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Shadow markets and hierarchies: comparing and modeling networks in the Dark Net

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Abstract. This paper analyzes the determinants of network structure, as measured by hierarchy and monopolization, by examining various black market networks. We examine structures of networks on the Internet Dark Net (Virtual) and compare it to network structures of traditional black markets (Ground), using agent-based modeling. The purpose of modeling these two different types of illicit markets is to understand the network structure that emerges from the interactions of the agents in each environment. Traditional black markets are relatively hierarchical, with high degree and high betweenness. We compare the density and average length of the shortest path of the simulated Ground black market networks with our simulated Virtual network. We find that hierarchy and monopolization tendencies in networks are products of different transaction costs and information asymmetries. The Internet is an effective way to lower multiple aspects of network structure. We observe that the network structure surrounding the interactions in the Virtual black market is less hierarchical and slightly more monopolistic than the network structure of the Ground market.

1. Introduction

In 2011, a young man by the name of Ross Ulbricht changed the game of illicit goods exchange. He created the first ever website that allows for illicit and anonymous exchange to happen over the Internet. No longer were sellers bound by their personal networks or geographic location. With the introduction of the Internet into direct illicit goods exchange, sellers could vastly expand their customer base to a global audience. They could now reliably exchange goods from the comfort of their home, rather than having to go to the streets. Ulbricht's

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new forum broke many rules that bound traditional black markets. In our paper, we investigate some of the limitations he surpassed and their consequences.

Before the advent of the Internet black market, illicit markets were characterized by face-to-face interaction, geographical proximity, and social connections. These features determined the way in which information about buyers, sellers, and the very goods exchanged emerged and circulated. Of course, technological innovation disrupts these underlying conditions, forcing market participants to adopt new institutional arrangements. The Internet black market has created new environments for illegal markets to develop. It is imperative to understand how these market networks emerge and function in order to understand why some persist and others fail (Everton, 2012; Gunaratna, 2006; Jones, 2016).

Criminal organizations, as detailed by Buchanan (1973), Fiorentini and Peltzman (1995), Leeson and Rogers (2012), and Schelling (1971), result in (1) a tendency to the monopolization of one or more illicit markets and (2) the adoption of a vertical organizational structure in order to both exploit economies of scale and restrict access to the market.

This paper focuses specifically on these characteristics and their manifestation in market networks. We compare the structure of illicit Ground networks (which rely on face-to-face or in-person transactions) with the network structure of illicit Virtual networks (which exist on the Dark Web). The purpose of modeling these two different types of illicit markets is to understand the characteristics of the network structure that emerges from the interactions of the agents in each environment, subject to different constraints, and to discuss their economic implications. We build upon the existing organized crime and network literatures by analyzing the different market structures that emerge for the same traditional illicit goods and services given different constraints.

We use an agent-based model to simulate the conditions in Virtual and Ground networks, which allows us to analyze the network structures that emerge. Distributions of degree and betweenness are compared, along with network-level measures of density and average path length. Degree tells us the number of connections each agent has while betweenness tells us the number of shortest paths that run through each agent; both are node-levels measure. These measures of network structure allow us to compare the network structures, including monopolization and hierarchy, of a simulated Ground drug network and a simulated Dark Web network. We define hierarchy as a system or organization with different levels of authority where groups are ranked in order of authority and central control (Mayntz, 2004). We also look at monopolistic tendencies (Ogus, 2002), which result in fewer prominent sellers dominating the marketplace.

In what follows, we examine the determinants of network structure and hierarchy on the Internet black market relative to traditional black markets. Section 2 includes an overview of the digital marketplace for illicit goods. In section 3, we frame our argument within the organized crime and network literatures and our hypothesis for how we can expect our network simulation to look. Section 4 provides testing of our hypothesis with an agent-based model. Section 5 concludes.

2. The digital marketplace for illicit goods

The Deep Web

To understand the Deep Web (also known as the Dark Net), we first define the Surface Web and the Deep Web. The Surface Web is comprised of content on the Internet that can be found using a search engine. If Google, Bing, or Yahoo can find certain information, it exists on the Surface Web. Surface Web information is both accessible and indexed. The Deep Web consists of information that cannot be found using a search engine.

For example, if you buy something online from Amazon using a credit card, this information cannot be accessed via a search engine. Online businesses encrypt this private information to secure their customer's privacy. Organizations such as public libraries, local governments, and businesses manage much data in the Deep Web (Christin, 2012). Information on the Deep Web is estimated to be hundreds, if not thousands of times larger than information on the Surface Web (Deep Web: A Primer, n.d.). This information is accessible but non-indexed: authorized individuals may access this data, but the public cannot. The Dark Net is a subset of the Deep Web: it contains information that is both restricted and non-indexed. Activity on the Dark Net that deals with exchange is done using anonymous routing technology (Gaup, 2008).

Tor: the Onion Router

Tor is a network within which users can search and exchange anonymously over the Internet. It is a volunteer-operated network that protects the privacy of hundreds of thousands of users daily (Tor Project, 2015). Tor enables users to protect their identity more effectively when searching online, avoiding surveillance, circumventing censorship, and bypassing firewalls. The network is decentralized and cannot be shut down from an administrative location. The routing system functions in a diffuse way, which prohibits law enforcement's ability to identify specific users (Martin, 2014). The robustness of its security lies in the diffusion of trust throughout the system (Johnson *et al.*, 2011). Using Tor is not costless; it takes a few extra steps to download and is extremely slow when making a transaction, relative to surface web sites, because of the encryption and evasion involved in each transmission being made (Dingledine and Murdoch, 2009).

As an open-sourced router, Tor connects users in its network and randomly "bounces its user's Internet traffic through several other computers to keep it anonymous" (Internet Freedom, 2015). The Tor network is made up of relays, which are publicly listed nodes in the Tor network that forward traffic on behalf of clients, and register with the directory authorities (McCoy *et al.*, 2008; Tor Metrics, 2015). There are roughly 3,000 relays in the entire Tor network (Tor Project, 2015). A client is a node in the Tor network, typically running on behalf of one user, which routes application connections over a series of relays.

Tor is like mix networks because messages are wrapped in layers of encryption. This encrypted information contains keys to all the intermediate nodes that the information will reach before it reaches its final destination. When the information reaches each node a layer of encryption is lost and the information continues traveling randomly throughout the network, losing layers of encryption as it goes (Gaup, 2008). This network allows for anonymous and untraceable communication because there is no correspondence between incoming and outgoing messages from each node the information travels through (Gaup, 2008).

This technology was originally funded and developed by the United States Navy to "protect intelligence gathering from open sources and to otherwise protect military communications over insecure or public networks" (Syverson, 2013). So, there are Tor users who are engaging in legal behavior, as the technology was originally intended; however, the black market on Tor has exploded in size and scope (Johnson *et al.*, 2011).

Cryptomarkets

The Internet black market is a widely used group of sites on Tor; this anonymous network, coupled with Bitcoin, allows users to make purchases securely and anonymously over the Internet. These cryptomarkets make hundreds of millions of dollars a year and their operations are continuing to expand (Kruithof *et al.*, 2016). In January 2016 alone, it is estimated that the cryptomarkets generated a monthly revenue of between $14.2 million (excluding the sale of alcohol and tobacco) and $25 million (including all visible listings) (Kruithof *et al.*, 2016). There have been over 80 platforms that have existed or still do exist on the Internet black market. Some have been hacked, raided, scammed or voluntarily shut down and over 20 different platforms are still in operation today (Branwen, 2015).

Internet black market websites look much like typical surface web vendors. When buyers enter a site, they are brought to the home page, which lists the categories of goods and services available. Image 1 (Norgaard *et al.*, 2017) shows the home page of Wall St. Market. Categories of goods and services sold on this market include drugs, counterfeits, jewelry and gold, and security and hosting (Wall St. Market, 2017). From the home page, buyers can click on a category of interest and they will be directed to a page listing all available products or services in that category. Image 2 (Norgaard *et al.*, 2017) shows some of the listings available under the "Drug" category on Hansa market (Hansa, 2017a). When buyers click on a good or service, they are brought to a page that shows the specifics of the product, including shipping procedures, quantity, description, and vendor rating.

Image 3 (Norgaard *et al.*, 2017) shows a type of MDMA being sold on AlphaBay Market. This listing describes various packaging options, shipping options, vendor level (some sites rate their vendors on a level scale rather than a star rating system), and other product details (AlphaBay Market, 2017). On each product page, buyers can also view feedback left by previous customers. Image 4 (Norgaard *et al.*, 2017) shows feedback left by buyers on the MDMA product in Image 3. Buyers can purchase goods in Bitcoins and most sites show the price equivalent in US dollars or Euros based on the exchange rate of that day. Buyers then type in their contact information, name and address, which is encrypted and sent to the seller. Most sites have an expiration date for when the seller can view the buyer's personal information.

This black market is an environment that, relative to traditional markets, has less asymmetric information, higher entry costs, and lower transaction costs (Hardy and Norgaard, 2015). Platforms on the Dark Net can identify and enforce property rights more effectively owing to the ease of contract enforcement, reliability of privacy, trustworthiness of sellers, use of branding, and use of anonymous currency, all of which will be discussed below.

Platform providers can use various code bases to make marketplaces within the Dark Net, sellers then advertise their goods on these different sites. Some sites are open to anyone; others require a referral (Bakken, 2015). Sellers utilize various techniques to attract buyers. The use of logos, community bonding through forums, and reputation through repeated interaction creates a more transparent and user-friendly community (Bakken, 2015). Marketplace administrators play a critical role in dealing with vendors who scam customers or sabotage each other. Kruithof *et al.* (2016) presents an analysis of the rules of ten cryptomarkets that keep the markets functioning. Vendors have explicit dispute resolution procedures to protect their users and prevent fraudulent behavior. Image 5 (Norgaard *et al.*, 2017) shows dispute resolution procedures on Hansa, an Internet dark market site (Hansa, 2017b). The platform encourages the buyer and seller to solve the dispute among themselves; if private dispute resolution is not possible, Hansa staff follow a delineated resolution procedure. If the dispute is ruled in favor of the buyer, the staff member will force the vendor to compensate the wronged buyer (Hansa, 2017b).

Various sites rank their members based on their tenure and the trust they have built up on their site, Image 6 (Norgaard *et al.*, 2017) shows different participants in Silk Road 2 (a specific Dark Net site), and their corresponding site rankings (Bakken, 2015). Customers also rate the vendor's products on a scale from 0 to 5 stars (Dolliver and Kenney, 2016). This rating system allows vendors with high ratings to charge a premium for their products because of their good reputation (Hardy and Norgaard, 2015).

The most popular and widely adopted anonymous crypto-currency, Bitcoin, is used as a medium of exchange on Tor. A Bitcoin is technically a solution to a mathematical equation with a fixed set of solutions (Grinberg, 2011). This digital currency is stored in a virtual "wallet," like cash, and is exchanged with low transaction fees through anonymous virtual transactions (Briere *et al.* 2013). As a peer-to-peer currency, it does not require verification from a central third party (Christin, 2012). Bitcoin uses the Blockchain, a transparent public ledger distributed by a peer-to-peer network. This Blockchain technology prevents 'double spending' of Bitcoins by certifying that the same Bitcoins haven't already been used in a transaction (Trautman, 2014). Thus, exchanges made using Bitcoins over the Tor network are extremely difficult, if not impossible, to trace.

Digital, anonymous drug communities are increasingly innovative in their capacity to retail and market drugs, provide information for users regarding drug sourcing mechanisms, advise around optimal use, and host discussions around popular choices, experiences and harm reduction practices (Gordon *et al.*, 2006; Griffiths *et al.*, 2010). Widespread drug product availability is fueled by novel drug-trading sites such as Black Market Reloaded, The Armory, and the General Store (Christin, 2012).

3. Markets and hierarchies

Organized crime

The organized crime literature explains the organization and actions of criminal groups in terms of the incentives faced by criminals as rational actors. A universally accepted definition of organized crime has yet to be delineated, thus there are various illustrations as to what constitutes organized crime. It has been characterized as a long-term arrangement among criminals without state enforcement (Leeson, 2007) and as more of a predatory relationship rather than a voluntary and firm-like exchange (Skaperdas, 2001).

Regardless of the technical definition, however, organized crime is a question of costs and benefits. Criminals decide to interact with one another when they can receive higher compensation from organizing rather than acting alone (Chang *et al.*, 2005). The organized crime literature explains the organization and actions of crime groups in terms of the incentives faced by criminals as rational actors.

The model of the rational criminal, developed by Becker (1968), lays the foundation for the literature of organized crime. He applies the basic economic framework of analysis to this peculiar non-traditional market. Schelling (1971) posits that the organizational and network structure that organized criminals seek is one of monopoly or hierarchy without competition. This, he argues, is a defining characteristic of organized crime; "organized crime is usually monopolized crime" (1971, 182). Schelling finds that there is a tendency toward monopolization because of the nature of illicit goods themselves. The exchange of illicit goods results in the potential for violence, thus organizations form with the ability to exclude outsiders (1971).

Because there is no third-party enforcement of criminal contracts, criminals must police themselves, thus tending to band together. The nature of this environment leads to one in which these organized criminals seek exclusive influence and authority of their territory and work to keep other criminal groups from invading. However, Schelling notes that "rival claimants to monopoly position sometimes find it cheaper to merge than to make war" (1971, 645). Therefore, Schelling also concludes, there is a tendency toward monopolization in organized crime settings (Schelling, 1971).

Buchanan (1973) argues that organized crime groups have monopolistic tendencies as well. Because monopolies limit the supply of goods, they are socially desirable in a criminal setting. The equilibrium amount of crime supplied by a monopoly is smaller than the amount of crime supplied by multiple criminal groups (Backhaus, 1979). The purpose of a monopoly has always been to suppress, not enlarge, supply, especially in a criminal setting (Schelling, 1971). Fiorentini and Peltzman (1995) characterize criminal organizations as groups that exploit monopolistic prices on the supply of illegal goods and services and establish a hierarchy that manages risky behavior. Leeson and Rogers (2012) attribute hierarchical criminal organization to market contestability. The lower the entry costs, the more the criminal organization is likely to organize hierarchically. The extent of the hierarchy is that of the current criminal organizations enforcing monopolistic control of the market against potential market entrants (Leeson and Rogers, 2012).

Garoupa (2000) and Dick (1995) emphasize the influence of transaction costs rather than monopoly power in organized crime groups. Transaction costs are the costs of identifying and enforcing property rights (Allen, 1999), something that can be very complex in criminal organizations. Garoupa (2000) argues that transaction costs in underground markets are relatively low, but with imperfect information they will be higher. Jennings (1984), likewise, does not emphasize monopolistic behavior in organized crime. Instead, "oath taking," he posits, is primarily driving organized criminal behavior. The act of committing oneself to a larger organization increases the cost of defection and thus decreases the risk of detection.

A more recent extension of the organized crime literature includes papers in which economic tools have been applied to historical cases of organized crime. These papers are like our work in the sense that they apply this lens to natural instances of organized crime. Gambetta (1996) and Varese (2001) find that Mafia groups, The Sicilian and Russian mafias, respectively, emerged in low trust societies as a substitute for formal property rights enforcement. These mafias had a centralized structure and a permanent and hierarchical organizational arrangement (Gambetta, 1996).

Skarbek (2010, 2011, 2012) likewise, in his research on prison gangs, finds that criminal organizations have emerged to protect inmates, lower transaction costs, and enforce property rights. He finds that "members of the Mexican

Mafia and Nuestra Familia established hierarchical organizations with effective information transmission and enforcement mechanisms" (Skarbek, 2012, 39–40). Leeson (2007, 2009, 2010) finds that some criminal organizations are so sophisticated as to have checks and balances in a constitutionally constrained democratic government like pirates did in the 1900s. Piano (2017), in his research on the Hell's Angels motorcycle club, finds that this criminal organization has been successful because of its hierarchical organization. This network structured has allowed it to mitigate internal conflict while expanding and profiting from its illegal activities.

The organized crime literature also supports the claim that hierarchy plays a very pivotal role in the network structures of criminal markets and is an appropriate component of analysis (Levitt and Venkatesh, 2000; Piano, 2017). Numerous studies suggest that criminal organizations are already embedded into preexisting societal hierarchies, and thus have some level of hierarchical structure themselves (Akerlof and Yellen, 1994; Jankowski, 1991; Spergel, 1995). Lazear and Rosen (1981) argue that, because criminals are overwhelmingly risk-loving individuals, there will be a tournament structure of organized crime where there is an incentive for upward mobility. Group members will compete to rise in the ranks of the organizational hierarchy (Lazear and Rosen, 1981).

Although many of these historical criminal organizations have hierarchal organizational structures, there is evidence to suggest that hierarchy impedes underground market transactions among criminals. In their study of POW camps during World War II, Holderness and Pontiff (2012) found that camps with less hierarchy had higher levels of survival and more flourishing markets within the camps.

Networks and hierarchy

Networks give us the ability to "bridge the gap between the individual and the population" (Comparing Networks, 2008). The importance of network structures for the transmission of knowledge and the diffusion of technological change has been emphasized recently in economic geography, which our paper considers in the Ground network and of which it notes the absence of in the Virtual network (Broekel *et al.*, 2014). Network structures are central in driving the innovative and economic performance of actors in regional contexts, and thus, it is crucial to explain how networks form and evolve over time and how they facilitate inter-organizational learning and knowledge transfer (Broekel *et al.*, 2014).

Barriers to trade, such as high transaction costs and information asymmetries, limit the quantity of individuals participating in the Ground drug network. The removal of these barriers, via digitalization, drives its expansion. "Networking is giving rise to unprecedented opportunities, facilitating internationalization," which is what we observe when the illicit drug market is made available via the Internet (Dana, 2001). Comparatively, the technological barriers to entering a digital market are significantly lower than the associated risks of a Ground network. Virtual networks are associated with much higher levels of efficiency (Buxton and Bingham, 2015; Martin, 2014) and Virtual networks are more likely to provide goods with minimal violence and superior product quality than traditional Ground networks (Martin, 2014).

The literature suggests that there are costs and benefits of hierarchy. Less hierarchical networks are more likely to persist because they are less likely to collapse if key players in the network are removed (Arquilla and Ronfeldt, 2001; Jones, 2016). The more diffuse the network is, the more difficult it is to target and disrupt communications between agents (Eilstrup-Sangiovanni and Jones, 2008). However, more centralized network structures are much more effective at carrying out complex tasks in a standardized way (Eilstrup-Sangiovanni and Jones, 2008).

Hypotheses

Buchanan (1973) and Schelling (1971) suggest that different black markets with different illicit goods for sale will result in varying market structures. We test whether we see varying market structures in the sale of the same goods with different constraints. The Internet black market is a network that, relative to illicit Ground markets, has higher entry costs, less asymmetric information, and lower transaction costs (Garoupa, 2000). We expect information asymmetries to be lower in markets with lower transaction costs. We hypothesize that, given that hierarchy emerges to manage risky behavior (Fiorentini and Peltzman, 1995) and in criminal organizations with low entry costs (Leeson and Rogers, 2012), we will observe a less hierarchical network structure on the Internet black market. We also anticipate that we will observe monopolistic market tendencies because such tendencies are a feature of markets that deal in illicit goods (Schelling, 1971). Our Virtual market network model will therefore be less hierarchical and have monopolistic tendencies.

Preliminary evidence

In the Internet black market, these crime groups are often organized by type of illicit good or by platform type. Many sites will specialize in a few illicit markets, drugs for example. Agora, one of the longest running and most prominent sites on the Dark Web decided to focus more on the sale of drugs and banned the sale of guns, poisons, and fraudulent IDs (I am a Tor, 2015). Some sites will only allow buyers and sellers who have a referral to exchange on the site, limiting the user base to only experienced users (DeepDotWeb, 2017).

We compare whether different constraints on different illicit drug marketplaces results in more or less hierarchy and monopolization. Image 7 (Norgaard *et al.*, 2017) shows a timeline of Dark Net sites that have existed, or still do exist. Over 80 sites have existed since the birth of the Dark Net in 2011 and over 20 are currently in business. The number of sellers has fallen from over

45 sites in business in 2014 (Darknet Market, 2017). In our model, we compare monopolistic tendencies in the Ground market versus the Virtual market by analyzing the number of prominent sellers that emerge. We expect monopolistic network structure to be a characteristic of both modeled marketplaces.

Although behavior on the Internet black market is risky, there are fewer information asymmetries, which makes risk, relative to illicit Ground markets, lower. Even with surface web exchange, transaction costs are much lower than in a traditional marketplace: it gives users access to many more vendors then they are geographically close to. Similarly, on the Internet black market, transaction costs are drastically lower than those of Ground markets. Like these historical cases covered by the literature, we emphasize the importance and prevalence of hierarchy, and analyze how hierarchy is different under different constraints.

4. Testing our hypothesis using agent-based modeling

Purpose

Schelling (1971) postulates: “in a purely descriptive sense this tendency toward monopolization surely seems to characterize organized crime” (1971, 183) and we test this descriptive claim on different network structures, along with claims that organized crime groups tend to be hierarchical, with empirical evidence and agent-based modeling.

Network analysis paves the way for a deeper understanding of various marketplaces, especially those for which the data is not plentiful. Due to the anonymous nature of the Internet black market, it is virtually impossible to gather data on real-world transactions made between buyers and sellers. Therefore, agent-based modeling provides an appropriate modeling platform from which we can build out the network structures of these two different marketplaces without knowing the specific transactions within them. Agent-based modeling allows us to simulate transactions in these types of marketplaces, using what we know of these markets as our given conditions, and observe the network structure that emerges from numerous interactions among agents.

The model is built using the object-oriented modeling package NetLogo. It makes use of the network extension that allows agents to interact on top of an imported or generated network. This agent-based model is a model of two different types of illicit drug markets. The first type of drug market modeled is a Ground market, a traditional black market, where interactions between agents take place in person and potential buyers do not have perfect knowledge about the reputation of sellers. The second type of drug market modeled is a virtual drug market, existing on the Internet, where interactions and exchanges between agents do not take place in person. Attributes about sellers’ reputation are salient. The purpose of modeling these two different types of illicit markets is to understand the network structure that emerges from the interactions of the agents in each environment, given the nature of the goods and services. We specifically look at the monopolistic tendencies of the networks as well as the hierarchical structures that emerge.

Substantive differences in the functioning of these different markets should give rise to different overall network structures. The hallmarks of the Ground network are spatial constraints on interaction and the limited or imperfect information that agents use to make the decision to engage in trade. The hallmarks of a Virtual network are the lack of spatial constraints on agent interaction and "perfect" information made available via the Internet. Agents can use this information to guide their decisions on interaction and exchange. A network analysis and examination of the networks and structures that emerge from both networks will be the basis for comparing the functioning of these two types of illicit markets.

The mechanics of agent-based modeling

In the past, scientific models have been limited in scope and scale by computational constraints. Computer simulations have expanded the potential for scientific models and have allowed them to include more characteristics of realistic systems. Agent-based modeling is a type of modeling that includes a system's individual characteristics and unique behaviors (Railsback and Grimm, 2012). This type of modeling allows us to model individual agents with unique constraints and endowments, unlike historical models, which often look at the state as an entire homogeneous entity. Each "agent" is like a person in an artificial society. Agents have unique behavioral rules and are given different internal states. Some of these states are variable, while others are constant for the agent's life (Epstein and Axtell, 1996).

The hallmark of agent-based modeling uses object-oriented programming that creates agents that are purposeful, heterogeneous, and interacting. Our model uses NetLogo, a package specifically designed for building, visualizing, and experimenting on agent-based models. This type of programming enables the agents to be purposeful and to interact in a given environment. It focuses specifically on the objects, their constraints, and their resulting interactions (Downey, 2012).

Our model

The Ground model and the Virtual model consist of agents who can both consume and acquire drugs. In the Ground model the agents exist in a two-dimensional spatial landscape. The Virtual model does not include this spatial dimension because the agents can be located anywhere and they use a Virtual network (i.e. the Internet) to interact and engage in exchange. The agents in both models share many of the same attributes like the types of goods and agent reputation; however, there are also attributes that are unique to each model. These differing attributes provide us the variation in our analysis to compare the two different emergent network structures.

Reputation is an agent attribute common to both models. The reputation variable is derived empirically from Deep Web data (Hardy and Norgaard, 2015) and, in the model, represents the true reputation of each agent. Reputation is included in the model because "[it] is crucial ... as a signal to other users that they are honest and credible individuals. This signal works to differentiate between honest and dishonest users to ensure that honest users are not driven out of the marketplace by dishonest users that are not properly identified" (Hardy and Norgaard, 2015). It is a latent variable in the Ground model because one of the hallmarks of the Ground model is imperfect or incomplete information. Reputation is a salient attribute in the Virtual model because all agents can use the Internet to view the derived reputation of every other agent. In Virtual markets users have strictly more information about sellers, including information about lack of reputation, than those in Ground markets.

Imperfect reputation is an agent attribute unique to the Ground model. An agent's imperfect reputation is based on the true reputation assigned to them based on an empirical distribution of the Deep Web data. It is normally distributed around the agent's true reputation and represents an agent's imperfect perception of another agent's reputation.

An agent's sophistication is an agent attribute that is normally distributed around the average sophistication specified in the model. In both the Ground and Virtual models it represents a latent variable that encapsulates information about an agent's involvement in the market, specifically on whether it is correlated with the stock of drugs with which each agent is instantiated. In both models, stock is an agent attribute that is normally distributed around an agent's sophistication. In the Ground model, sophistication is also correlated with how far each agent can see around their unique spatial environment and consequently, it determines what other agents with whom they can interact. An agent's vision specifies the other agents with whom she may interact, based on location.

Consumption is normally distributed around the around the average rate of consumption specified in the model, it is the amount of drugs an agent consumes each time they use drugs. Tolerance is another agent attribute for the number of "doses" of a drug an agent wants to have available to them. It is a threshold value above which an agent will not feel the need to acquire more drugs but that below the threshold would cause them to make the decision to search for and acquire more drugs.

Commenting is an agent attribute unique to the Virtual model. This variable is empirically derived from Deep Web data (Hardy and Norgaard, 2015) and represents the number of comments an agent has received on their Virtual seller profile. The number of comments are included as a property on the agents because:

> Due to the anonymity aspects of The Silk Road, buyer information is not formally posted like seller information and feedback is on the site. Unlike Surface Web marketplaces like Amazon or EBay, if a buyer leaves a comment and/or rating, an individual identifier is not attached to their message to protect buyer anonymity. The only information that we can glean about the buyer is that the Silk Road site has confirmed that that particular buyer did make a purchase from a particular seller. Therefore, buyers cannot leave comments on seller's pages from which they did not buy a product. (Hardy and Norgaard, 2015)

Commenting is a salient attribute in the Virtual model because all agents can use the Virtual network to view the number of comments on every other agent when making their decision to acquire more drugs.

There are two agents' attributes that are unique to the Virtual network and that deal with the risk preferences of the buying agent and the riskiness of a selling agent. Risk is an attribute noting if the buyer is risk loving, risk averse, or risk neutral. This variable is assigned based on a survey conducted by Gallup (2014) which quantified the distribution of investors that were risk loving, risk averse, or risk neutral. The variable for a high-risk seller is a flag that denotes whether an agent's reputation falls above or below the risk threshold specified as a global variable in the model.

Process overview and scheduling

At each step in the model a random activation scheme is used to activate all the agents in the model become active. Each one of these agents uses drugs (i.e. buyers can be sellers and sellers can be buyers) as supported by the findings of Van Hout and Bingham (2014); they write, "vendors described themselves as 'intelligent and responsible' consumers of drugs. Decisions to commence vending operations on the site centered on simplicity in setting up vendor accounts, and opportunity to operate within a low risk, high traffic, high mark-up, secure and anonymous Dark Web infrastructure. The embedded online culture of harm reduction ethos appealed to them in terms of the responsible vending and use of personally tested high quality products." In both models, the agents continue to engage in transactions as their individual stock and overall stock decreases. Individual agents can have a "negative stock" of drugs. This results from many agents wanting to buy drugs from the same supplier. After models in which a popular selling agent's supply drops below its tolerance threshold have been ticked they will no longer be included in the list of possible sellers that other agents in the model can buy from. Agents are endowed with a certain stock of drugs at the beginning and never have their stock replenished by some outside supplier of drugs. This aspect of drug market models is outside the scope of this paper but could be a rich area for further research and modeling. The model continues to run until the total stock of drugs falls to zero or below.

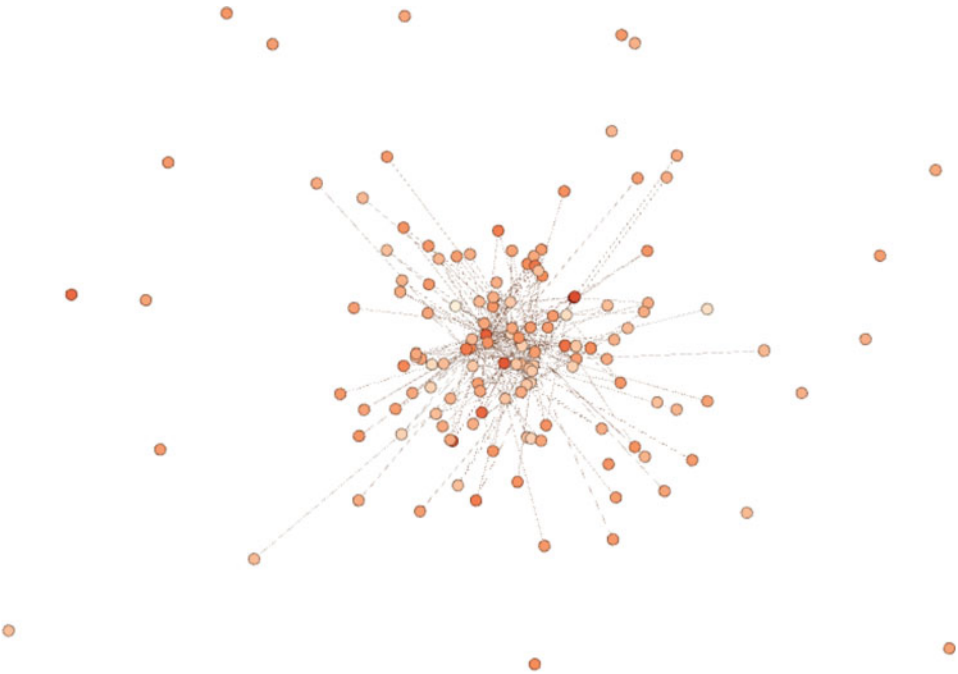
Process overview of Ground model

The Ground model is a spatially explicit model that is set up by assigning each agent a random position on a 2D x–y plane. Agents can only interact with other agents that are within their own-vision. At each tick of the model, every agent reduces their stock of drugs by the amount of their consumption. After this, each agent checks to see if the number of "doses" they have left is less than their tolerance. Agents subtract their consumption from their current stock to arrive at the number of "doses" they have remaining. If this number is less than their tolerance they will decide to buy more drugs. The amount that the buying agent wants to buy is normally distributed around five, meaning that on average whenever an agent buys drugs they are buying five doses of drugs. The buying agent creates an agent set (called possible-sellers) of agents that are within their own-vision (i.e. agents with whom they can interact with in the model). This simulates the geographic constraints faced by the agents in the Ground model. The agents that don't meet this criterion are thrown out of the possible-seller agent set. The remaining possible-sellers set their variable, called imperfect reputation, according to a standard normal distribution that is centered on their actual reputation. The buying agent then picks the seller with the highest imperfectly perceived reputation and this agent becomes the final dealer. A link is made with the final dealer; the final dealer has their stock reduced by the buying amount and the buying agent has their stock increased by the buying amount.

Process overview of the Virtual model

The Virtual model is not spatially explicit and is setup by instantiating the agents with their own reputation, number of comments, and their risk and risk aversion. At each tick of the model every agent reduces their stock of drugs by the amount of their consumption. Agents then divide their current stock by their consumption to arrive at the number of "doses" they have remaining. They check this against their tolerance: if the number is less than their tolerance they will decide to buy more drugs. The amount that the buying agent wants to buy is normally distributed around five, meaning that on average whenever an agent buys drugs they are buying five doses of drugs. The buying agent can view every other agent in the simulation and creates an agent set of those agents (called possible-sellers) that have enough drugs to sell such that their selling of their drugs will not cause their number of doses left to fall below their tolerance. If the buying agent is risk-averse they limit the existing possible sellers to those that are low risk and if the buying agent is risk loving then they limit the existing possible sellers to those sellers that are high risk. If they are risk neutral then there is no change to the existing set of possible sellers. At this point the buying agent looks at the number of comments each possible seller has and limits their choices to those agents with the higher numbers of comments. The agent with

Figure 1. (Colour online) Network structure of Virtual network (Average Degree: 2.03; Density: 0.014)



the highest reputation in this group is selected as the final dealer. A link is made with the final dealer and the final dealer has their stock reduced by the buying amount and the buying agent has their stock increased by the buying amount.

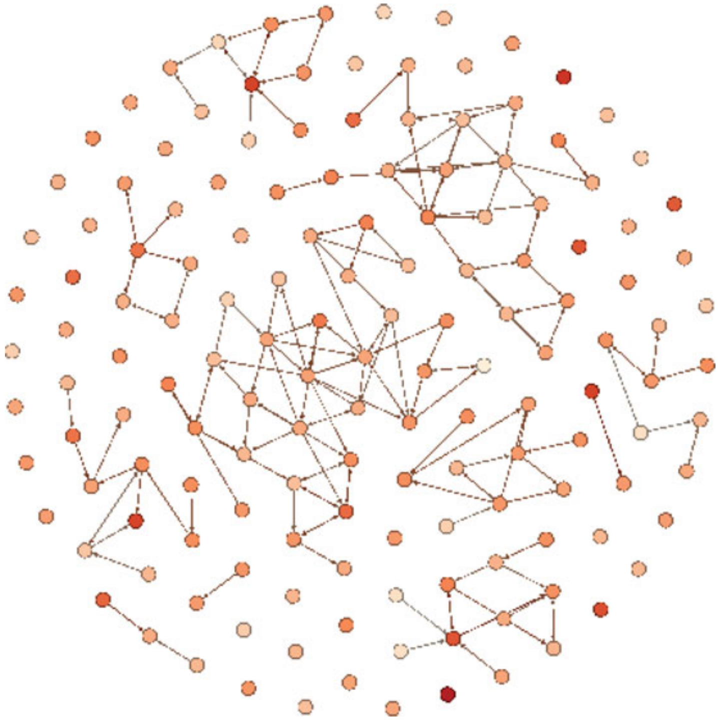
Results

Casual visual inspections of the directed networks that emerge from the interactions that take place inside the Virtual and Ground models reveal two very different network structures. Figures 1 and 2 show examples of the networks that emerge from the Virtual and Ground models, respectively.[1] Both models were run using a value of 3 for the sophistication parameter and an average rate of consumption equal to 0.4. The risk threshold, which is unique to the Virtual model, was set at 4.19. Nodes are differentiated on the agent attribute of reputation.

A series of parameter sweeps were conducted on both the Virtual and Ground models. The global parameter called "sophistication" was swept at five different levels in both models, and each time the simulation was run a total of 100 times. The metrics used to compare the two models are the following: average

1 These graphs were created from the outcomes of the model in NetLogo using Gephi, a network analysis and visualization tool.

Figure 2. (Colour online) Network structure of Ground network (Average Degree: 1.17, Density: 0.008)



path length, average degree, average betweenness, average network density, the number of weakly and strongly connected components of a graph, and the average percentage of the total transactions that could have happened in the model.

Average path length will give us some idea about the number of agents you would have to go through to get in touch with another random agent. Longer average paths would suggest that it is more difficult to reach out to another agent in the network. A lower average path suggests that the network is less hierarchical because each agent has to go through fewer levels of rank to reach another agent. Shorter average path length can also suggest more monopolization. If buyers have fewer options of who to buy their goods from, they will have fewer agents to connect through to reach the monopolistic seller.

Figure 3 (Norgaard *et al.*, 2017) shows that the average path length, at all levels of sophistication, is between 2.5 and 2.7 in the Virtual network. This Virtual network measure has a much smaller range than the average path length of the Ground network, which ranges from 1 to 6. This means that, when assigned another random agent, an agent in the Virtual network would have to go through less than three other agents to reach them. The Virtual network is less hierarchical than the Ground network, according to this measurement.

Degree, betweenness and network density are standard measures in network analysis that will give us an idea about how central and connected the agents in the network are. Degree and betweenness are node-level measures. Degree tells us the number of connections each agent has, while betweenness tells us the number of shortest paths that run through each agent. Density is a network-level measure, and tells us the portion of *possible* connections in a network that are *actually* connections. Average degree tells us the average number of connections that an agent has and this metric is reported at all five levels of sophistication. Average betweenness tells us the average number of times an agent acts as a bridge between two other agents. Average density gives us the average density of the networks at each level of sophistication after running the model 100 times.

Figure 4 (Norgaard *et al.*, 2017) shows the average degree in the Virtual and Ground networks, respectively. Average degree in the Virtual network ranges from 3.5 to 5, depending on the agent's sophistication, whereas it ranges from 0 to 6 in the Ground network. It is very difficult for agents in the Ground network to make any connections if they have low levels of sophistication because of the prohibitively high transaction costs. Although average degree changes slightly, on average agents in the Virtual network have more connections than agents in the Ground network. This suggests that the Virtual network promotes more peer-to-peer exchange, rather than making agents go through middlemen to buy a product. By this measure, we also observe evidence of monopolization. Because of their market characteristics, transaction costs in cryptomarkets are very low. It is virtually costless for an agent to buy goods from a seller with a 5.0-star reputation rather than from a seller with a 4.9-star reputation. This leads to the emergence of dominant sellers who are highly connected to many buyers. This measure of average degree reflects the large number of connections that each prominent seller has, relative to sellers in the Ground network.

The average betweenness in the Virtual and Ground networks is shown in Figure 5 (Norgaard *et al.*, 2017). Betweenness is a measure of middlemen. In the Virtual network, agents act as a bridge between two other agents between 25 and 38 times, depending on the agent's sophistication. In the Ground network, this number is between 0 and 600 times. This network measure demonstrates how much more direct exchange there is in the Virtual network versus the Ground network. The Virtual network is much more diffuse and less hierarchical, according to this measure.

Figure 6 (Norgaard *et al.*, 2017) shows the average density in the Virtual and Ground networks, respectively. Higher levels of density suggest more monopolization. In the Virtual network, density ranges from 0.012 to 0.016, relative to sophistication levels that range from 1 to 5. The density of the

Ground network ranges from 0 to 0.020. Only at sophistication levels 4 and 5 is the density somewhat higher than the Virtual network. The Virtual network is much more consistently dense, suggesting that it has more monopolization tendencies than the Ground network.

The numbers of strongly and weakly connected components tell us about how well connected a network is. A subgraph (a component of a larger graph) is strongly connected if every vertex (agent, in the case of this agent-based model) is reachable from every other vertex. Figures 7 and 8 (Norgaard *et al.*, 2017) show the average number of strongly and weakly connected components, respectively, at five different levels of sophistication for both the Virtual and Ground models. The more strong clusters a network has, the more monopolistic the network is. Each agent has fewer options and the connections they do have are very strong. The greater the number of weak clusters, typically the more competitive a network is. We observe that the Virtual network has between 120 and 134 strong clusters and between 26 and 37 weak clusters, at various levels of sophistication. Whereas the Ground network has between 40 and 140 strong clusters and between 0 and 130 weak clusters. This measurement demonstrates that Virtual networks are more monopolistic at various levels of sophistication and Ground networks are less monopolistic.

The only non-network measure drawn from the modes and analyzed is the percentage of transactions that took place in the model. This metric is defined as the number of transactions divided by the number of possible transactions. More exchange will take place if there are lower transaction costs. It tells us the level of activity inside the model. Figure 9 (Norgaard *et al.*, 2017) shows the average percentage of transactions that took place at each level of sophistication. The average percentage of possible transactions in the Virtual network ranged from 22 to 40%, and in the Ground network they ranged from 4 to 30%. We observe many more possible transactions taking place in the Virtual network because of the overall lower transaction costs and increased information availability.

5. Conclusion

Due to their high entry costs, low transaction cost environment, and relatively symmetric information, Virtual black markets exhibit much less hierarchy but more monopolistic tendencies than Ground black markets. We measure hierarchy using path length, degree, and betweenness and measure monopolistic tendencies using density and strong and weak clustering. We build upon Buchanan's (1973) and Schelling's (1971) work about the emergence of varying market structures. However, we find that different market network structures emerge with the same illicit goods, given different constraints. The concentration of the market on the Internet black market is higher than in the Ground market, suggesting that the extent of monopolistic tendencies is attributable to the structure of the market, not the good being exchanged.

This paper is a first attempt to disentangle the peculiar differences between digital drug marketplaces and Ground markets, particularly with regards to network structure. This research serves to inform future study on digital market structure, and has numerous applications in other fields of research. The way in which this digital market shortens the distance between buyers and sellers is important to understanding the emergence of other digital markets. Because we find that Virtual markets are less hierarchical and more monopolistic than Ground markets, we build upon the contributions of Eilstrup-Sangiovanni and Jones (2008) and Arquilla and Ronfeldt (2001). We find that different market constraints, namely geographical limitations and the availability of reputation, are driving the extent to which a network is hierarchical and/or monopolistic. Our results suggest directions for future work, particularly in the field of market monopolization, namely what market characteristics lead to more or less monopolization and when we can expect monopolistic markets to emerge.

The less hierarchical nature of the Virtual black markets suggest that they will be much more difficult to dismantle and disrupt. Standardized, overarching improvements and changes will be more difficult in this type of network, however, because it is so diffuse, it will be more difficult than Ground markets to target and take down. As the global economy shifts toward digital trade, how will participants adjust their behavior? How will policy makers and law enforcement adjust their behavior? Our analysis suggests that Virtual markets result in a further shortening of the links between market participants and a further flattening of the market. This decentralized network structure suggests that it is quite robust.

Finally, this opens new avenues of analysis in law and economics with regards to the legalization of drugs. Legislation based on old models of the structure of modern drug markets will inevitably fail to meet their goals. They will bring in less tax revenue as users continue to use digital black markets, or even push more users into the digital black markets.

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