade structures' role in building trust and social capital among market actors, even in the absence of preexisting social ties. While past research details how endogenous trade structures facilitated unsupervised trade by increasing surveillance and circulating reputational information (Greif 2006; Hillmann and Aven 2011), we show that endogenous trade structure can promote trade even when networks are not depended on for information exchange. Therefore, our results provide an important addendum to current wisdom on the social sources of economic action: the structure of trade networks may be sufficient to facilitate cooperation in risky exchange, net of exogenous social ties and information exchange.

Although we develop our study with attention to online illegal markets, we expect such mechanisms to generalize to legal trade and that endogenous trade structures can contribute to social capital formation in offline settings. We, therefore, expect that future research on the sociology of legal and illegal markets can gain much insight by accounting for the effect of endogenous trade structures on many economic outcomes. Although we focus on cooperation in illegal exchange, illegal markets face additional coordination problems, including competition and valuation (Beckert and Wehlinger 2013; Bakken et al. 2018; Ladegaard 2020). We anticipate that, much like cooperation, valuation and competition are also shaped by endogenous trade networks, where clustering and embeddedness facilitate competitive advantage and may influence the prices charged for illegal goods (see also Moeller and Sandberg 2019).

Results carry further implications for research on criminal group dynamics. While theoretical and qualitative work on criminal organizations suggests that social ties promote trust (Gambetta 2009), other research finds that social relationships between specific offenders are usually short-lived and that membership in criminal groups is short lasting (Warr 1993; Ouellet et al. 2019). Our findings reveal that economic ties tend to increase illegal trade by facilitating social bonding between pseudonymous online actors. Thus, while social ties may be short lasting in many criminal contexts (i.e., Warr 1993), those ties that do persist across time are critical for illegal market success. These results are consistent with recent evidence that long-term social relationships are a robust determinant of criminal organization structure (Smith and Papachristos 2016) and are positively related to the life span of gangs (Pyrooz et al. 2013; Ouellet et al. 2019).

Further, our findings shed light on why transaction network structures have remained undetected in prior research on online markets. Prior studies do not use comprehensive data on online exchange covering the life course of a market. Because prior studies do not measure online trade in markets' nascent stages, they are likely omitting the critical period when transaction networks matter most from their data and analyses (see also Kollock 1999). More research is necessary to uncover how transaction networks emerge in online markets and what social dynamics promote the formation of specific transaction network structures (i.e., graph motifs) that influence online trade.

To policy, we provide an empirical assessment of recently proposed strategies for policing online drug markets. Criminal intelligence agencies have struggled to develop effective policing methods for disrupting online drug markets, as law enforcement interventions tend to have minimal effect despite huge overhead costs (Decary-Hetu and Giommoni 2017; Ladegaard 2019) and may even strengthen online drug markets by promoting technical innovation (Ladegaard 2020). Some scholars have argued for new context-specific "trust-based" policing strategies that seek to undermine trust in online drug markets (Duxbury and Haynie 2018*b*). While this strategy is theorized to be ineffective for deterring activity among the most active actors on large markets, it is expected to deter trade on new markets. Finding that transaction networks, which facilitate illegal trade by establishing trust, are particularly important in the early stages of market development lends support to this policy recommendation, suggesting that online drug markets are especially vulnerable to trust-based policing interventions during this stage of market development. It also implies that network interventions designed to disrupt illegal trade by breaking up network clusters (e.g., Malm and Bichler 2011; Wood 2017) will be most effective when implemented in the early stages of market development but will be largely ineffective once markets mature.

Although digital trace data provide a unique and information-rich setting to study criminal trade, it is important to qualify conclusions concerning selection effects on online drug markets. Users of online drug markets tend to be more affluent and younger than offline drug buyers (Barratt et al. 2016), and buyers and vendors often cycle in and out of such markets. Since the time of data collection, Silk Road 3.1 grew into a relatively large market. While case studies of relatively large markets are beneficial for theory-driven inquiry, we cannot comment on other markets' growth processes in their early stages. We expect that a well-formed trade network structure may be a factor in determining some markets' success over others. Future research should seek to replicate our findings by comparing networks' role in successful and unsuccessful emerging online illegal markets to determine whether well-formed network structures determine market success.

Further, our use of public ratings to construct trade networks suggests that private transactions are missed. While Bradley's (2019) study suggests that the aggregate network structure of online illegal markets is mostly preserved by examining public sales ratings alone, further work may benefit by considering the role of networks in private exchanges.

Recent studies show that drug supply restrictions can significantly affect darknet drug trafficking (Martin et al. 2018; Ladegaard 2020). For instance, some have suggested that government-mandated social distancing during the COVID-19 pandemic has throttled drug supply through online channels by jeopardizing the ability to deliver drugs through postal services (Bergeron, Décary-Hétu, and Giommoni 2020). As many new drug buyers enter unfamiliar and highly risky online drug markets, they likely rely on transaction networks to ascertain vendor trustworthiness and make purchasing decisions. The the current coronavirus pandemic may carry implications for not only the overall trajectories of darknet drug purchasing but also the transaction networks that sustain darknet drug markets.

In sum, this study examined the growth and development of online illegal markets. Results reveal that the network structure of buyer-vendor economic relations promotes criminal drug trade and that these effects are pronounced in the early stages of market development. Collectively, results provide persuasive evidence that transaction networks are a powerful force patterning risky social exchange under illegality and anonymity conditions, comparable even to the reputation systems credited with maintaining legal online markets. As federal spending on combating illegal drug use continues to climb alongside fatal drug overdose rates, it is critical to continue examining the social processes that promote illegal market growth and how these insights can be used to cull illicit substance distribution.

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