Université de Montréal

Are Cryptomarkets the Future of Drug Dealing?
Assessing the Structure of the Drug Market Hosted on Cryptomarkets

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Résumé

Les cryptomarchés sont des plateformes virtuelles, similaires à eBay, qui permettent d'échanger de la drogue en ligne en tout anonymat, de manière professionnelle et sécuritaire. Cette étude vise à caractériser la structure du marché de la drogue sur les cryptomarchés, afin de comprendre le contexte économique. La structure du marché est évaluée selon le degré de concurrence ainsi que la portée et l'importance des vendeurs de drogue en termes de visibilité, de diversité et d'expérience. Les résultats de l'étude illustrent que le marché est concurrentiel mais également très inégal. Les vendeurs ont une portée et une importance relativement limitées. Ceci s'explique par le fait que les transactions en ligne, anonymes et illégales imposent d'importantes contraintes aux vendeurs. Le statut d'illégalité oblige les vendeurs à limiter leurs activités hors ligne, diminuant leur potentiel de croissance en ligne. De plus, le contexte en ligne favorise la concurrence, mais les risques qui découlent de l'anonymat des transactions intensifient la tendance des acheteurs à choisir des vendeurs réputés et expérimentés. Les vendeurs font donc face à des « barrières à la vente » et 90% agissent comme des spectateurs dans le marché. En plus, les vendeurs expérimentés utilisent des techniques agressives de publicité, afin d'empêcher leurs compétiteurs d'entrer sur le marché, gardant ainsi leur position avantageuse et contribuant à l'inégalité du marché. Un paradoxe émerge : le marché est compétitif, mais également peuplé de quelques vendeurs « superstars » qui ont une portée et une importance relativement limitées. Suite à cette analyse, il est peu probable que les cryptomarchés représentent l'avenir de l'industrie de la drogue, en raison des difficultés rencontrées par les vendeurs lors de la vente de drogue en ligne.

Mots-clés : cryptomarchés, marchés illégaux en ligne, structure de marché, compétition

Abstract

Since 2011, drug market participants have had the opportunity to trade illegal drugs through online anonymous marketplaces dubbed cryptomarkets. Cryptomarkets offer a user-friendly infrastructure, similar to eBay, where market participants can meet and conduct business together. These well-designed anonymous platforms offer a professional setting for drug sales, but to what extent they are the future of drug dealing is unclear. This study characterizes the structure of the drug market hosted on cryptomarkets in order to better understand the economic setting of cryptomarket drug vendors. Market competition and the size and scope of drug vendor activities are analyzed. We find that the drug market hosted on cryptomarkets is fiercely competitive and deeply unequal. The size and scope of vendors' activities are limited. Challenges arise due to the online, anonymity and illegality features of cryptomarket drug transactions. The illegality status of drugs forces vendors' offline activities to stay within a small size and scope, limiting their potential growth online. The online nature of cryptomarkets fosters competition, but the risks that arise from anonymous transactions exacerbate buyers' tendency to choose well-reputed and experienced vendors. Thus, vendors face strong barriers to sales and 90% of them act as spectators in the market. This inequality is exacerbated by aggressive advertising conducted by established vendors to push out potential competitors. A paradox is found: the market is fiercely competitive, but also populated by market superstars, whom, however, still have limited size and scope. We conclude that cryptomarkets are not likely be the future of drug dealing because of the challenging environment they offer to cryptomarket drug vendors.

Keywords: cryptomarkets, online illegal markets, market structure, competition

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"I don't do drugs. I am drugs."
— Salvador Dalí

Introduction

The global trade of illicit drugs is a massive industry worth upwards of tens of billions of dollars US (Reuter and Greenfield, 2011). Its customers (individuals who used illicit drugs at least once during the year) represented 3.3% to 6.1% of the worldwide population in 2008 according to the UNODC (2011). The illegal drug market is large, but also dynamic; market participants adapt to new constraints and to new opportunities quickly. Opportunities like technological innovations help the development of new techniques or new tools that make the commission of crimes easier (Natarajan et al., 1995). For instance, in the 1990s, cellphones were considered a technological innovation which eased communication among drug dealers (Natarajan et al., 1995).

Nowadays, two technological innovations combined, The Onion Router (Tor) and the cryptocurrency Bitcoin, have enabled the development of anonymous online drug marketplaces, dubbed cryptomarkets. Tor is an international network allowing one to browse online with anonymity, ensuring privacy and security on the Internet (Tor Project, 2015). Bitcoin is a digital currency based on peer-to-peer technology with no central authority or banks (Bitcoin Organisation, 2015). With these technologies combined, cryptomarkets allow market participants to meet and conduct transactions anonymously on a user-friendly online platform similar to eBay (Barratt, 2012).

These platforms represent a new channel for the sale of illegal drugs, one that is anonymous and global, localised in neither space nor time. The well-known newspaper The Economist published an article in June 2016 mentioning that *"*The drug trade is moving from the street to online cryptomarkets". Are drug vendors actually shifting their dealing activities towards these online platforms, *"upping their game",* as stated in the article? In fact, are cryptomarkets the future of drug dealing? One way to assess this inquiry is to understand the market structure and the economic dynamics behind this new online drug market. Cryptomarkets represent an innovative channel for the sale of drugs, and understanding the structure of the drug market evolving in this new channel will provide an assessment of the extent to which cryptomarkets are profitable for vendors.

This study characterizes the structure of the online drug market hosted on cryptomarkets in order to evaluate if these platforms are, indeed, the future of drug dealing. Through data collected on one of the largest cryptomarkets to date, market competition and the size and scope of drug vendors are evaluated. The size and scope of drug vendors lie in three dimensions: exposure, diversity and experience. The study provides an holistic understanding of the economic market in which cryptomarket drug vendors evolve, as well as the challenges and opportunities they face when selling online.

Transactions in online drug markets have specific features: they are online, anonymous and illegal. These features are known to influence the structure of markets towards less or more competition. The first chapter provides a comprehensive overview of these three features and the changes they may create on market structure. The second chapter presents the data collection process, the dataset and the methodology of the research. The strategies used to measure market competition, evaluate the size and scope of drug vendors and develop proxies for vendors' exposure, diversity and experience are exposed. The third chapter presents the results of the analyses. The conclusion considers the features of cryptomarket drug transactions -online, anonymity and illegality- and their potential impact on market structure while discussing the findings. This provides a deep understanding of the market dynamics behind the online drug market hosted on cryptomarkets. The limits of the study are then presented, along with possible further research and a coda note.

Chapter 1

Online Transactions, Anonymity and Product Illegality

This study characterizes the structure of the drug market hosted on cryptomarkets. Transactions in online drug markets have features that need to be taken into account when characterizing the subsequent market structure: they are online, anonymous and illegal. This chapter presents the changes these features could engender in the structure of markets. To begin, we present the economic dynamics behind online markets. We then focus on the specific setting related to this study: online anonymous markets and, more specifically, cryptomarkets. We afterwards shift to the offline world and discuss the consequence of product illegality on market structure. Finally, the problematic arising from the literature review is presented at the end of this chapter.

Online Markets

A main feature of economic transactions on cryptomarkets is the fact that they are taking place in an online environment and participants in these online illegal markets have no border to cross or time zone to face (Décary-Hétu and Leppänen, 2013). In the legal world, online markets are a common place to conduct economic transactions and the Internet is now a robust channel for e-commerce (Cambini et al., 2011; Smith et al., 2001). This section presents the characteristics of online markets -and the economic forces behind them- that alter the structure of markets towards more or less competition.

First, Wigand (1997) defines e-commerce as “any form of economic activity conducted via electronic connections” and electronic markets as electronic settings where e-commerce takes place (p. 2). For this study, the terms “digital”, “electronic”, “e-” or “online” refer to activities and/or processes that happen through computer networks and are enabled by the Internet. For simplicity, we use the term “online”, unless a citation requires the use of another word.

Online markets possess features that allow them to be more competitive than traditional offline markets (Cambini et al., 2011). First, search costs -the costs of searching for products and comparing their prices- are reduced in these markets, especially with the help of search engines. This imposes higher competitive pressures for online sellers and, consequently, decreases products' prices compared to those of traditional offline markets (Brynjolfsson et al., 2003; Brynjolfsson and Smith, 2000). Also, lower search costs provide greater product variety for consumers, thereby increasing their welfare (Brynjofsson et al., 2003).

Second, buyers' switch costs -consumers' costs related to changing supplier for a specific product or service- decrease in online markets. This imposes higher competitive pressures for online sellers because consumers can switch to other sellers easily when unsatisfied with their purchases (Cambini et al., 2011). Lower search and switch costs result in a higher elasticity of demand. The elasticity of demand is a measure of buyers' sensitivity toward an increase in price. Ellison and Ellison (2009) found that online buyers are highly sensitive to prices. Online sellers can face price elasticity of demand of -20 when buyers have access to efficient search engines. This means that a 1% increase in the price of a product sold online could lead to a 20% decrease in the demand for the product.

Third, seller menu costs -the costs for sellers to change prices- are expected to be quasi-null on online markets, allowing retailers to optimally adjust prices according to market demand. Brynjolfsson and Smith (2000) found that online prices change more frequently, allowing better flexibility for sellers. However, they mention that online sellers are inclined to make small price changes when they face higher competition.

Hence, online markets' features: low search, switch and menu costs, as well as high price elasticity of demand, promote competition among sellers. However, Cambini et al. (2011) point out that, despite these features, online markets do not reach perfect competition as predicted by them. There seems to be a high level of concentration of market power in online markets (Brynjolfsson and Smith, 2000; Clay et al., 2001; Elberse, 2008; Wang and Zhang, 2015).

In fact, online search costs are not limited to products' "price attributes", but also include "non-price attributes", such as delivery time, shipping costs and product availability. This creates product differentiation because online products that seem homogenous at first are in fact differentiated by non-price attributes (Cambini et al., 2011). Absolute search costs decrease online, but buyers' relative search costs increase, because they have to search among different sellers for non-price attributes related to the same product (Kauffman and Walden, 2001). Due to non-price attributes, sellers can trick consumers and charge different prices, altering market efficiency and competition online.

Brand and reputation are two other significant non-price attributes that create product differentiation in online markets, allowing sellers to charge higher prices. Consumers in online markets are willing to pay higher prices for well-reputed sellers compared to unknown ones (Smith and Brynjolffson, 2001). Brynjolfsson and Smith (2000) found that the online company Amazon.com was able to charge a price premium of 7-12% because of its strong reputation in book retailing. Good reputation provides a certain level of trust in specific sellers, which is directly translated into a price premium. Moreover, Chevalier and Goolsbee (2003) found that consumer price elasticity depends on market sellers. Sellers with a well-established reputation, known as market-leaders, face lower price elasticity of demand than do others.

Branding is of great importance for buyers in online settings, mainly because buyers are concerned about unobservable quality control (Latcovitch and Smith, 2001). Advertising can be considered as a signal of reliability and security in online shopping. With product development, advertising and revenue data, Latcovitch and Smith (2001) found that consumers respond more to advertising -rather than low prices- when shopping online. They posit that online sellers may need to spend more on online advertising than traditional ones do to develop a branding and consequently establish a good online reputation. This can induce market power for those who invest largely in advertising to gain a good reputation in online markets and push out smaller competitors with lesser advertising budgets. Moreover, according to Wang and Zhang (2015), the fact that the market is one large virtual place where sellers face high fixed costs and low marginal costs influences online sellers to act aggressively in advertising. Popular products sold online are stunningly profitable compared to other, less-known products (Latcovich and Smith, 2001; Wang and Zhang, 2015).

Wang and Zang (2015) conclude that the winner-takes-all theory better explains the effect of the Internet on industry competition. The winner-takes-all-theory of Frank and Cook (1996) states that contemporary society tends to concentrate wealth in a small number of winners, dubbed “the superstars”. As an example, Elberse (2008) found that blockbusters capture even more market than they used to with their online music services, as niche products have even less share of the market. The increasing multiplication of choices available on the Internet would therefore have the opposite effect, converging customer purchases and habits towards popular similar products.

Hence, online markets have features, such as low search costs, switch costs and menu costs, that should create greater competition in online markets (Cambini et al., 2011). However, consumers' tendency to choose branding and reputation online over low prices favors market leaders (Cambini et al., 2011; Ellison and Ellison, 2009; Latcovictch and Smith, 2001; Pozzi, 2012; Ulph and Vulkan, 2000). The effect of the Internet on industry competition would therefore be associated with a decrease in industry competition, rather than an increase (Elberse, 2008; Wang and Zhang, 2015). This review shows that there is a need to be prudent when assessing the structure of online markets, as several economic forces come into play and influence variously the degree of competition among sellers. Keeping this in mind, we now look at online illegal markets where illegal goods and services are sold.

On the Anonymous Features of Online Illegal Markets

The section above illustrates that online markets present different features that may influence their structure to be more or less competitive. However, online illegal markets are quite different from legal ones: they are anonymous and market participants cannot rely on the legal system if they are swindled. Online illegal markets often evolve within a marketplace, such as discussion forums or cryptomarkets. This section briefly presents the first generation of online marketplaces selling illegal products: discussion forums and chat rooms. It then discusses more thoroughly the second generation: cryptomarkets. The aim is to provide a better understanding of how markets operate in an anonymous context and to present the setting in which this study takes place: cryptomarkets.

Discussion Forums and Chat Rooms

The first generation of illegal online marketplaces is hosted in forum discussions and chat rooms. They can be considered a form of online social networks, as online participants maintain personalities, add fellow users and engage in private or public conversations to learn and exchange information, but one of their principal purposes is the sale of illegal goods and services (Motoyama et al., 2011). Stolen financial information, exploit kits, fake identity papers, account credentials, spam or hacking services and much more are sold on these online platforms, filling a market demand for such products (Yip et al., 2013).

With the appropriate use of technology, market participants in these forums conduct their online activities anonymously, through pseudonyms, allowing a certain degree of concealment from law enforcement (Yip et al., 2013). However, the anonymity feature also generates uncertainty, as participants can steal and act opportunistically while keeping a high level of impunity. According to Wehinger (2011), being a victim of a fraud or a scam is a bigger threat for market participants than the threat of being arrested by law enforcement. Furthermore, the absence of quality control of products bought and sold and -again- a lack of means to enforce agreements increases the risk of unsuccessful transactions. All this results in higher transaction costs for market participants (Yip et al., 2013). Trust must be created and maintained -despite anonymity- to ensure successful transactions and prevent market failures.

Wehinger (2011) investigated the functioning of illegal online marketplaces and illustrated that these marketplaces use alternative mechanisms to create trust among market participants and overcome the risks associated with online transactions. For example, the reporting of routines for fraud or granting “verified status” to participants are mechanisms frequently used by administrators of discussion forums and chat rooms to generate institution-based trust among market participants. Wehinger (2011) concluded that, by "policing" the marketplace, administrators provide a minimum level of stability.

Also, process-based trust can reduce the overall level of risk of failed transactions in the marketplace (Wehinger, 2011). Process-based trust develops through past exchanges among participants. Lusthaus (2012) and Radianti (2010) showed that forums allow participants to communicate and develop trust relationships among one another. Active participation in forums, especially for sellers, creates a visibility and subsequently augments process-based trust among market participants. Active participation in online forums can also be considered as signals sent by sellers to show to the community that they are serious businessmen. This idea comes from Gambetta (2009), who theorized that the criminal underworld abounds with uncertainty and those involved in market crimes need to interpret and respond to "signals" in order to ensure that they are not conducting business with an undercover policeman or with a scammer. In the case of online illegal markets, buyers need to look for signals before deciding whom to trust and conduct business with. As stated in Décary-Hétu and Leppänen (2013), "buyers need to carefully assess the signals that each seller broadcasts in order to reduce the chances of being scammed" (p. 5). Good reputation, positive feedbacks, and active participation are all signals sent by sellers to the community to show that they are serious in conducting business. These signals, when well interpreted, also ensure successful transactions in the market.

Also, there has always been a concern related to the use of multiple accounts by one individual in online illegal markets. Due to the online and anonymous nature of these markets, there is no possible way to verify if an individual uses many accounts or solely one. Vendors can use several accounts to avoid being detected as “large vendors” by law enforcement. However, Décary-Hétu and Eudes (2015) found that only 8.9% of vendors owned multiple accounts on an online carding forum. Motoyama et al. (2011) in their study of six underground forums also consider that using multiple accounts to mask the level of an illegal trader’s online activity is unlikely. They argue that reputation is hard to accrue online and using multiple accounts on which reputation needs to be built is not viable for high volume traders. Moreover, Radianti (2010) observed that administrators in a credit card-related forum established a rule that required an online persona to post a minimum number of times in beginners’ forums before being allowed to interact in the more serious and formal forums. According to Radianti (2010), this rule was implemented by market administrators to prevent multiple account creations by an individual.

Once trust is established within the platform, these illegal online markets are known to be global, competitive and driven by market dynamics (Yip et al., 2013). Forums become an open advertising space (Holt, 2013) where sellers can post their listings knowing they will be exposed to many potential buyers. They create threads within the forums and list their products and services to the rest of the community (Chu et al., 2010; Holt and Lampke, 2010 and Motoyama et al., 2010). Also, the relationships among buyers and sellers are structured around communication, price, quality and services (Holt and Lampke, 2010). Quickly responding to customers, offering low prices with good quality products and providing resources and concern to customers ensures successful transactions (Holt and Lampke, 2010). To entice customers, sellers offer products with competitive pricing and consumer support, ensuring positive feedbacks for future successful transactions (Holt, 2013; Holt and Lampke, 2010; Motoyama et al., 2011). Studies on online illegal markets conclude that these markets are competitive and driven by market dynamics (Holt, 2013; Holt and Lampke, 2010; Yip et al., 2013).

Cryptomarkets

Lately, a second generation of illegal online marketplaces has emerged, called cryptomarkets. As opposed to chat rooms and discussion forums, cryptomarkets offer a clean and user-friendly infrastructure for market participants to meet and conduct business together (Christin, 2013). The visual design is similar to eBay or Amazon (Barratt, 2012). Vendor's listings permit advertisements and description of products sold and are centralized into a profile, allowing a global vision of what is sold by a vendor.

The key innovation of cryptomarkets is to offer stronger anonymity properties to its participants than the usual illegal online marketplaces (Martin, 2014ab; Soska and Christin, 2015). Anonymity is provided through a combination of two technological innovations: The Onion Router (Tor) network and cryptocurrencies. The Tor network provides anonymity by making IP addresses of clients and servers unknown to each other; users connect through a series of virtual tunnels rather than through direct connections (The Onion Router, 2015). Cryptocurrencies, such as Bitcoin, are currencies based on peer-to-peer technology with no central authority or banks (Bitcoin Organization, 2015). According to Martin (2014a), the participants' reliance on encryption technology is what differentiates cryptomarkets from other illegal online marketplaces.

Cryptomarkets also provide sophisticated mechanisms to ensure institution-based trust among participants. They provide feedback systems on listings, allowing market participants to rate sellers according to the quality of products and services provided; they impose escrow services, where a third party holds payment until delivery of the product; and they encourage market participants to interact through encrypted messaging. When problems emerge during transactions (e.g., no delivery of the product bought), some marketplaces offer a customer resolution service, where the problem between a vendor and a buyer is mediated by market administrators (Morselli et al, forthcoming). Discussion forums are also established, where market participants can interact and build process-based trusts. Participants routinely interact in these forums to talk about, for example, drug experiences (Buxton et Bingham, 2015; Maddox et al., 2016).

Also, both digital and physical products are sold on cryptomarkets. When delivery of a physical product is needed, vendors disguise the good in a package that will resemble a package from large online retailers such as eBay, and send it through postal services to the address provided by the buyer (Volery, 2015). To ensure that sellers are cautious, some marketplaces require buyers to rate sellers according to stealth skills. Sellers may also choose to sell at the international level - incurring more risk of package interception because of multiple frontiers - or at the domestic level, in the seller’s country (Décary-Hétu et al., 2016).

The first cryptomarket to appear was called Silk Road. It was launched in February 2011 and ran for more than two years with almost total impunity, until the Federal Bureau of Investigation (FBI) seized the site in October 2013 (Aldridge and Décary-Hétu, 2014). The shutdown of the first cryptomarket, Silk Road, received international press and media attention. During the following weeks, Silk Road sellers and buyers moved to other markets or started their own anonymous marketplaces and, ever since, numerous marketplaces following the same model have appeared (Soska and Christin, 2015). Even Silk Road 2.0, the “sister site” of the first Silk Road, emerged no later than a few weeks after the first shutdown.

Of course, even with the use of several good encryption technologies, cryptomarkets are not totally exempted from the threat of law enforcement and fellow criminals. Arrests and seizures have been made by law enforcement, as well as voluntary closures by scam administrators, but these online marketplaces continue to appear and disappear. Soska and Christin (2015) find that, after a shutdown, market participants' confidence is re-established after two to three months, suggesting it is a resilient online ecosystem.

Most listings advertised on cryptomarkets are related to drugs, which is a major shift from the first generation of illegal online markets. In the first Silk Road, drugs accounted for 17 of the 20 largest categories (Aldridge and Décary-Hétu, 2014; Christin, 2013); marijuana, prescriptions, narcotics, prescription medicine and benzodiazepine were the top categories in terms of items available (Christin, 2013). Moreover, since 2015, cannabis, MDMA (ecstasy) and cocaine-related products are the most popular drugs sold online, averaging about 70% of all sales (Soska and Christin, 2015). Hence, cryptomarkets are principally an infrastructure for drug dealing, even though other products such as E-books are sold.

The experience of selling online has been reported as convenient and pleasant. Vendors reported that they enjoyed the "simplicity in setting up vendor accounts and the opportunity to operate within a low risk, high traffic, high mark-up, secure and anonymous Deep Web infrastructure" (van Hout and Bingham, 2014, p.183). They also reported appreciating the harm reduction ethos and the professionalism of the site, as well as the possibility for "professional advertising of quality products, professional communication and visibility on forum pages […]" (van Hout and Bingham, 2014, p.183). However, Christin's (2013) study found that Silk Road sellers did not stay long on the marketplace, as the majority of them disappeared within three months of market entrance and only 9% of Silk Road sellers (112 sellers) were present for the entire period of the study (a few months in 2012). The overall lifespan of listings was also found to be quite short, less than three weeks, with a very low ratio of long-lived listings (Christin, 2013). Following the fall of Silk Road, Soska and Christin (2015) conducted a two-year period of observation on multiple cryptomarkets, between 2013 and 2015, and found that the number of sellers had considerably increased. A large proportion of them also sold on multiple marketplaces at the same time to reduce the uncertainty associated with sudden marketplace closures.

During this two-year period of observation, Soska and Christin (2015) found that about 70% of sellers sold less than $1,000 worth of products and only 2% sold more than $100,000. The same study found that the total volume of sales across all cryptomarkets was stable between $300,000-$500,000 USD per day, reaching sometimes up to $650 000 USD daily. However, since the methodology of Soska and Christin (2015) does not consider listings with a price over $1,000 USD, the numbers mentioned above may be undervalued.

On the other hand, drug consumers buying on cryptomarkets noted that transactions were more convenient, professional and safer, avoiding the face-to-face meeting with the dealer (Barratt et al., 2013; van Hout and Bingham, 2013a; van Hout and Bingham, 2013b). They also mentioned that they enjoyed the harm reduction ethos within the virtual community, the wider range of products available, the better quality of the drugs and the use of vendor rating systems (Barratt et al., 2013). In a van Hout and Bingham (2013b) study, buyers reported that escrow service protected them from scamming and they appreciated online forums with information on the quality of sellers and products sold. They mentioned that cryptomarkets enhanced their decision-making process and broadened their drug consumption horizons (van Hout and Bingham, 2013b). Lastly, the participants (N=20) surveyed by van Hout and Bingham (2013b) “reported intentions to continue using the site in the future, with several intending to set up vendor accounts” (p. 527).

Since the first cryptomarket, Silk Road, the size and scope of this online market ecosystem has expanded (Aldridge and Décary-Hétu, 2014; Soska and Christin, 2015). Barratt et al. (2013) added questions on cryptomarkets in the 2012 Global Drug Survey and found that no more than a year since the appearance of Silk Road in 2012, 40% of consumers in Great Britain, Australia and the United States had heard of Silk Road and at least 7% of them had purchased once online. Barratt et al. (2013) also found that differences in the kind of drugs bought by Silk Road users appear to reflect drug trends in their own countries. van Buskirk et al. (2013) concluded likewise in their bulletin on drug trends sold via the Internet to Australia. Also, Aldridge and Décary-Hétu (2014) illustrated that an important proportion of the Silk Road transactions were more business-to-business like, with sales in quantities and at prices not typical of a consumer’s purchase. Hence, if transactions in cryptomarkets are not for reselling to end-consumers, their impacts on the international drug trade - and local drug markets - could be substantial.

The resilience of cryptomarkets, their relative growth over time and participants’ strong appreciation suggest that cryptomarkets fill a void for a market demand. They are therefore not expected to disappear anytime soon. Yet, little is known on the structure of these markets. This research is about developing a first understanding of the structure of drug markets hosted on cryptomarkets. However, as drugs sold online have an illegality status, we now discuss the consequence of product illegality on market structure.

Revisiting the Consequence of Product Illegality on the Organization of Markets

Even though transactions take place online, drugs sold on cryptomarkets need to be packaged and shipped once the online transaction is completed. Part of the process takes place in the physical world and this is why understanding the structure of traditional illegal drug markets is useful to understand the structure of online illegal markets. In this section, we first present Reuter's work on the consequence of product illegality on the size and scope of illegal firms, and, subsequently, the organization of markets. Second, we present empirical research on the drug market.

Size and Scope of Illegal Firms

Reuter's (1983) study on the organisation of illegal markets followed a supply-side approach to study the structure of illegal markets and argued that the legal status of a product -its illegality- should affect the way in which its production and distribution is undertaken by enterprises[1]. From this argument, he aimed at assessing the size and scope of firms producing and distributing illegal products in order to have a better understanding of the organization of illegal markets.

For his study, Reuter (1983) worked in a sub-field of industrial organization that accounts for firms' mode of transactions: Williamson's (1973) transaction costs economics (TCE), and aimed at assessing the size and scope of illegal firms through an analysis of the transaction costs

[1] For simplicity, the terms "enterprise" and "firm" will be employed as synonyms throughout the text. A definition of what is an illegal firm/enterprise – for purposes of clarification throughout this paper – is provided by Haller (1990), as an entity that conducts the "sale of illegal goods and services to customers who know that the goods or services are illegal" (p.207). Illegal enterprises may be composed of one individual – the entrepreneur – or several who work together, as long as this/these individuals are involved in the sale of illegal goods and services.

associated with expansion. This gave him insights into illegal firms' mode of governance and, subsequently, into the organization of illegal markets.

Reuter (1983) argues that, as opposed to legal enterprises, illegal ones operate in a risky and uncertain environment. He establishes two operational consequences – or driving forces – of product illegality: (1) contracts are not enforceable by law and (2) there is a risk of arrest and/or seizure of assets by law enforcement. First, contracts, however formal or informal they may be, are of great importance for enterprises and the lack of legal recourse in the illegal world is likely to affect the internal organization of firms. Second, arrests and asset seizure are costly for illegal firms and need to be minimized. This can be done by controlling the flow of information about the firm's illegal activities, something that is likely to influence the mode of transactions among individuals in a firm on a day-to-day basis.

To assess the costs of expansion, Reuter (1983) formulates the assumption that most costs associated with the supply of illegal goods (e.g., drugs) and services (e.g., bookmaking or loansharking) originate from the number of individuals involved in the distribution and their subsequent coordination. Factors affecting the costs curves of illegal firms are therefore considered "human factors" and are mostly associated with the coordination of group activities. To analyze the mode of governance of illegal firms, three angles associated with expansion are used: internalize functions within illegal firms (vertically integrating activities such as wholesales or retails of drugs), geographic scope (expanding to other locations) and diversification (producing multiple lines of products). These expansions depend primarily on the costs associated with investments in human factors, such as the level of employment or investments in human capital. Reuter's assessment of the size and scope of illegal firms allows him to conclude that illegal markets are likely to be populated by localized, fragmented, ephemeral and undiversified enterprises, which creates a very competitive environment. We provide below a short review of Reuter's line of inquiry that brought him to conclude that the size and scope of illegal firms are limited.

The decision to vertically integrate the production of goods or services within an illegal firm depends on the costs and benefits associated with this activity versus buying it in the market. The integration of production requires an increase in the number of employees. However, as Reuter (1983) states, the level of employment in illegal firms is likely to be limited because employees are a significant threat[2] to the entrepreneur. They are witness to the entrepreneur's involvement in the criminal business and they are aware of past deals in the enterprise, as well as future ones. This prevents the entrepreneur from tapping economy of scale in production and tends to reinforce pressures for illegal enterprises to stay small in the number of employees hired.

The integration of production – forward or backward – determines the number of autonomous firms an entrepreneur has to deal with. Employment relationships in the legal context are advantaged by the possibility of being long-term, thus encouraging human capital investment. Illegal enterprises, on the other hand, are always subject to shut-down and entrepreneurs are consequently less inclined to invest in human capital within their firm. Plus, because employees need to cover their activities from the possible threat of law enforcement, the costs of monitoring employees' performance dramatically increase. According to Reuter (1983), the relative instability of enterprises and the uncertainty of their relationships is a sufficient explanation for

[22] The conclusions on the level of employees can also be applied to partners, as they also represent a threat for the illegal entrepreneur.

firms to be unintegrated and to buy in markets instead. Also, Reuter (1983) demonstrates that entrepreneurs have little motivation to integrate activities forward up to the end of the chain of distribution. Final customers are the most significant threat to the entrepreneur, because they have little loyalty, take fewer precautions and are a source of information for the police. If the entrepreneur really wishes to integrate the final sale, she/he will have a strong incentive to fragment the enterprise to isolate the end-dealing activity. Illegal firms therefore tend to be more fragmented instead of integrated.

Illegal enterprises, furthermore, lack the durability to invest in time and money, according to Reuter (1983). The lifespan of illegal enterprises is shorter than that of legal ones. Illegal firms do not exist independently from the entrepreneurs and they do not have access to external credit markets, compared to their legal counterparts. Indeed, in the legal market there is usually a legal distinction between ownership and management of firms; creditors do not have to get involved directly in the management of the firm, which ensures its longevity. However, illegal enterprises cannot rely on or attract external creditors because bookkeeping with proof of the firms' activity can be a serious liability for the entrepreneur. Illegal enterprises' operating time is therefore usually no longer than the criminal lifetime of the entrepreneur, which, as Reuter (1983) states, may be terminated by either a lack of willingness to continue or an arrest. Illegal firms are consequently more likely to be ephemeral.

Moreover, Reuter (1983) argues that illegal enterprises are expected to be geographically small because illegal enterprises cannot monitor the overall level of exposure of the firm to the police when geographically dispersed. As Reuter (1983) mentions, aversion to risk is personal to every individual and entrepreneurs may not be able to monitor the level of risk taken by their employees in remote locations and sanction them if needed, because of the limited information available. Higher costs of transportation and communication due to risk may also hinder the growth of the illegal enterprise, just as the multiplication of law enforcement agencies at the interstate level may prevent illegal entrepreneurs from expanding geographically. Also, illegal enterprises cannot advertise their products efficiently because advertising provides information to the police and attracts attention. This prevents illegal enterprises from tapping consumer brand loyalty and from expanding geographically to new markets.

Additionally, Reuter (1983) argues that illegal enterprises are more likely to be undiversified in their production. Pure conglomeration – diversification into unrelated product lines - is unlikely for illegal enterprises because it increases the exposure to law enforcement. The costs associated with monitoring multiple production activities are too high.

When assessing the costs of firms' expansion, Reuter (1983) concludes that illegal markets are more likely to be populated by small, fragmented, ephemeral and undiversified firm due to the driving forces preventing them from gaining expansion. This creates a very competitive environment where no market players can easily expand and gain market power.

About the Functioning of Illegal Drug Markets

Illegal drugs are basically consumer goods; they are primarily exchanged through markets, just as any other products (Caulkin and Reuter, 1998). The market "consists of the buyers and sellers whose interaction determines the price and quantity of the good that is traded" (Hindriks and Myles, 2006, p. 209). The idea that large-scale criminal organizations dominate illegal markets by controlling the supply of drugs and their prices has been demystified (Paoli, 2002). Even when criminal organizations sell illegal goods or services in markets, a more flexible approach -taking into account market dynamics and networks- has been found to be a better fit to understand the underlying economic activities of their members and associates (Morselli, 2009). Participants in illegal markets are involved in a small and flexible network of free independent entrepreneurs who seek financial opportunities (Desroches, 2007; Morselli, 2009; Pearson et al., 2001). Their governance is more a market type than a hierarchy. Pih, Hirose and Mao (2010) found that members in Taiwanese criminal gangs are governed by the availability of financial opportunities and their relations consisted of market-like weak ties, these ties being usually interpreted as gang affiliations.

Illegal entrepreneurs associate for a few transactions with large economic gains and split afterwards (Adler, 1993; Desroches, 2007; Morselli, 2001; Pearson et al., 2001). The time-to-task is also recognized to be generally short. According to Morselli et al., (2007), criminal operations for enterprises pursuing economic gains are recognized as being much shorter than those of other more ideological organizations, such as terrorist groups. Plus, illegal entrepreneurs and their fellow employees sometimes have a sense of attachment together, but will rarely prevent themselves or their partners/employees from taking advantage of a profitable operation because of their prior association (Adler, 1993). Illegal enterprises are therefore expected to be short-term, ephemeral, and mostly composed of specialized independent entrepreneurs associating for a few deals or to grasp an opportunity (Paoli et al., 2001). Although specialized, entrepreneurs and their associated group may sometimes grasp opportunities and switch position. For example, in Adler's (1993) study, some illegal firms specialized in wholesale deals did grasp an economic opportunity and got involved in smuggling or the other way around. Others switched the product they sold due to profitable opportunities. As shown in Adler (1993), some high-level dealers were involved in smuggling or selling of marijuana for a few years and subsequently diversified their activities to include cocaine for economic and law enforcement reasons. Entrepreneurs and their associated groups tend to diversify their activities when a profitable opportunity emerges (Dorn and South, 1990).

These associated groups involved in the sale of illegal drugs are known to be quite small, consisting of fewer than 10 participants (Bouchard and Morselli, 2014), but emerging from larger networks of offenders who loosely collaborate depending on the opportunities. In interviews, illegal entrepreneurs asserted that smaller groups of individuals are considered more secure than larger groups (Adler, 1993; Jacobs, 1999; Reuter and Haaga, 1989) because little economic advantage can be gained from formal large or enduring corporations. In addition, smaller groups are more resilient to external shocks (Morselli and Petit 2007).

Drug prices are set according to the characteristics of the markets in which they are sold (Adler, 1993; Desroches, 2007). Indeed, the price at which illegal drugs are traded depends on the extent of the demand for the drug and its overall availability in the geographic location of the transaction (Adler, 1993). Caulkin and Reuter (1998) found that drug prices are extremely variable across time and space. The lack of advertising and trademarks makes it harder for customers to compare the prices of different products (Kleiman, 1991). The price difference is sometimes large enough for illegal entrepreneurs to make a living out of buying cheap drugs at one specific place and selling them at a higher price somewhere else, making a profit from the geographic price differences, a phenomenon called “arbitrage” (Kleiman, 1991). Moreover,

the price elasticity of demand for drugs tend to be elastic. Estimates range from -0.7 to -2.0 (Wilson and Stevens, 2010). These estimates are much lower than what is found in online markets where buyers have access to efficient search engines (Ellison and Ellison, 2009).

Within a market, both high and low-level drug sellers face a competitive setting; they cannot fix the price as they want (Adler, 1993). Instead, prices are set according to the supply and demand in the specific market, but also according to the risks associated with production and distribution of the drug. These risks explain the high prices found in drug markets (Caulkin and Reuter, 1998). Also, many entrepreneurs are specialised at each level and, from importation to retailing, each of them takes their own share, increasing the price of drugs by up to 10 times the price at import (Adler, 1993; Haller, 1990; Reuter and Kleiman, 1986). This complements Reuter's (1983) analysis on the organization of illegal markets. The costs of drugs sales are related to human capital, but also to the risks taken by all individuals involved in the supply chain.

Moreover, little knowledge or skills are needed to enter the drug trafficking market. The barriers to entering drug markets to conduct drug business are minimal (Bouchard, 2007) even at the higher levels of the drug supply (Reuter and Haaga, 1989). With minimal investment required, participants can enter, quit and re-enter drug markets without much difficulty (Adler, 1993).

The three sections above exposed what is known on the online, anonymous and illegal features of transactions that may affect market structure. The last section of this chapter reviews the findings and states the purpose of this study.

On the Structure of the Drug Market Hosted on Cryptomarkets

The Internet has become a robust channel for e-commerce for both legal and illegal market participants. Lately, new technologies, such as the Internet, encryption and cryptocurrencies, have given an opportunity for drug vendors to conduct online transactions on anonymous marketplaces dubbed cryptomarkets. This study characterizes the structure of the online drug market hosted on cryptomarkets. However, cryptomarket drug transactions have features that change the structure of online drug markets: they are online, anonymous and the product sold is illegal.

Indeed, online markets have low search, switch and menu costs that should foster competition among vendors (Brynjolfsson et al., 2003; Brynjolfsson and Smith, 2000; Cambini et al., 2011). However, buyers' susceptibility to branding and advertising tends to decrease competition, especially when large firms conduct aggressive advertising in online markets (Cambini et al., 2011; Latcovictch et al., 2001; Pozzi, 2012; Wang and Zang, 2015). Thus, although the online markets have competitive features, there is a need to be prudent when assessing the structure of the market. Some studies even state that the structure of online markets is closer to that described in the winner-takes-all-theory where market shares are concentrated among a few market leaders, dubbed "the superstars" (Elberse, 2008; Wang and Zhang, 2015). Online cryptomarket drug transactions are also anonymous. Anonymity protects market participants from law enforcement but also creates uncertainty in the transactions because market participants cannot rely on the legal system if they are swindled. Yet, despite the risks, anonymous online markets have been found to be quite competitive, driven by market dynamics (Wehinger, 2011; Yip et al., 2013). Finally, the status of the products sold is illegal. Product illegality constrains illegal firms' activities to stay within a small size and scope (Reuter, 1983), creating a very competitive setting.

Although the distinct features of cryptomarket drug transactions have been studied separately, no research has focused on integrating them to understand a setting that includes all these features, such as cryptomarkets. This is what this study does: it characterizes the structure of the drug market hosted on cryptomarkets while considering the potential impact of the online, anonymity and illegality features of cryptomarket drug transactions. Such an approach provides an in-depth understanding of the economic dynamics behind this specific online drug market. Moreover, understanding the structure of markets allows an assessment of the challenges and opportunities vendors face when selling products; it gives a wide-ranging overview of the relative competition within the market. It also helps in apprehending the potential social consequences of new markets, consequences such as the prospective number of participants and their possible profits. Cryptomarkets represent an innovative channel for the sale of drugs, and understanding the structure of the drug market evolving in this new channel will provide an assessment of the extent to which traditional vendors may switch and start selling online.

To characterize the market structure, we focus on the supply-side and study market structure by assessing the number of firms, their relative size and what they offer within the market (Armstrong and Porter, 1989, p. 1845). The concept of market "consists of the buyers and sellers whose interaction determines the price and quantity of the good that is traded" (Hindriks and Myles, 2006, p. 209).

In this study, the drug market encompasses all drugs sold -and their related vendors- on a cryptomarket. The decision to study the market for all drugs has limitations because it may encompass some vendors that do not compete against each other because, for example, hashish and marijuana may not be considered perfect substitutes for buyers. Yet, it remains relevant to consider the market for all drugs for three major reasons. First, some vendors may sell a wide range of products, such as cocaine and marijuana, as well as pills. By assessing the whole market for drugs, we can consider the relative power of a vendor compared to other vendors, regardless of the types of illegal drugs advertised. Second, a large variety of products are available on cryptomarket platforms and easily accessible through a few clicks, which increases the range of choices available for buyers. This wide range of products offered has been reported to be one major reason for buyers to shop on these platforms (Barratt et al., 2013; van Hout and Bingham, 2013b). Third, studying the whole market for illegal drugs allows us to consider all drug market players instead of only a fringe. Future studies should look closely into the sub-markets of the larger illegal-drug market.

The selling entities on cryptomarkets are named “sellers” or “vendors” in the literature; they represent illegal firms that conduct online selling activities. For concision purposes, the term *vendor* will be employed in the rest of this paper as an overall term referring to illegal firms selling drugs on cryptomarkets.

Drawing from the literature, we expect the drug market hosted on cryptomarkets to have a market structure that is relatively competitive, with multiple firms earning little market share. We expect this because online markets have features that foster competition (Brynjolfsson et al., 2003; Brynjolfsson and Smith, 2000; Cambini et al., 2011) and online illegal markets on discussion forums and chat rooms are known to be relatively competitive (Wehinger, 2011; Yip et al., 2013). Yet we are aware that the literature review on the structure of online markets suggests that we remain prudent when assessing competition in an online setting, as certain economic forces push online markets to be less competitive than previously believed (Elberse, 2008; Wang and Zhang, 2015).

To characterize the structure of the online drug market hosted on cryptomarkets, we establish two objectives. The first objective aims at assessing market competition in the online drug market through two dimensions: the concentration of market shares and their distribution. The second objective aims at evaluating the size and scope of drug vendors. This second objective is inspired by Reuter (1983) who assessed the size and scope of firms in illegal markets. First, we conduct a group-based trajectory model on vendors' market shares. Second, we compare the grouped trajectories found according to the size and scope of their vendors based on three dimensions: exposure, diversity and experience. These three dimensions allow us to go beyond market share to assess the size and scope of vendors. The exposure measure is a proxy for advertising. It assesses to what extent a vendor is visible in the market in terms of drug listings advertised online. A vendor with more exposure is expected to have large size and scope. The diversification measure is based on the degree of diversity in the types of products offered by a vendor. A vendor diversified in the types of products he/she offers is expected to also have large size and scope. The experience dimension measures how long a vendor has been on the market. An experienced vendor is expected to be well-known in the community, thereby having a large size and scope. These dimensions were determined according to the data available and inspired from Reuter's conclusion. With these two objectives, the structure of the drug market hosted on cryptomarkets is characterized from several angles, thus providing a holistic overview of the online drug market structure.

Chapter 2

Methodology

This research characterizes the structure of the drug market hosted on cryptomarkets. To do so, two objectives have been established. The first objective assesses competition through the concentration and distribution of market share and the second objective evaluates, with the results of the group-based trajectory model, the size and scope of vendors based on three dimensions: exposure, diversity and experience.

This chapter provides the methodology of the study. It gives a full understanding of the measures and techniques used to determine the structure of the online drug market hosted on cryptomarkets. The data collection process and the sample are firstly presented. Then, we explain how we calculate market share along with the measures we use to assess its concentration and distribution. Next, we present our strategy to assess the size and scope of firms. We present what is group-based trajectory modeling and how we use it to find the distribution of vendors' market share trajectories. We explain how we operationalise the three dimensions of the size and scope of vendors: exposure, diversity and experience and how we put these measures in relation with the results of the group-based trajectory model in a one-way ANOVA analysis.

Data Collection and Sample

To assess the structure of the drug market hosted on cryptomarkets, we decided to gather information on one cryptomarket platform, the largest up to date. We used the DATACRYPTO software tool developed by Décary-Hétu and Aldridge (2015) to download all the listings, feedbacks and vendors' profile pages available on the chosen cryptomarket. DATACRYPTO is a software tool designed to crawl the web. The tool connects to a website and automatically downloads all pages available. It functions through an iterative process: when connecting to a website (in this case, the targeted cryptomarket), it downloads the home page and remembers all the hyperlinks available on it. The tool then visits and downloads every hyperlink stored in memory one after the other, while storing any new hyperlinks available on the pages visited in its memory. Through this iterative process, DATACRYPTO can download an entire website. Moreover, specific features of the tool facilitate the data collection process. For example, the tool is state-aware: it signals the researcher when logged out from a website. It can also filter out uninteresting pages according to predetermined rules and it can validate the results based on previous data collections on the website.

To visualize the data collection and understand its limitation, it is best to imagine that a screenshot was taken of the entire cryptomarket. No assessment of the changes that happened on the platform before or after the screenshot is possible. This means that, if a listing is taken down a day before the data collection, the dataset does not include it.

With this DATACRYPTO tool, we collected information on one cryptomarket platform, one of the largest up to now, at six successive points in time for six months: end of September, end of October, end of November and end of December of 2015, as well as end of January and end of February 2016. The period of study spans from September 2015 to February 2016. At the beginning of the period of study, the tool took five days to download the entire cryptomarket whereas, at the end, it took up to 10 days. This suggests that the cryptomarket expanded throughout the period of the study, with more and more pages to download.

This study is about the drug market hosted on cryptomarkets; it therefore focuses on vendors, listings and feedbacks that are related to drug sales. However, a wide range of products and services are offered on cryptomarkets, from drugs to jewels, hacking services to eBooks. For this reason, we did a selection in the dataset to keep only drug listings and their associated drug vendors and feedbacks. Drug listings encompass any listing posted in the drug section of the cryptomarket that offers the sale of drugs. We removed from the dataset any listings that sold materials related to drugs, but were not actual drugs, such as smoking pipes or syringes.

The sample contains drug vendors, listings and feedbacks collected by the DATACRYPTO tool at six points in time for six months. Table I presents the distribution of the sample through time, taking into account only the drug listings and their associated vendors and feedbacks. It shows that the number of drug listings, vendors and feedbacks increases through time. This increase indicates an expansion in the market, but can only be considered partial. As mentioned above, listings that were posted before or after the data collection are not included in the dataset. Hence, this increase is only a partial picture of the real change in vendors, listings and feedbacks on the cryptomarket. The more we go back in time, looking at feedbacks left months ago, the less accurate the assessment of the market is because of the likelihood that other similar listings were taken down by competitor vendors. To avoid any bias in our research, we decided to be conservative and consider only feedbacks left two weeks prior to the data collection. This gives us a more accurate picture of the number of sales conducted by vendors every two weeks in order to compare vendors' total number of sales together. The number of feedbacks left two weeks prior to data collection is presented in the last column of the table below.

Table I - Distribution of the six samples over the period of study

Month of data collection	Number of Vendors	Number of Listings	Number of Feedbacks	Number of Feedbacks two weeks before data collection
September 2015	692	6,923	21,749	2,176
October 2015	813	10,734	34,303	3,462
November 2015	1,210	16,139	51,972	5,356
December 2015	1,369	20,112	87,616	4,389
January 2016	1,416	22,040	121,708	7,312
February 2016	1,582	25,395	153,331	6,134

To conduct our analysis, we extracted information on every relevant page collected. On vendors' pages, we collected (1) the pseudonym and (2) the date the vendor started to sell on the cryptomarket, usually dubbed "since date" on vendors' profile. On the listing pages, we collected (1) the listing's title (2) the description and (3) the drug category. Finally, on the feedback section, usually posted under listings, we collected (1) the date the feedback was posted and (2) its associated listing and vendor. We stored all information extracted in a MySQL database in order to facilitate the analysis. How the extracted information is used to develop variables for market share, exposure, experience and diversity is presented further below.

Competition on the Online Drug Market Hosted on Cryptomarkets

The first objective of this research is to assess the degree of competition on the drug market. To do so, competition is measured based on two dimensions: concentration of market share and its distribution. The first dimension -on the concentration of market share- is measured according to the Herfindhal-Hirshmann Index (HHI) on competition. The second dimension is based on the Lorenz curve and depicts the distribution of market share in the vendors' population. This section presents the HHI Index and the Lorenz curve, the measures needed to assess market competition. First, however, how market share is conceptualized and calculated is presented, because this variable is central to achieve both the first and the second objective.

Conceptualization and Operationalisation of Market Share

The market share variable is key to assessing the structure of the drug market hosted on cryptomarkets. The concept of "market share" refers to the portion a firm sells compared to the total amount available for sale in a market. It shows the relative power of a firm in a market compared to firms (Hindriks and Myles, 2006).

We decided to measure the total sales of vendors according to the number of feedbacks left on their listings. On cryptomarkets, leaving a feedback after a purchase is not mandatory for buyers, but it is highly recommended. The proportion of buyers who leave a feedback on cryptomarkets is unknown. According to Resnick and Zeckhauser (2002), about 51.1% of buyers leave a feedback after a purchase on eBay. Aldridge and Décary-Hétu (2014) estimated that the feedbacks metric matched the total transactions metric, available on the vendor's profile for Silk Road 1, by 88%. They conducted the same analysis on a second cryptomarket, two years later and concluded that feedbacks were representative of 80% of total sales (Kruithof et al., 2016).

Even though the feedbacks metric does not indicate the total number of sales, it is a good proxy of a vendor's total sales relative to others. It can be considered a credible market dynamics indicator, assuming that the probability that a vendor does not receive a feedback from a buyer is consistent across all buyers and at all levels of purchase (Li et al., 2008; Lin et al. 2006). In this study, feedbacks are considered indicators of vendors' total sales relative to others.

We believe that the number of feedbacks left on a vendor's listing is a better indicator of the relative power of a vendor on the market compared to vendor's estimated total revenue. The number of feedbacks is indicative of the number of transactions completed by a vendor; it indicates the level of activity of this vendor. This metric does not take into account if a vendor sells grams, ounces, cocaine or MDMA, but instead indicates to what extent a vendor is successful in terms of the number of trades completed on the market. The estimated revenue, on the other hand, may be a more biased proxy of vendors' levels of activity on cryptomarkets for three reasons. First, considering a vendor's total revenue as a proxy of his/her overall sales could give importance to a few vendors who listed expensive listings, but only completed one or two transactions on the platform. These vendors could well be scammers who left with the buyer's money without shipping the product. Yet, with the revenue proxy, they would still be considered as important market players due to the listing's high price. Second, holding price is the practice of increasing the price of a listing up to thousands during shortage of products to keep the listing online with its feedbacks. This practice could inflate the total revenue of vendors, because the total revenue is based on the price of a listing during data collection, and biases the results. Third, vendors may also keep the same listings and change the price and the quantity offered, in order to keep the feedbacks left on that listing. Taking into account the number of feedbacks and the listing's price at the moment of the capture may, again, not be indicative of the exact sales completed, in terms of price and quantity sold. For all these reasons, we considered the number of feedbacks to be a better indicator of vendors' market power.

To calculate market share, we divided the total sales of a vendor by the sum of all market sales as shown in the equation below:

$$Market\ share_i = \left(\frac{TS_i}{TMS}\right) * 100$$

Where TS_i is the total number of sales conducted by vendor i divided by TMS, the total market sales. Note again that the number of sales is based on the feedbacks left two weeks prior to data collection. Market share is calculated at each period of the study and consists of the proportion (in percentage) of a vendor's sales compared to the total number of sales in a market.

We consider that vendors having no market share due to nil sales are part of the cryptomarket drug supply. We therefore include them in the analysis since they are part of the market and show willingness to conduct online drug transactions. Concentration of market share is known to be a good indicator of the overall competition in a market.

Concentration of Market Share

The first dimension of market competition, concentration of market share, is calculated with the Herfindahl-Hirshmann Index (HHI). This index - also known as full-information statistics - originates from the theory of oligopoly and is one of the most commonly used measures of competition in the literature (Diallo and Tomek, 2015; Hindriks and Myles, 2006). Precisely, the HHI characterizes the distribution of a variable of interest according to its concentration across units (Owen et al., 2007). It is defined as:

$$HHI = \sum_{i=1}^{n} (MS_i)^2$$

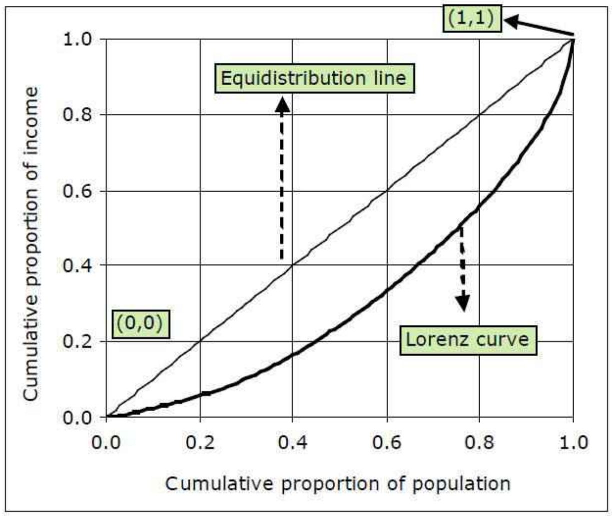
Where MS represents the market share of firm i in a market with n firms. The HHI is bound between $1/n$ and 1 because market share is distributed between $0 \leq MS_i \leq 1$ and $\sum_{i=1}^{n} MS_i = 1$. An index close to 1 represents a pure monopoly market and an index close to $1/n$ represents a highly competitive market (Owen et al., 2007). Since market share in the formula is squared, more weight is given to firms with more market power. In the end, the Index gives an indication of the degree of competition in the market and is calculated at each period of study.

However, the more firms there are in an industry, the less sensitive the HHI becomes to changes in the number of firms (Biker and Haaf, 2002; Davies, 1979). Biker and Haaf (2002) mentions that the Index has been often criticized for not taking into account the distribution of market share. To counter this loss of sensitivity, several attempts have been made in the literature to link the Index with the distribution theory. We link the Index to the distribution theory by assessing the distribution of market share with a Lorenz-like curve graph.

Distribution of Market Share

The second dimension of market competition, distribution of market share, is depicted with the Lorenz curve. The Lorenz curve is a graphical representation of an inequality distribution that "plots the percentage of total income earned by various portions of the population when the population is ordered by the size of their incomes" (Gastwirth, 1971, p. 1037). The curve starts at zero and ends at one (or 100%). It depicts on a graph the degree of inequality in the distribution of revenue across a predetermined population. The line in the graph $y = x$, known as the equidistribution, represents perfect equality in the distribution of wealth among a population. The farther the Lorenz curve is from the equidistribution line in the graph the more unequal the distribution is (Bellù and Liberati, 2005). An example of a typical Lorenz curve is presented below.

Figure 1 - Example of typical Lorenz curve graph



(Taken in Bellù and Liberati (2005) Charting Income Inequality: The Lorenz Curve, p. 3)

The Lorenz curve will indicate the degree of equality/inequality in the distribution of the vendors' market shares in the online drug market. We calculate distribution curves for the six periods of study and present them in one graph.

Size and Scope of Drug Vendors

The second objective of this research is to assess the size and scope of cryptomarket drug vendors' activities. This objective follows a vendor-based approach -a micro approach- to characterize the structure of the drug market hosted on cryptomarkets. First, we conduct a trajectory cluster analysis on vendors' market shares through time. This shows if groups of vendors with similar trajectories in market shares emerge in the market. We then compare the trajectory groups that emerge in the population according to the three dimensions that characterize the size and scope of vendors: exposure, diversity and experience. The section below first explains group-based trajectory modeling and the model that better fits market share trajectories for this study. A walk through the model selection process and model fit is also presented. After, we expose the operationalisation of the three dimensions of size and scope of vendors. Lastly, we present the strategy analysis -a one-way ANOVA analysis- to compare the results of the three dimensions among the groups.

Group-Based Trajectory Modeling

Group-based trajectory modeling (GBTM) was developed in criminology by a group of scholars (Jones et al., 2001; Jones and Nagins, 2013, 2007; Nagin, 2005, 1999) to assess developmental trajectories in delinquency. Group-based trajectory models are latent class analyses that aim to identify homogeneous trajectory groups within a heterogeneous population (Dodge et al., 2006). "The statistical question is how to best model the population heterogeneity of individual-level trajectory" (Nagin, 2005, p. 45). GBTM tests for taxonomic theories (assumed differences across subpopulations), identify distinctive developmental pathways in longitudinal datasets and respect a "person-based approach" for analysis (Nagin and Odgers, 2010). The longitudinal method uses finite/discrete trajectories to approximate a continuous population distribution of trajectories. The finite trajectories can be considered "points of supports" of an unknown continuous distribution of trajectories (Nagin, 2005).

Nagin (2005, 1999) explains that the semi-parametric model uses maximum likelihood estimation to identify clusters of individuals with similar trajectories. The objective is to define a set of parameters that will maximize the probability of an outcome. The model defines the shape of trajectories and states random assignment probabilities. First, the shapes of trajectories are developed following a polynomial function over time. They vary freely across groups because a set of parameters is determined for each group. Moreover, the programs that calculates the polynomial functions in group-based trajectory modeling (SAS/STATA) can go up to the cubic form to determine trajectory shapes. Second, random assignment probabilities, dubbed π, calculate the proportion of a population that belongs to a group. For example, a random assignment probability of 0.7 for a group would mean that, at random, an individual has a 70% chance to end up in this group. In other words, it gives the probability that an individual, chosen randomly, belongs to one of the groups (Nagin, 2005).

The model has been developed with three specific forms of likelihood functions: censored normal, Poisson and logit. The choice of the likelihood functions for each group depends on the distribution of the outcome variable in the model. In this study, the model follows the form of a censored normal because of the distribution of market shares. Market shares span from zero to one hundred and cluster at the low end of the scale. Further description of the specific model for this study is presented in the next section.

Extensions of the GBTM are available, such as time-stable and time-varying covariates. Time stable characteristics, known as risk factors, allow "statistical testing of whether such individual-level characteristics distinguish trajectory group membership" (Nagin, 2005, p. 95). Time-varying covariates models include other time variables in the specification of a trajectory (Jones et al., 2001). This extension of the model tests whether a variable fluctuating over time is associated with a change in the direction of a group trajectory. Time-varying estimates are group-specific because they consider only within-group changes.

The model also allows dealing with data missing at random, which prevents deleting subjects with missing data at certain points in time.

Modeling Trajectories of Vendors' Market Shares: A Censored Normal Model

Group-based trajectory modeling aims to identify groups with similar trajectories in a population. This study assesses whether groups of vendors with similar market share trajectories emerge. As mentioned above, the group-based trajectory model offers three specific forms of likelihood functions: censored normal, Poisson and logit (Nagin, 2005). The outcome variable for our model is market shares. The distribution spans from zero to one hundred, with more than half of vendors having zero market share.

The censored normal (CNORM) model is the most appropriate model for our data. CNORM allows for censoring when the data tends to cluster at the maximum or minimum scale (Jones et al., 2001). The linkage between the outcome variable and time is determined with a latent variable. The latent variable can be considered a measure of subjects' potential to engage in the observed action or behavior at each period (Nagins, 2005). The latent variable is determined according to a polynomial function (i.e. $y^* = \beta_0^j + \beta_1^j T_{it} + \beta_2^j T_{it}^2 + \varepsilon_{it}$) where the error term ($\varepsilon_{it}$) is normally distributed with a mean of zero and a constant standard of deviation (Nagin, 2005). The reference to "censored normal" comes from the fact that the latent variable distribution of its observed and censored (potential action) counterpart is assumed to be normally distributed.

In the model, the distribution of vendors' market shares clusters at the minimum scale, with more than half of vendors having no market share. Vendors with no sales have a potential to actually make some sales. If the demand for drugs on a cryptomarket increased, a portion of vendors making zero sales would start making some transactions. Our model considers vendors' censored market shares and allows us to consider the vendors' potential to start making transactions. In sum, the latent variable in our model measures the potential for drug vendors to actually engage in the market and start making some sales.

Walking Through Model Selection

The objective of group-based trajectory modeling is to identify groups of individuals with a similar trajectory through time. There are infinite possibilities, because the number of approximated groups can go up to the number of individuals in a sample and each trajectory has the possibility of going up to the cubic form.

Nagin (1999, 2005) determined a formal procedure to select the most appropriate model based on formal statistical references: The Bayesian Information Criterion (BIC). The procedure can be complemented with subjective judgment based on researchers' domain knowledge and the model diagnostics presented in the next section.

The first step of the procedure is to determine the appropriate number of groups for the model. This is done by fitting the model with predetermined polynomial functions, based on prior knowledge of the data, and subsequently adding groups to the model. The Bayesian Information Criterion is considered a suitable statistical method to determine the best model (Schwarz, 1978). The BIC is determined according to the formula:

$$BIC = \log(L) - 0.5klog(N)$$

where L is the value of the model's maximized likelihood, N is the size of the sample and k represents the number of parameters (Nagin, 2005). The largest BIC is desired. The formula takes into account the improvement of the model fit with the addition of a group ($Log(L)$), but also subtracts a penalty for its addition ($-0.5klog(N)$). To determine if a change in BIC, between two models with a different number of groups, is significant, Kass and Wasserman

(1995) developed the formula $B_{ij} = e^{BIC_i - BIC_j}$. They determined that if B_{ij} is larger than ten, ($B_{ij} > 10$), there is strong evidence in favor of the ith model. If B_{ij} is between three and ten ($3 < B_{ij} < 10$) there is moderate evidence in favor of the model ith and if B_{ij} is smaller than three ($B_{ij} < 3$), there is weak evidence in favor of the ith model. The ith model is the one that contains an additional group. Also, group-based trajectory modeling comprises two BICs, a BIC based on the number of subjects and a BIC based on the number of observations in the model. These two BICs bracket the "theoretical correct BIC" (Nagin, 2005).

Sometimes, the BICs do not identify the best number of groups, because they constantly increase when more groups are added. In such a situation, model selection must balance the parsimony of the model and the distinctive features of the data (Nagin, 2005). The model diagnostics can help the researcher to decide which model is the best fit according to the data. Also, Nagin mentions: "the recommendation is to select a model with no more groups than is necessary to communicate the distinct features of the data" (2005, p. 77). Once the best model has been determined according to the number of groups, the second step in model selection is to determine the polynomial functions that will define the shape of the trajectories of the groups, based on the highest BICs.

Finally, Nagin (2005) emphases the importance of domain knowledge and subjective decisions during model selection:

> "Model selection must balance the sometimes competitive objectives of model parsimony and capturing the distinctive features of the data. When BIC not useful in identifying a preferred model, the recommendation is to select a model with no more than the groups necessary to communicate the distinct features of the data" (p. 75).

Diagnostics of Model Fit

Once the number of groups and the form of the polynomial functions are determined, four additional diagnostics are available to assess the model's fit to the data.

The first indicator is a group average of individuals' posterior group membership probabilities, dubbed AvePP. Posterior group membership probabilities (π_i) are calculated for each individual as "the probability that an individual with a specific behavior profile belongs to a specific trajectory group" (Nagin, 2005, p. 79). They are calculated, at posteriori, according to the estimated coefficients of the model. Nagin's (2005) personal rule of thumb for adequate AvePP is 70%, meaning that individuals associated to a group have on average a 70% probability of actually belonging to this group.

The second indicator is the odds of correct classification (OCC), which is based on the formula:

$$OCC_j = \frac{\frac{AvePP_i}{1 - AvePP_i}}{\frac{\pi_i}{1 - \pi_i}}$$

where $AvePP_i$ is the average posterior probability for group i and π_i is the random assignment probabilities for group i. The larger the OCC_j, the more accurate the model is. Nagin's (2005) personal rule of thumb is $OCC > 5$. Also, when $OCC = 1$, "the maximum probability rule has no predictive capacity beyond random chance" (Nagin, 2005, p. 88).

The third diagnostic compares the estimated group membership probabilities with the proportion of the sample assigned to the group, dubbed P_i. P_i is equal to : N_j/N where N_j is the number of subjects assigned in group j and N is the total number of subjects. If all subjects are assigned to a group with perfect certainty (AvePP = 1), π_i and P_i are equal. As the assignment error increases, the difference between the two measures increases as well. Nagin (2005) mentions that reasonable correspondence among the two measures is an indication of model accuracy.

The fourth indicator is confidence intervals calculated on group membership probabilities (π_i). Small confidence intervals indicate that the probability is accurate (Nagin, 2005). However, confidence intervals cannot be calculated with the standard method because “the probabilities are not a linear function of the parameter estimates”, but “are a function of multiple parameter estimates” (p. 111). Confidence interval should therefore be calculated with a bootstrap method (Enfron, 1970) over at least 10 000 random draws. However, Jones and Nagin (2007) mention that the bootstrapping resampling requirements make the model estimation time excessive.

The Three Dimensions of Vendors’ Size and Scope

Once the best GBTM is created and group trajectories on market shares are found, we look at the size and scope of groups in terms of exposure, diversity and experience in order to achieve the second objective of this study.

This is possible because results of group-based trajectory models can be used to compare group characteristics. A cross-tabulation “of individual-level assignments with individual-level characteristics that might be associated with trajectory group membership” can be conducted (Nagin, 2005, 1992). Comparing the size and scope of vendors among trajectory groups provides an understanding of the relative importance of each group in the market, beyond market share.

Nagin (2005) mentions that individual’s group membership probability needs to be taken into account when comparing groups characteristics. Indeed, simply comparing groups does not take into account the uncertainty that an individual belongs to another group trajectory. Using group probabilities to weight individuals' characteristics in each group ensures better precision. It answers the question: should the characteristics of an individual with 99% post-probability of group membership be worth the same as an individual with 70% post-probability of group membership? (Nagin, 2005).

We compare the groups according to the three dimensions of the size and scope of vendors: exposure, diversity and experience. These three dimensions illustrate to what extent a vendor has exposure on the market, how diversified he/she is and how experienced he/she is. Also, we weight the results according to each vendor's post-probability of group membership. The three sections below present how the three dimensions are operationalised.

The Exposure Measure

Cryptomarkets are designed so users can easily browse through listings and compare prices. Vendors advertise their drugs through listings. They can attract consumers with nice pictures or discounts. They can also expand their exposure by posting many listings related to the drugs sold. The exposure measure is the first dimension of the size and scope of vendors. We consider the number of listings as a proxy for advertisement because listings increase vendors' visibility on the platform. Vendors can post one listing related to their products, or post many in order to gain more exposure. Vendors' exposure is meant to attract buyers to their profile and shops, increasing the probability of making successful sales. A vendor with many drug listings has more chance of being viewed and noticed by a buyer shopping online.

Thus, exposure is calculated according to the number of listings posted by a vendor at each period of the study and is assumed to be a proxy for advertisement. The measure is calculated for each vendor at each period of study.

The Diversity Measure

The second dimension of the size and scope of vendors is their degree of diversification. This dimension measures to what extent a vendor is diversified according to the types of drugs advertised in his/her listings. A vendor selling many types of drugs is involved in many submarkets and has large size and scope. We also assume that a vendor advertising two types of drugs must have the capacity to supply for both. Selling more than one type of drug increases one's size and scope online in terms of capacity and visibility.

To calculate vendors' diversity, we categorize listings according to their drug type. To do so, we use the predetermined category extracted from each listing's page on the cryptomarket. This category variable represents the drug category in which the listing was posted on the cryptomarket platform under the drug section. More specifically, the categories are: (1) ecstasy (2) cannabis (3) psychedelics (4) stimulants (5) prescriptions (6) opioids and (7) others. Table II illustrates the specific drugs included in the seven broader categories.

Table II - Drug type categorization

Category	Most common drugs included in the category
Ecstasy	MDMA, euphoric stimulants, cathinone, combinations of pills and powders
Cannabis	Herbal cannabis, hash, synthetic cannabinoids, edibles, extract and oil
Psychedelics	Psychedelics, hallucinogens and dissociative
Stimulants	Cocaine, crack, speed (amphetamines) and synthetic stimulants
Prescriptions	Benzodiazepines, sedatives, hypnotics and barbiturates
Opioids	Heroin and codeine
Others	Steroid, tobacco and alcohol

Since we used the categorization of the cryptomarket platform, we went through the results of one data collection manually and looked to see if the drug categorization was correct. In total, 95% of the listings were placed in the right drug category. This was surprising, at first, because Soska and Christin (2015) implemented a complex machine learning classifier to find product categories of each listing. However, their analysis spanned multiple cryptomarkets. Our study includes only one cryptomarket, in which the sub-sections are well-divided. Also, our categorization includes large categories of drugs: a vendor who misplaced a listing in cannabis edible instead of cannabis extract, would still end up in the cannabis category. This explains the high validity in the categorization.

With the seven categories, we use the Diversity Index developed by Agresti and Agresti (1978) to operationalise the diversity dimension. This Diversity Index has been used in several criminological studies to construct measures of offenses dispersion or specialization in offending (Mazerolle et al., 2000; Piquero et al., 1999; Sullivan, 2006). The Index "measures the amount of heterogeneity, within a population with respect to variables at the nominal level, such as race and gender" (Agresti and Agresti, 1978, p. 204). The Index is defined as:

$$D = 1 - \sum_{i=1}^{k} p_i^2$$

where k represents the number of categories and p_i is the proportion of observations in the ith category ($i = 1, \dots k$). In this study, k represents the number of categories associated to a vendor's listings and p_i is the proportion of listings in each of the ith categories. We decided to standardize the diversity index ($SDI = \left[\frac{k}{k-1}\right] D$) in order to facilitate the interpretation of the results. SDI ranges from 0 for no diversity to 1 for perfect vendor diversification.

Overall, the Index indicates the probability that two listings, selected at random in a population of listings related to one vendor, are in different categories (Agresti and Agresti, 1978). The measure is calculated for each vendor at each period of study.

The Experience Measure

The last dimension of the size and scope of vendors is the experience measure. This dimension evaluates to what extent a vendor is experienced on the cryptomarket platform. Christin's (2013) study found that Silk Road sellers did not stay long on the marketplace; the majority of them disappeared within three months of market entrance and only 9% of Silk Road sellers (112 sellers) stayed for the entire period of Christin's study (a few months in 2012). We assume that vendors with more days of experience have large size and scope because they are likely to be known by other market participants.

Vendors' experience is assessed according to the number of days a vendor has been selling on the cryptomarket. We calculate vendors' experience at every data collection. Subsequently, vendors that stay throughout the period of study have 30 days more experience at every period.

One limit of this measure, however, is the fact that vendors can delete their accounts and create a new one with a new and similar pseudonym. If so, they lose their sales history, but their reputation acquired from their experience on the platform could be preserved because market participants may recognize that the same vendor is behind the new account. This is a problem because we assume the date the vendor has entered the market is representative of the beginning of the vendor's selling history. Yet, we cannot control for this limitation because we do not have the information. We could have tried to do an in-depth qualitative analysis of the profiles, but we considered that this type of analysis would create another, different bias to the results. For example, finding that two accounts under two names are from the same vendors is difficult and involves subjective decisions. Also, even if we assess that two accounts belong to the same vendor, we do not know to what extent one account's experience is transferred to another based on market participants' perception. For these reasons we decided to consider every account with different pseudonyms as different vendors. Moreover, no studies have raised, so far, questions or issues regarding the fact that vendors may have multiple accounts on one cryptomarket.

To ensure that all three variables are not correlated, a correlation matrix is presented in Annex I. Highly correlated variables would mean that only one variable could be used as a proxy for the three of them.

Group Comparison on Vendors' Size and Scope

The three sections above illustrate how each dimension of the size and scope of vendors is computed. Based on these operationalisations, the degree of exposure, diversity and experience for each vendor is calculated. Then, following Nagin's (2005) suggestion, we weight the results of vendors' exposure, diversity and experience according to their group membership probabilities. This ensures precision and minimizes bias when comparing groups.

To evaluate whether differences in the size and scope of vendors in each group emerge, a simple analysis of variance (ANOVA) is conducted. Explicitly, ANOVA calculates if significant differences subsist in the exposure, diversity and experience means among the groups found in the model. The null hypothesis (H_0) is: there are no significant differences in the experience, diversity and exposure means among the groups. The alternative hypothesis (H_a) is: there are significant differences in the experience, diversity and exposure means among the groups.

The one-way analysis of variance makes the assumptions that: (1) observations are independent; (2) data is randomly sampled from a population; (3) the variable tested is sampled from a population with a normal distribution; and (4) the variance is homogenous (Salkind and Rasmussen, 2007). Even though ANOVA assumes that the data fits a normal distribution, the statistical method is not very sensitive to moderate deviations from this assumption (Harwell et al., 1992; Lix et al. 1996). The ANOVA model compares groups based on significant or non-significant differences in the means of each group for each dimension.

Chapter 3

Market Competition and the Size and Scope of Drug Vendors

Following the statistical methods discussed in the methodology, this chapter presents the results of the analyses that characterize the structure of the online drug market hosted on cryptomarkets. The results are presented formally below and discussed more thoroughly afterwards.

To achieve the two objectives established in this study -assess market competition and the size and scope of drug vendors- four variables are required: market share, exposure, diversity and experience. This chapter starts by presenting their values with descriptive statistics. After, the results of the first objective on the concentration and distribution of market share are presented. We turn afterwards to the second objective. The steps taken to select the best group-based trajectory model are explained, followed by the model results and the model diagnostics. Once the trajectory groups are found, we compare them according to their associated vendors' level of exposure, diversity and experience, based on the results of a one-way ANOVA analysis.

Descriptive Statistics

To characterize the structure of the drug market, we established two objectives that require the operationalisation of four concepts: market share, exposure, diversity and experience, into four variables. Market share is a key variable for this study because it is used to assess competition in the market, but also to determine vendors' trajectories. Variables on exposure, diversity and experience, on the other hand, allow us to determine the size and scope of drug vendors. This section presents the descriptive statistics on the values of the four variables in order to provide a full understanding of the operationalisation of the concepts.

Market Share

The market share variable represents the proportion, in percentage, of a vendor's total sales compared to the total number of sales in a market. It is calculated according to the number of feedbacks left on vendors' drug listings two weeks prior to each data collection. Table III presents the distribution of the drug feedbacks left two weeks prior to each data collection.

Table III - Descriptive statistics on drug feedbacks

	Number of vendors	Min	Max	Mean	S.D.	Median	Sum
September 2015	692	0	68	3	6	1	2,176
October 2015	813	0	103	4	10	1	3,462
November 2015	1,210	0	131	4	9	1	5,356
December 2015	1,369	0	93	3	7	1	4,389
January 2016	1,416	0	181	5	11	1	7,312
February 2016	1,582	0	115	4	8	1	6,134

Table III illustrates that, during the six periods of study, the maximum number of sales a drug vendor completed is 181 and the minimum number of sales is zero. The mean varies between three and five sales every two weeks, with large standard deviations. The median shows that, for the period of study, half of the vendors did not make more than one sale in two weeks. The sum of the feedbacks suggests that the market is increasing with more feedbacks left every month, except for the month of February.

Based on these feedbacks, the market share variable is calculated. Market share is considered an indicator of a vendor's importance in the market in terms of his/her total sales. It is a key variable for this study. Table IV gives the descriptive statistics on market share for the six periods of study.

Table IV - Descriptive statistics on market share

	Number of vendors	Min	Max	Mean	S.D.	Median
September 2015	692	0 %	3.13 %	0.14 %	0.27 %	0.05 %
October 2015	813	0 %	2.98 %	0.12 %	0.28 %	0.03 %
November 2015	1,210	0 %	2.45 %	0.08 %	0.17 %	0.02 %
December 2015	1,369	0 %	2.12 %	0.07 %	0.16 %	0.03 %
January 2016	1,416	0 %	2.48 %	0.07 %	0.16 %	0.01 %
February 2016	1,582	0 %	1.87 %	0.06 %	0.14 %	0.02 %

Table IV illustrates that, for the period of study, the maximum percentage of market share owned by a single vendor is 3.13% and the minimum percentage of market share is zero. Throughout the six months, the mean ranges between 0.06% and 0.14% and the market share median is even lower as it ranges between 0.01% and 0.05%. The descriptive statistics on the market share variable already suggest that the drug market is not concentrated around a few market players.

The Exposure Measure

The exposure measure is the first dimension of the size and scope of vendors. It is a proxy to assess the degree of vendors' advertisement and subsequent visibility on the platform. The exposure variable is calculated according to the number of drug listings posted by a vendor for each period of study. Table V illustrates the exposure variable's descriptive statistics.

Table V - Descriptive statistics on vendors' exposure

	N	Min	Max	Mean	Std. Dev.	Median
September 2015	692	1	89	10	12	6
October 2015	813	1	219	13	17	8
November 2015	1,210	1	343	13	19	8
December 2015	1,369	1	367	15	22	8
January 2016	1,416	1	369	16	24	8
February 2016	1,582	1	383	16	24	9

Table V shows that the maximum number of listings posted by a vendor, during the period of study, is 383 and the minimum is one. The average number of listings ranges from 10 to 16 listings with large standard deviations. The median indicates that the number of listings posted ranges between six and nine for half of the vendors. Table V also illustrates that the number of listings posted on average increases through the period of study.

The Diversity Measure

The second dimension of the size and scope of vendors is about vendors' degree of diversity in the types of drugs advertised in their listings. The diversity measure is calculated according to the Standardized Diversity Index (SDI) developed by Agresti and Agresti (1978) and spans from zero to one, where zero represents perfect specialization whereas one represents perfect diversification. The SDI indicates the probability that two listings, selected at random in all listings related to a vendor, end up in two different categories. Table VI illustrates the descriptive statistics on the diversity variable for each period.

Table VI- Descriptive statistics on vendors' diversity

	Number of vendors	Min	Max	Mean	S.D.	Median
September 2015	692	0	0.94	0.23	0.29	0
October 2015	813	0	0.93	0.26	0.30	0
November 2015	1,210	0	0.94	0.25	0.30	0
December 2015	1,369	0	0.96	0.25	0.31	0
January 2016	1,416	0	0.92	0.22	0.29	0
February 2016	1,582	0	0.96	0.27	0.31	0

Table VI shows that vendors' maximum degree of diversification, during the period of study, is 0.96 and the minimum degree of diversification is zero, indicating perfect specialization. The mean ranges from 0.22 to 0.27. This indicates that the percentage chance that two listings - taken at random in a population of a vendor's listing - end up in two different categories is between 22% and 27%, on average. According to the median, half of the vendors are specialized with a zero probability that two random listings will end up in two different categories. The results in table VI suggest that drug vendors are much more specialized than diversified in terms of the types of drugs advertised.

The Experience Measure

The experience measure is the third dimension of the size and scope of vendors. The experience variable evaluates to what extent a vendor is experienced according to the number of days he/she has been registered as a vendor on the platform. Table VII illustrates the descriptive statistics on the experience variable for the six periods.

Table VII - Descriptive statistics on vendors' days of experience

	Number of vendors	Min	Max	Mean	S.D.	Median
September 2015	686	5	281	110	67	126
October 2015	802	0	315	124	80	129
November 2015	1,206	3	342	119	88	93
December 2015	1,365	2	373	130	94	109
January 2016	1,412	0	400	146	99	122
February 2016	1,578	5	439	162	106	133

The number of vendors varies by about five vendors in the table, compared to original sample, because we did not have their registration date.

Table VII shows that the most experienced vendor has been registered for 439 days – about 15 months - in February 2016. The fact that the minimum number of days ranges between zero and five indicates that new vendors entered the market during the period of study. On average, vendors have between 110 and 162 days - three to six months- of experience on the cryptomarket platform. The average increases through the six periods and suggests that some vendors tend to stay on the market. The median in number of days ranges between 93 and 133 -three to four months- and indicates that about half of the vendors had less than four months' experience during the period of study.

The correlation matrix in Annex I shows that there is little correlation between the three measures for each period of study. This illustrates that all three measures are relevant for the subsequent analyses.

Market Competition

The two measures that characterize the online drug market competition are the concentration and the distribution of market share. The section below presents the results of the concentration of market share, calculated with the Herfindhal-Hirhsmann Index (HHI), and the results of the distribution of market share, depicted with Lorenz curves.

Concentration of Market Share

Already, market share descriptive statistics indicate that the vendor with the highest proportion of market share -throughout the period of study- earned no more than 3.13% of the total market. From these results, low market share concentration can be inferred. Table VIII illustrates the results of the HHI on the concentration of market share for the online drug market for each period of study.

Table VIII - Results on the concentration of market share

	Number of vendors	Total market feedbacks	HHI
September 2015	692	2,176	0.006614
October 2015	813	3,462	0.007397
November 2015	1,210	5,356	0.004366
December 2015	1,369	4,389	0.001832
January 2016	1,416	7,312	0.001871
February 2016	1,582	6,134	0.001343

Results in Table VIII show that the online drug market is highly competitive throughout the period of study. Indeed, they indicate that the structure of the online drug market is much closer to perfect competition ($HHI = 1/N$) than to a monopoly ($HHI = 1$). Market share is not concentrated among a few important market players. The last three months of the period of study even illustrate a marginal decrease in market share concentration compared to the first three months.

Distribution of Market Share

To assess market competition, we decided to also evaluate the distribution of market share, because the HHI is often criticized for not taking into account the distribution of the targeted variable in the population (Biker and Haaf, 2002). The distribution of vendors' market share is depicted with a Lorenz curve, for each period of study, in Figure 2. The Lorenz curve shows the cumulative percentage of market share in relation to the cumulative percentage of vendor population.

Figure 2 - Distribution of market share

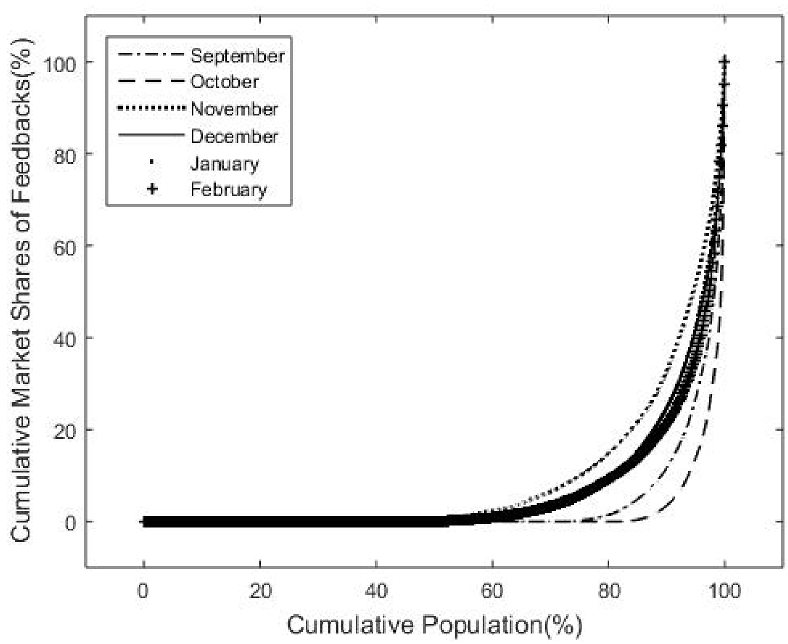


Figure 2 shows distribution curves that are concentrated towards the right of the graph, far from the center. This suggests that the distribution of market share is unequal, with about 60% of vendors making near zero sales.

The results on the concentration and distribution of market share indicate that the online drug market is competitive, but also unequal, with more than 60% of vendors making near zero sales. Drug vendors therefore face a competitive setting in which the opportunity to make some sales does not seem to be accessible to all. We now turn towards the results of the size and scope of vendors, the second objective of this study.

The Size and Scope of Vendors

The size and scope of vendors is evaluated according to group trajectories of vendors' market shares and three dimensions of their size and scope: exposure, diversity and experience. The dimensions evaluate the importance of drug vendors in online markets beyond market share.

The section below begins by presenting the several steps undertaken to select the best group-based trajectory model on vendors' market shares. The results of the model are then presented along with the outcomes of the model fit diagnostics. The size and scope of vendors -in terms of exposure, diversity and experience- is afterwards compared, based on the trajectory groups found in the model.

Model Selection

In this study, the group-based trajectory model aims to find group trajectories on vendors' market share between September 2015 and March 2016. The model selection procedure follows the one developed by Nagin (2005). It includes two steps: (1) determine best model fit in terms of the number of groups; and (2) determine the form of the polynomial function for each group in the model. To find the best model fit, we use BICs and random assignment probabilities.

The censored normal (CNORM) model is the most appropriate model for the data because the distribution of market share spans from zero to one hundred, with more than half of vendors having zero market share.

First, to determine the best number of trajectory groups, we fix the predetermined polynomial functions to be linear in the model. This assumes that drug vendors make more or fewer sales in a relatively constant manner through the six periods. The assumption of linearity in trajectories of market share is the most plausible, but we still evaluate other polynomial function forms in the second part of this section.

With linear polynomial functions for all group trajectories, we add one group at a time to the model and evaluate if the changes in the BICs are significant, based on the formula developed by Kass and Wasserman (1995).

The model generates two BICs. The first BIC is based on the number of observations in the sample (N=708) and the second one is based on the number of possible trajectories -or vendors (N= 2479). The highest BICs are favored. The formula $B_{ij} = e^{BIC_i - BIC_j}$ allows us to assess if the changes in the BICs are significant, supporting evidence for an additional group in the model. Recall that $B_{ij} > 10$ is strong evidence in favor of the *ith* model; $3 < B_{ij} < 10$ is moderate evidence for the model *ith* ; and $B_{ij} < 3$ is weak evidence for the ith model. The ith model is the one that contains an additional group.

To determine the best number of groups in the model, we also use random assignment probabilities (π_i). Random assignment probabilities show whether the distribution of the vendor population among the trajectory groups is adequate.

Table IX illustrates the results of the model selection process. How the two BICs change when groups are added into the model are presented, along with how significant the changes are according to Kass and Wasserman's (1995) formula (B_{ij}). The column to the right shows the distribution of random assignment probabilities for every group combination.

Table IX – Model selection process – Number of groups

	BIC_1	BIC_2	B_{ij_1}	B_{ij2}	Random Assignment Probabilities (%)[a]						
	N=7082	N= 2479			1	2	3	4	5	6	7
2 groups	-1,949.77	-1,946.62			96.8	3.2					
3 groups	**-1,666.89**	**-1,671.61**	**7.13**	**2.73**	**90.3**	**8.7**	**1**				
4 groups	-1,482.65	-1,476.35	1.03	6.31	84.2	13.8	1.8	0.2			
5 groups	-1,412.46	-1,404.59	3.04	1.46	76.7	20.0	2.2	0.9	0.1		
6 groups	-1,325.31	-1,315.86	7.06	3.43	57	36.40	4.7	0.8	1.0	0.1	
7 groups	-1,333.22	-1,322.20			5.7	64.7	23.9	1	3.9	0.8	0.1

a Numbers for the random assignment probabilities are rounded to the nearest tenth

Table IX shows that, every time a group is added to the model, both BICs increase until the addition of the sixth group, for which the two BICs decrease. Comparing the two groups model with the three groups model indicates that B_{ij1} gives moderate evidence in favor of the three groups model, while B_{ij2} gives only weak evidence in favor of this model. The vendor population in the third model, based on random assignment probabilities, is distributed as: 90%, 9% and 1%. Comparing the three groups model with the four groups model shows that B_{ij1}

gives weak evidence in favor of the four groups model while B_{ij2} gives moderate evidence for the model. The vendor population in the four groups model, based on random assignment probabilities, is distributed as: 84%, 14% 1.8% and 0.2%. The four group model displays a group that contains only 0.2% of the vendor population. This group, according to the sample, would represent about five vendors and would be too small for any further analysis. In fact, table IX illustrates that adding more groups to the model generates groups that contain only a tiny portion of the population. Also, in the process of adding groups, only weak or moderate evidence supports the new model with an extra group.

We do not want to keep a model with groups containing tiny portions of the vendor population because these groups would be too small for subsequent analyses. As mentioned by Nagin (2005), the model selection must balance the parsimony of the model and the distinctive features of the data. The distinctive feature of the data, in this case, is the fact that a small number of vendors have a distinctive trajectory, which makes them stand out in the analysis as outliers. To keep this distinctive feature, but also favor the model with no more groups than necessary, we select the three groups model. This model displays an adequate distribution of the vendor population (90%, 9%, and 1%) and is better than the two groups model because weak to moderate evidence is in favor of the three groups model.

The second step of the model selection is to determine the groups' polynomial function forms. In the first step of the procedure, the polynomial functions are linear. The second step requires testing other polynomial function forms to find the best model that fits the data.

The model selected has three groups and the polynomial functions can go up to the cubic form (constant, linear, squared and cubic). Hence, 64 possibilities of function forms are possible (4^n

= 4^3 = 64 possibilities). Several attempts with different forms mixing constant, linear, squared and cubic were tested. However, functions taking squared or cubic forms did not show higher BICs than the simpler, linear ones. For purposes of concision, Table X presents the results of the BICs for models with functions that take either a constant or a linear form ($2^n = 2^3 = 8$ possibilities). The model with the highest BICs is preferred.

Table X - Model selection process – Polynomial function forms

	Group 1 β_1	Group 2 β_2	Group 3 β_3	BIC_1	BIC_2
1	Linear	Linear	Linear	-1,671.61	-1,666.89
2	**Constant**	**Linear**	**Linear**	**-1,668.89**	**-1,664.69**
3	Constant	Constant	Linear	-1,728.49	-1,724.80
4	Constant	Constant	Constant	-1,744.06	-1,740.91
5	Linear	Constant	Linear	-1,730.76	-1,726.57
6	Linear	Linear	Constant	-1,677.91	-1,673.71
7	Linear	Constant	Constant	-1,745.59	-1,741.92
8	Linear	Linear	Constant	-1,675.86	-1,672.18

Table X shows that the model with the highest BICs is that with one function taking a constant form and two functions taking linear forms. Hence, one group has a constant trajectory, and two groups have linear trajectories.

Model Results

Through the model selection process exposed above, the best model is the three groups model that has one group with a constant trajectory and two groups with linear trajectories. The model estimates and results are presented in table XI.

Table XI - Results of the group-based trajectory model on market share

	Estimate	SE	P-value
Group 1			
Intercept	-0.039	0.004	0.000
Group 2			
Intercept	0.492	0.026	0.000
Linear	-0.057	0.005	0.000
Group 3			
Intercept	1.239	0.060	0.000
Linear	-0.072	0.013	0.000
Random Assignment Probabilities	π	SE	P-value
Group 1	90%	1.038	0.000
Group 2	9%	1.004	0.000
Group 3	1%	0.220	0.000
BIC			
N = 7082		-1668.89	
N = 2479		-1664.69	

A key feature of group-based trajectory models is that all estimates determine the shape of a group trajectory regardless of the other group trajectory shapes. In this model, the estimates are all significant.

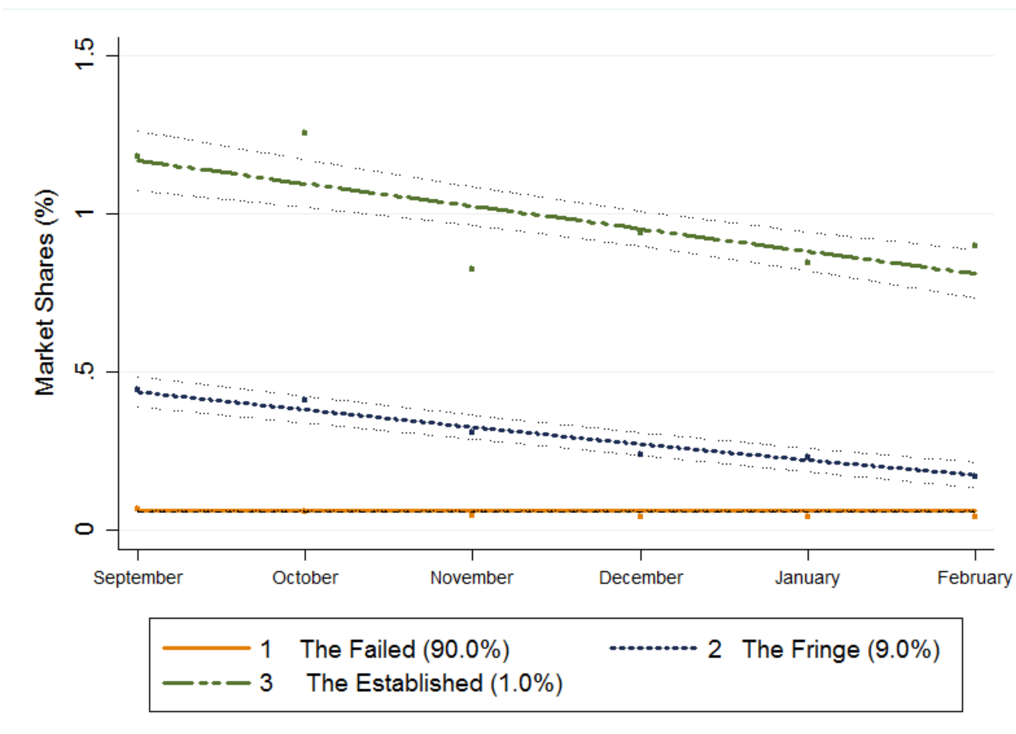
The first group accounts for 90% of the population and the trajectory is constant and negative. This is the result of our censored data that cluster at a minimum of zero. The model assesses the group trajectory on market share with a latent variable that accounts for the potential of vendors to start making some sales. These potential transactions are assumed to be normally distributed. The potential of vendors starting to make some sales is therefore negative. Let's assume, for simplicity, that it equals zero.

The second group accounts for 9% of the population. Its intercept is positive at 0.492 and the slope is negative at -0.057. This indicates that the second group includes vendors who make some sales at the beginning of the period of study (earn on average 0.492% of market share), but their market share decreases in time.

The third group accounts for 1% of the population. Its intercept is positive at 1.239%, which indicates that, at the beginning of the period, vendors in this group earned on average 1.239% of market share. The slope is however also negative, suggesting that vendors' market share in this group also decreased through time.

Figure 3 below illustrates the three trajectories found in the model, with 95% confidence intervals for the six periods of study.

Figure 3 - The three trajectories of drug vendors' market share



Based on these results, names were given to the three trajectory groups. The first group accounts for 90% of the vendor population and is called "The Failed." We see in Figure 3 that they are the ones making very few to no sales throughout the period of study[3]. The second group is dubbed "The Fringe" and accounts for 9% of the vendors' population. They are the ones in the middle, making between zero and 0.5% of total market share. The last group is called "The Established" and accounts for 1% of the population. Vendors in this group are the ones making between 0.5 and 1.5% of total market share. Since all slopes are negative, we can infer that drug vendors, on average, earn less market share throughout the period of study. This does not mean that vendors are making fewer sales. The descriptive statistics on total sales showed that the market was growing, with relative increases in number of sales through time. The negative slopes indicate that the market is more competitive and vendors earn, on average, less in proportion of the total sales.

Model Diagnostics

Finally, to ensure that the model is solid and fits the data on market share, the results of the model diagnostics are presented in table XII, except for the confidence intervals. We did not calculate the fourth diagnostic, because the bootstrapping requirements makes the model estimation time-excessive (Jones and Nagin, 2007) and the three model diagnostics presented below already indicate that the model is a good fit to the data.

The AvePP is the average posterior probability of vendors in a group. The model calculates a posterior probability for every vendor in each group and AvePP is the average of the posterior probabilities of all vendors assigned to this group. The π_i is random assignment probabilities and needs to be compared with the P_i, which is the ratio of the number of subjects assigned in a

[3] Even though the parameter is negative in the result table for this group, the expected value is positive in the figure. This is because the expected value of market share is a function of the estimate, the cumulative distribution function, probability density function of the normal distribution, and sigma.

group against the total number of subjects. The closer π_i is to P_i the better the model fit is. Finally, OCC represents the odds of correct classification, which needs to be larger than one.

Table XII - Diagnostic of the group-based trajectory model on market share

	Number of vendors	AvePP	S.D AvePP	π_i	P_i	OCC
The Failed	2 304	0.96	0.24	0.900	0.929	2.67
The Fringe	150	0.89	0.22	0.009	0.061	81.81
The Established	25	0.97	0.10	0.010	0.010	3233
Total	2 479					

The first indicator is the average posterior probability (AvePP) for each group, based on the posterior probability of group members. The posterior probability of group membership accounts for the probability that a vendor with a specific profile belongs to a specific trajectory group. Nagin's (2005) personal rule of thumb for adequate AvePP is 70%. The AvePP in the model is 0.96 (SD=0.24). 0.89 (SD=0.22) and 0.97 (SD=0.10) for The Failed, The Fringe and The Established respectively. The three AvePPs in this model greatly surpass Nagin's (2005) rule of thumb.

The second diagnostic is P_i which is equal to: $\mathrm{N_j/N}$ where $\mathrm{N_j}$ is the number of individuals assigned in group j and N is the total number of individuals. The closer P_i is to π_i (random assignment probabilities) the more accurate the model is. In this model, the P_i for two groups, The Fringe and the Established, is extremely close or almost identical. However, the P_i for The Fringe is a little lower and equals 0.061 compared to the π_i, which equals 0.09. This means that the proportion of individuals assigned to this group is lower than the random assignment predicted by the model.

The third diagnostic is the odds of correct classification (OCC). Nagin's (2005) personal rule of thumb is $OCC > 5$. The OCC for The Fringe and The Established are well above Nagin's criteria. However, the OCC for The Failed is not. This may be explained by the fact that the group incorporates 90% of the population and the odds of being randomly assigned to this group are high. When $OCC = 1$, “the maximum probability rule has no predictive capacity beyond random chance” (Nagin, 2005, p. 88). With an OCC at 2.67 and The Failed accounting for 90% of the population, the predictive capacity of the OCC is beyond one, which is more than expected.

Size and scope of Vendors Within Each Group

The size and scope of vendors is based on the exposure, diversity and experience variables and is compared between each trajectory group. To ensure that group means are adequate, we take into account vendors’ uncertainty of belonging to his/her associated group by weighting each vendor’s scores according to his/her posterior probability of group membership. This weighting is computed for the three dimensions and for each individual at each period of the study. For example, a vendor with an exposure score of 10 (holding 10 listings) in September and a posterior group membership probability of 0.97% for the first group has a weighted exposure score of 9.7. Hence, the weighted score on each dimension takes into account the vendor’s uncertainty of belonging to a group and prevents us from finding differences in groups where there is none.

To assess the differences in the size and scope of vendors in each group we conducted a one-way analysis of variance (ANOVA). The variance analysis determines if there are significant differences in the means of each group for the three dimensions. As stated in the methodology section, the null hypothesis tested is: there are no group differences in group means and the alternative hypothesis is: there are differences in group means.

We first conducted the analysis on experience, diversity and exposure scores for the six periods of study. We then conducted the same analysis, but with vendors' mean scores on experience, diversity and exposure for the whole period of study. The results were identical. For purposes of concision, we decided to present in Table XIII the results of the one-way ANOVA based only on the second analysis: vendors' mean scores for the six-month period. We present afterwards figures with trends to illustrate the longitudinal differences in the three groups.

Table XIII - Group comparison on vendors' size and scope

	The Failed A	The Fringe B	The Established C				
	Group Mean	Group Mean	Group Mean	F Ratio	A-B*	A-C*	B-C*
Experience	105	135	167	15.38	0.000	0.001	0.187
Diversity	0.22	0.25	0.22	1.78	0.173	0.961	0.896
Exposure	10	20	38	65.62	0.000	0.000	0.000

* p-value determines if there are significant differences between two groups.

Table XIII illustrates that there are some significant differences in the size and scope of vendors among the three groups. These differences are discussed below, along with the longitudinal group scores on exposure, diversity and experience.

Exposure

The first dimension of the size and scope is exposure, which is calculated according to the number of listings posted by a vendor. The results of the one-way ANOVA analysis illustrate that there are significant differences in exposure among the three groups. We can reject the null hypothesis that there is no difference in group means. Vendors in The Established have more exposure than vendors in the two other groups and vendors in The Fringe have more exposure than vendors in The Failed.

Vendors in The Failed post, on average, 10 listings whereas vendors in The Fringe post, on average, 20 listings. Vendors in The Established surpass the other two groups and post, on average, 38 listings.

Figure 4 - Vendors' Exposure

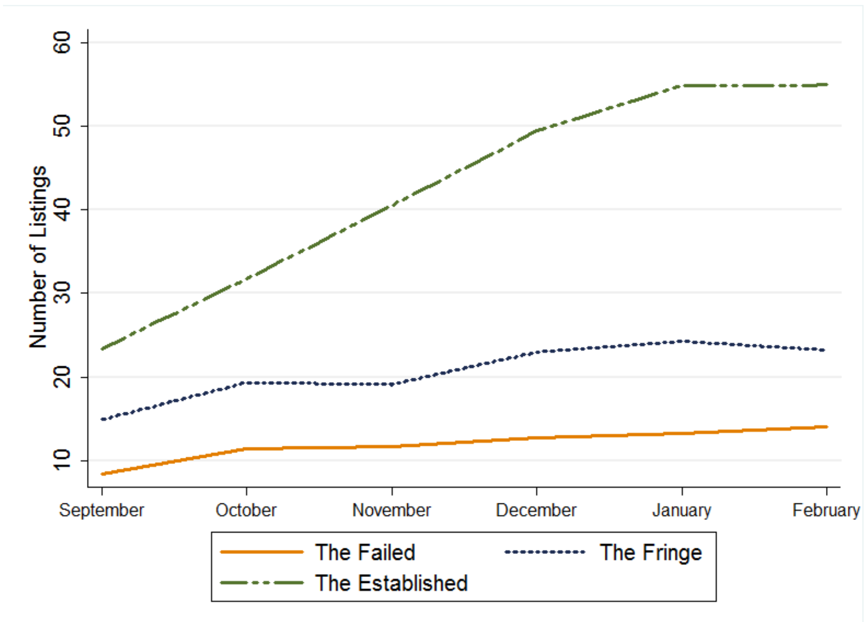


Figure 4 illustrates the weighted exposure mean scores for the three groups during the six periods of study. It shows that vendors in The Established have significantly more exposure than vendors in the other two groups during the whole period of study. Vendors in The Fringe, on the other hand, hold between 10 to 25 listings and vendors in The Failed do not surpass 15 listings. The differences among the three groups persist throughout time. Vendors in The Established also post more and more listings as time passes, compared to the two other groups.

Diversity

Diversity is the second dimension of the size and scope of vendors. However, the results of the one-way ANOVA analysis are not significant. We cannot reject the null hypothesis that the means among the three groups are different. The Failed, The Fringe and The Established are not more or less diversified in terms of the types of drug listed.

Figure 5 - Vendors' Diversity

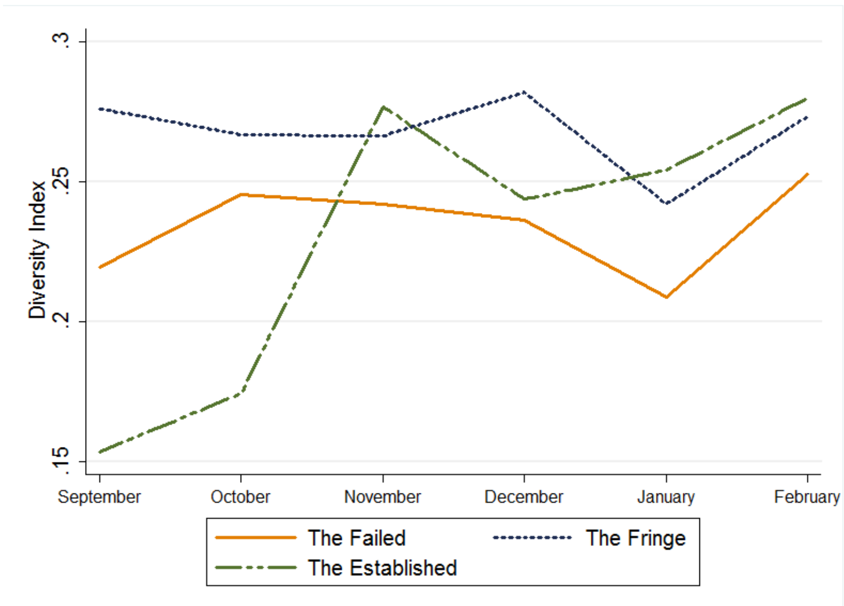


Figure 5 illustrates the weighted diversity mean score for the three groups during the six periods of study. It shows that the three groups have, on average, a diversity score between 0.15 and 0.30 throughout the whole period of study. This means that, on average, the percentage chance that two random listings end up in different categories ranges between 15 and 30%. From this, we can induce -again- that all drug vendors are, on average, quite undiversified.

Experience

The third dimension of the size and scope of vendors is experience. The results of the one-way ANOVA analysis illustrate that there are significant differences in the experience mean scores between The Failed and the other two groups. There is, however, no significant difference in the experience mean score between The Fringe and The Established. We can therefore partially reject the null hypothesis that there is no difference in group means. Vendors in The Established have, on average, 167 days of experience, whereas vendors in The Fringe and The Failed have, on average, 105 and 135 days of experience.

Figure 6 - Vendors' Experience

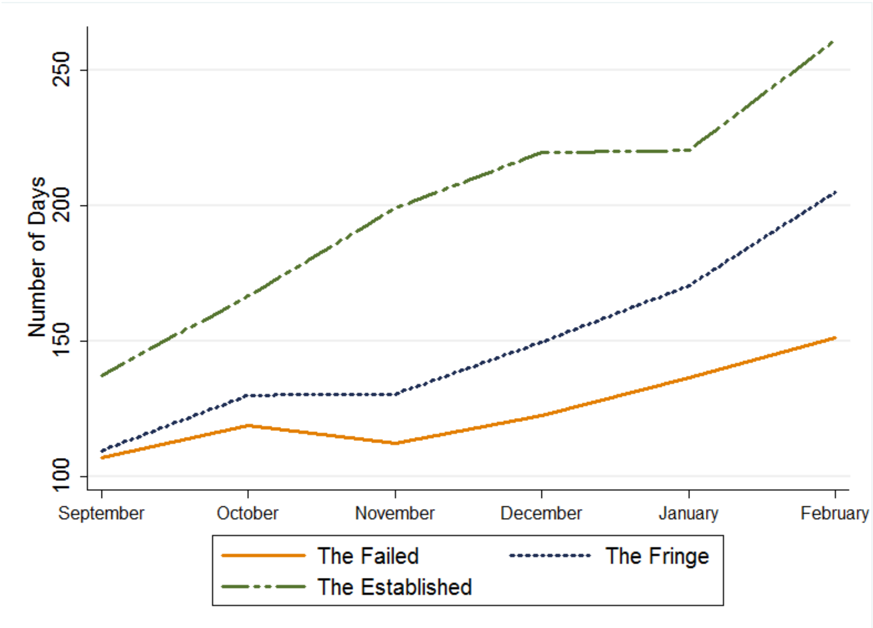


Figure 6 illustrates the weighted experience mean score for the three groups during the six periods. It suggests that vendors in The Established and The Fringe have more days' experience than The Failed throughout most of the period studied. Vendors in The Established start the period of study with, on average, 140 days of experience whereas the other two groups start, on average, with 110 days of experience. Also, experience increases through time for the three groups, which illustrates that vendors stay on the market and gain experience through time.

Moreover, by February 2016, the vendors in The Established have, on average, 250 days of experience on the cryptomarket. This illustrates that drug vendors on the market have, on average, less than a year of experience during the period of study.

Finally, the results suggest that the size and scope of vendors within each group are relatively different. Vendors in The Established account for 1% of the population, have more exposure and more experience. They are the ones with a larger size and scope and the ones that make the most sales. On the other hand, vendors in the Failed account for 90% of the population, have less exposure and less experience on the platform. They are the ones with a smaller size and scope and they make almost no sales. Vendors in The Fringe account for 9% of the population and have an *average* size and scope compared to the other two groups. They have more exposure than The Failed, but less than The Established. They have also more experience than The Failed. Overall, vendors are quite undiversified on the platform, with a diversity score ranging between 0.15 and 0.30.

Information on each group advertising activities

While this is not the focus of the present study, we still wanted to provide some background information on the selling activities of each group. Table XIV shows the proportion of vendors advertising a type of drugs in each group. For simplicity, we took an average of the six periods for each group and for each type of drugs. Vendors could advertise many drugs; the sum of the percentages are therefore not 100.

Table XIV – Proportion of vendors advertising a type of drugs in each group

	Ecstasy	Cannabis	Psychedelics	Stimulants	Prescriptions	Opioids	Others
The Failed	26 %	34 %	22 %	36 %	28 %	18 %	11 %
The Fringe	34 %	46 %	24 %	44 %	25 %	21 %	5 %
The Established	28 %	61 %	12 %	44 %	20 %	24 %	18 %

Table XIV shows that The Failed and The Fringe advertise all types of drugs, with no strong tendency towards one type of drug. On the other hand, The Established seem to advertise more cannabis. Indeed, 61% of Established vendors advertise at least one cannabis listing.

Conclusion

Fierce Competition and Market Superstars

This study characterizes the structure of the online drug market hosted on cryptomarkets. To do so, market competition and the size and scope of drug vendors are assessed. The results suggest that selling drugs on cryptomarkets is not an easy task. The setting is competitive and only a few vendors manage to make any sales. Moreover, the size and scope of vendors is limited. This chapter discusses the structure of the online drug market and how it is related to the online, anonymous and illegal features of cryptomarkets drug transactions. To begin, we suggest that the virtual world of cryptomarket drug vendors is embedded within their physical world; offline drug-related activities need to stay within a small size and scope due to the consequence of product illegality. After, we discuss the fierce competition and barriers to sales found in the online drug market. Then, we discuss the paradox of fierce competition and market superstars that emerges from our findings. We conclude this section with the limits of this study and possible further research.

Drug Vendors' Virtual World Embedded in their Physical World

A characteristic related to the activities of cryptomarket drug vendors is the fact that the product they sell needs to be produced (or, for middle-market dealers, exchanged), packaged and shipped once sold. This is not the case for online vendors selling virtual products, such as stolen information or hacking services. Drug vendors have to conduct offline activities when selling on cryptomarkets; their virtual world is embedded in the physical one. Figure 7 illustrates a typical shift of vendors' activities from offline to online.

Figure 7 - Typical online/offline cryptomarket drug vendors' activities

Offline activities are most likely to stay within a small size and scope due to the driving forces of product illegality. The risky environment in which illegal firms evolve prevents them from growing, hiring employees or internalizing production functions (Reuter, 1983). Groups involved in the sales of illegal products are known to be quite small, consisting of fewer than 10 participants (Bouchard and Morselli, 2014), as smaller groups are considered more secure than larger groups (Adler, 1993; Jacobs, 1999; Reuter and Haaga, 1989). For cryptomarket drug vendors, expansion in selling activities would require an increase in production (or buying drugs for middle-market drug dealers), packaging and shipping activities. Yet, these offline activities are intensive. For example, the drugs need to be carefully hidden in the package to ensure that they will not be intercepted at the borders. When posting the package, vendors also need to take all precautionary measures to ensure that enforcement agencies will not be able to trace the package back to them. Otherwise, vendors face risks of arrests and seizures. Moreover, interception can be costly for vendors in terms of risk to profit and reputation (Décary-Hétu et al., 2016). Thus, the packaging and the shipping activities require extensive management on the vendors' side, and potential growth would require more human capital. However, more human capital implies more costs in monitoring, increasing the risks of arrests and seizures (Reuter, 1983). Thus, vendors selling drugs online still need to keep their offline activities small.

Moreover, cryptomarket drug vendors' activities are fragmented and rely on independent actors. First, drug distribution is subcontracted to legal postal services since buyers expect their physical products to arrive through mail delivery. Legal postal services are unwillingly part of the cryptomarket drug distribution process and they are completely independent of vendors' control (Volery, 2015). Plus, since the product sold is illegal, drug vendors have no legal recourse if the package disappears or is intercepted; they cannot claim their loss. Thus, drug distribution through postal services is an enormous constraint for cryptomarket drug vendors, one that fragments their activities and prevents them from growing, mainly due to product illegality (Reuter, 1983).

Second, cryptomarket platforms control part of drug vendors' activities, such as payments and advertisement. Cryptomarket administrators are responsible for designing and maintaining the online marketplace as well as the smooth functioning of transaction payments. They provide an infrastructure for drug vendors to access consumers and advertise drug products. Thus, cryptomarkets provide a service that is cost-economizing for drug vendors, but that is also completely independent from vendors. Dysfunctionalities in cryptomarket features can impact vendors' drug-dealing activity. Scam exits from administrators or law enforcement shut-downs can terminate drug vendors' selling activities without notice. Such cryptomarket shut-downs have happened often in the past (Soska and Christin, 2015) and they prevent cryptomarket drug vendors from gaining experience and growing.

In fact, we found that cryptomarket drug vendors' experience is relatively short. The Failed, which accounts for 90% of drug vendors, has a group average of three and a half months of experience throughout the period studied. The Established, the 1% elite, has a group average that does not surpass five and a half months of experience. Vendors' experience is, in absolute terms, quite short. This finding is in accordance with Christin's (2013) study, which found that sellers do not stay long on the marketplace, as the majority of them disappeared within three months of market entrance and only 9% of Silk Road sellers (112 sellers) were present for the entire period of the study (a few months in 2012). Also, Soska and Christin (2015) mentioned that multiple cryptomarkets appeared and disappeared. Cryptomarket shut-downs in the past years can partially explain vendors' brief experience on the platform. The timeframe of existence for cryptomarket vendors and cryptomarket platforms is ephemeral, which prevents drug vendors from gaining significant size and scope in terms of experience.

We also found that most cryptomarket drug vendors are relatively undiversified. Advertising multiple types of drugs on cryptomarkets implies that one can supply them. However, diversification may require an increase in a vendors' offline activities. Reuter (1983) mentioned that illegal enterprises are more likely to be undiversified because pure diversification in multiple lines of products increases the exposure to law enforcement and subsequently the risk of arrests and seizures. However, although drug vendors tend to be specialized, they may sometimes grasp profitable opportunities (Adler, 1993; Dorn and South, 1990). Cryptomarket drug vendors may grasp profitable opportunities by selling another type of drug, but overall they seem to remain relatively specialized. The results on the relative non-diversification of cryptomarket drug vendors indicate that the driving forces of product illegality push them to keep their offline activities within a small scope, thus staying relatively undiversified.

One new feature of online markets is the possibility to advertise. Reuter (1983) mentions that advertising is not possible in traditional illegal markets because it provides information to the police and attracts attention. Subsequently, illegal enterprises cannot enjoy the benefits from advertising and are unable to develop customer loyalty.

Online, however, drug vendors can advertise their products and reach many potential buyers. Online illegal markets are known to be an open advertising space (Holt, 2013). Moreover, cryptomarkets offer an even better setting for advertisements than illegal discussion forums and chat rooms, they provide a well-designed platform, similar to eBay, where vendors can advertise products (Barratt, 2012). By posting listings on cryptomarkets that will be exposed to many market participants, drug vendors can benefit from advertising, expanding their pool of potential buyers. However, they may not be able to fully enjoy the benefits of massive advertising due to the consequence of product illegality that prevents them from growing.

Thus, selling drugs on cryptomarkets requires offline activities that need to stay within a small size and scope due to the driving forces of product illegality (Reuter, 1983). The results on market share illustrates that all drug vendors earn a small proportion of market share; no vendor earned above 3.13% of market share throughout the period of study. This suggests that their activities need to stay within a small size and scope. Moreover, although drug sales fairly increased during the period of study, market share trajectories are negative. This result does not illustrate that vendors made fewer sales, but instead that they earned less and less in proportion to the size of the market. The three negative market share trajectories suggest that none of the three groups could capture the market expansion observed, not even The Established.

This implies that the growth capacity of the drug market may be limited to the growth in the number of players in the platform, because every player has a limited capacity for selling due to the consequence of product illegality.

However, some vendors may overcome this capacity constraint by becoming online middle-market dealers, buying drugs online and selling them online, becoming the courtier between buyers and sellers. In this case, the vendor could gain large size and scope since he/she would not have offline activities. This vendor would however be dependent on the online seller from whom the drug is bought, who would in turn be constrained by the consequence of product illegality. Factors such as package interception would affect the courtier as much as the seller. Further research on vendors' potential to expand online selling activities, based on qualitative interviews, could further help clarify how the drug vendors' virtual world is embedded in the physical one.

Yet, the fact that vendors have a limited capacity to grow may explain why the structure of the drug market is characterized by fierce competition, along with other factors. These other factors are discussed below.

Fierce Competition and Barriers to Sales

The myth that the drug market is dominated by large-scale hierarchical and criminal organizations has been demystified (Paoli, 2002). Drug markets have been found to be quite competitive and driven by market dynamics (Desroches, 2007; Morselli, 2001; Pearson et al., 2001). Online drug markets are the perfect example of how drugs are basically consumer goods that are exchanged through markets (Caulkin and Reuter, 1998). The results indicate that the online drug market hosted on cryptomarkets is highly competitive and far from a monopoly-type market, but also that it is highly unequal, with strong barriers to sales.

The fierce competition is found because drug transactions on cryptomarkets take place online, and features of online markets, such as low search, switch and menu costs, are known to foster competition (Brynjolfsson et al., 2003; Brynjolfsson and Smith, 2000).

Also, online illegal markets hosted on discussion forums and chat rooms are known to be driven by market dynamics and be quite competitive (Holt, 2013; Holt and Lampke, 2010; Yip et al., 2013). Cryptomarkets are even more sophisticated than the first generation of illegal online markets as they are designed so that buyers can shop through listings and compare prices in an easy and friendly manner (Barratt, 2012). Moreover, although the lack of advertising in traditional markets made it harder for customers to compare the prices of different products (Kleiman, 1991), customers on cryptomarkets can easily compare prices through the advertised listings. Buyers' search costs are therefore decreased on cryptomarkets due to the efficient design of the platform and the possibility of advertising products. Vendors can also easily change the price of their listings, their menu costs being nil.

Thus, certain features of cryptomarkets foster competition and this competition is exacerbated by the limited capacity of vendors to expand their offline activities due to the consequence of product illegality (Reuter, 1983). Competition on cryptomarkets is fierce. However, market competition analysis also shows that the market is also greatly unequal, with about 60% of vendors making near zero sales. This finding is even further supported by the results of the GBTM model showing that 90% of vendors belong to The Failed group. Vendors in The Failed are spectators in the market; they have vendor a status but they are making few to no sales.

Research on traditional markets suggests that entering drug markets as a vendor is fairly easy because there are few barriers to entry either at low or high levels of drug dealing (Bouchard, 2007; Reuter and Haaga, 1989). This is because little knowledge or skill is needed to enter the drug trafficking market. Drug vendors on cryptomarkets likewise do not face any barriers to entry: they can easily register on the cryptomarket and start posting drug listings. When advertising drug products, vendors are considered to be part of the drug supply. However, being part of the drug supply does not guarantee that actual sales will be completed. Indeed, the results indicate that the great majority of vendors who post drug listings on cryptomarkets do not make any sales. This suggests that drug vendors are facing barriers to sales instead of barriers to entry on cryptomarkets.

Thus, although anyone can enter the market and post listings -making the drug market superficially big- only a few manage to make a fair number of sales and overcome the barriers to sales. When studies on cryptomarkets are undertaken to discuss their importance as distributors of illegal drugs, vendors' inactivity due to barriers to sales needs to be taken into account. Assessing the size and scope of the online drug market according to the number of listings posted on cryptomarkets is unrepresentative of the real market activity.

Barriers to sales may arise due to the online and anonymous features of drug transactions on cryptomarkets. The paradox of fierce competition on cryptomarkets and few important market players -The Established- is discussed in the next section.

The Online Drug Market Paradox: Fierce Competition and Market Superstars

A paradox arises from the results of this study. How can the online drug market be highly competitive, but also highly unequal? Market shares inequality is depicted with the Lorenz curve, but also with the distribution of vendors' market share trajectories. The fact that the majority of vendors are part of The Failed group and only a few manage to make a relatively high number of sales may be due to the online and anonymity features of transactions.

In online markets, buyers grant importance to non-price attributes, such as shipping costs or delivery time (Cambini et al., 2011; Ellison and Ellison, 2009 Latcovictch and Smith, 2001; Pozzi, 2012; Ulph and Vulkan, 2000). They are moreover willing to pay higher prices for well-reputed sellers and products with good branding (Smith and Brynjolfsson, 2001).

In cryptomarkets, the risks associated with conducting a transaction are greater than in online legal markets due to the anonymity of market participants. The risks of unsuccessful transactions are greater because dishonest market participants can steal and act opportunistically with a high level of impunity (Wehinger, 2011; Yip et al., 2013). The anonymity features of online drug transactions may exacerbate the tendency of buyers to favor branding and reputation over prices in order to minimize their risk of transaction failures. This could explain not only the strong barriers to sales discussed above, but also the inequality distribution found in vendors' market share trajectories.

We found a distribution of vendors' market share trajectories of 90%, 9% and 1%, where the 90% consists of vendors in The Failed group and the 1% consists of vendors in The Established, those accounting for the greatest proportion of market share through time. Interestingly, this distribution is the same as for the famous "90/9/1" principle of the Internet: "This 90%, 9%, and 1% are also known as Lurkers, Contributors, and Superusers, respectively" (van Mierlo, 2014, p. 1). Many studies have illustrated that most often 90% of participants are readers, 9% edit new content and only 1% actively create new content (Sun et al., 2014). In this study, the 1% represents active vendors and the 90% represents vendors acting as spectators in the market.

Vendors in The Established, forming the 1%, are the superstars of the market; they are the ones holding the most market share through time. More than half of them advertise at least one cannabis listing. This is not surprising since the vast majority of sales on Silk Road were cannabis sales (Aldridge and Décary-Hétu, 2014). The Established also have more exposure on the cryptomarket by posting more listings on the platform. To minimize their risks, buyers may therefore tend to buy more from The Established, the vendors with most visibility and branding, a tendency seen in legal online markets (Cambini et al., 2011; Ellison and Ellison, 2009; Latcovictch and Smith, 2001; Pozzi, 2012; Ulph and Vulkan, 2000). Vendors in The Established are also more experienced than The Failed. In online anonymous markets, buyers need to look for signals before deciding whom to trust and conduct business with (Décary-Hétu and Leppänen, 2013). Experience may be a good signal of a vendor's reliability and credibility for buyers. Experience is a signal that cannot be faked and can only be gained through time; it may be the best signal for buyers to ensure successful transactions and fully minimize risks. This explains why the most experienced vendors are the ones making the most sales.

The anonymous feature of cryptomarkets may intensify buyers' tendency to buy from vendors with branding, reputation and experience, thus explaining the high inequality distribution and the barriers to sales. However, the fact that only a few vendors manage to be in The Established does not mean that the structure of the online drug market supports the winner-takes-all-theory, discussed by Wang and Zang (2015). The fact that a few market players stand out in the analysis does not imply that they hold market power. The market is still fiercely competitive.

Competition in online markets is so fierce that The Established vendors even seem to do aggressive advertising. The results on the exposure of vendors illustrate that The Established post many more listings than do the other vendors. Moreover, this tendency increases through time during the period of study. The second dimension of the size and scope of vendors also indicates that they are relatively undiversified. Combined, these two results suggest that established vendors offer multiple listings of the same type of drugs. They either offer many listings of the same drug, but in different quantities, or they offer different alternative products of the same type of drugs. Doing so may be indicative of aggressive advertising techniques. Wang and Zang (2015) mentioned that firms face high fixed costs and low marginal costs when conducting business online. This, combined with the fact that the online market is one large virtual place, influences large firms to act aggressively to prevent other niche products from being sold. By posting many listings on the same drugs, established vendors may conduct aggressive advertising to push out potential competitors and keep their position. This could also increase the barriers to sales faced by other vendors, reducing their chance of making sales. Aggressive advertising allows established vendors to offer more variation of the product they sell and better respond to consumer demand, ensuring a better chance of making the most sales they can manage.

Finally, the fact that The Established consists of only 25 vendors who manage to make the most sales may be considered a significant result for law enforcement agencies. Yet, because the market is fiercely competitive, any other vendor is ready to replace anyone in higher groups that leaves the market due to arrests and seizures. If vendors sell drugs online for profits, an important vendor quitting the market would create a hole that any other vendors with the capacity would fill.

Limits and Further Research

The limits of this study provide interesting ideas for further research. First, this study is based on the entire drug market hosted on cryptomarkets, which limits the results. To further understand the structure of drug markets that evolve in cryptomarkets, the same analysis could be conducted on the different submarkets, such as the cocaine, marijuana or prescription market. Their structure may be much different from the one found in this study because vendors selling different types of drugs face different constraints. Moreover, we found that, on average, 61% of vendors in The Established advertised at least one cannabis listing. This is in accordance with Aldridge and Décary-Hétu (2014) who found that most drug sales in Silk Road were related to cannabis. Yet, since these market superstars sell more cannabis, analysing another market -such as the market for stimulants- could show a different picture.

Moreover, this study calculates market share according to feedbacks left on listings. Repeating the analysis with a reliable and accurate proxy of vendors' total revenue could provide another picture of the market structure and lead to a further understanding of the profitability of the market. This might be possible with the new BitCluster tool that tracks bitcoin transactions (Lavoie and Décary-Hétu, 2016).

Another limit of this study is the fact that it does not explain why a vendor is in one group instead of another. An interesting research could track the trajectory of new vendors to understand how barriers to sales are overcome and what makes a vendor switch from The Failed to higher groups. Such a study would give another perspective on the challenges and opportunities faced by vendors because it would indicate to what extent intensive effort is needed to be successful.

This study focuses on only one cryptomarket. However, Soska and Christin (2015) have found that a large proportion of sellers sell on multiple marketplaces at the same time to reduce the uncertainty associated with sudden marketplace closures. A study assessing the size and scope of vendors throughout all marketplaces could better depict vendors' relative importance within the larger cryptomarket ecosystem. This would provide a greater understanding of the structure of the drug market within this wider ecosystem.

Finally, the fact that this study considers that an account is related to a single vendor is an important limit of this research. This is because many accounts can be held by a single individual. If this is the case, the results of this research are unreliable. This limit has been -and will be- faced by many research related to online illegal markets. Yet, an empirical research (Décary-Hétu and Eden, 2015) showed that only 8.9% of individuals used many accounts on an illegal carding forum. Also, Motoyama et al. (2011) replied to this critic by emphasizing the unlikeliness of serious and high-level traders using many accounts on one forum, due to the difficulty to accrue a reputation in online markets. Our responses to such critics are close to those of Motayama et al. (2011). The costs in building a reputation on cryptomarkets are high, due to the many challenges that arise from the anonymity and illegality features of cryptomarket drug transactions. Also, if a vendor uses many accounts to disseminate the risks of being detected as an important vendor by law enforcement, then he/she will need to avoid making clear statements that the accounts are related. However, considering the strong barriers to sales, the costs related to accrue online reputation on many accounts is high and thus unlikely. However, more research on the use of multiple accounts by cryptomarket vendors could better support this theoretical argument.

Coda

This research characterizes the structure of the drug market hosted on cryptomarkets through two objectives: assessing market competition and the size and scope of drug vendors. Characterizing the market structure provides an understanding of the challenges and opportunities drug vendors face when selling on cryptomarket platforms.

Achieving these two objectives revealed that the structure of the drug market hosted on cryptomarkets is fiercely competitive and deeply unequal, with few online sellers making any sales. The size and scope of vendors is limited. Selling drugs on cryptomarkets seems, in fact, to be quite difficult; vendors face many challenges. This is due to the online, anonymity and illegality features of cryptomarket drug transactions.

The fact that selling drugs on cryptomarkets requires offline activities and that the product sold is illegal pushes drug vendors to keep their activities within a small size and scope. The virtual world of drug dealers is embedded in the physical world, which prevents them from growing and gaining a greater share of the market. Also, the product is sold online, on a well-designed platform with advertised listings. This reduces the buyers' absolute search costs and fosters market competition.

However, the anonymity feature of cryptomarkets also increases the risk of unsuccessful transactions and pushes buyers to favor well-reputed and experienced vendors, creating serious inequality in the market and subsequent barriers to sales. This is even exacerbated by aggressive advertising techniques employed by established vendors. Yet, even if only a few manage to make any sales on cryptomarkets, these vendors still face fierce competition that prevents them from growing and gaining market power.

Fierce market competition and the rise of market superstars is the paradox in the structure of the online drug market hosted on cryptomarkets. The three features of drug cryptomarket transactions, online, anonymity and illegality, create an arid environment for drug vendors to conduct successful sales, with only a few managing to make constant sales through time. Cryptomarkets are therefore not likely to be the future of drug dealing due to the many challenges cryptomarket drug vendors face while trying to sell online.

However, even considering that the structure of the market is fiercely competitive and deeply unequal, with strong barriers to sales, the online drug market on cryptomarkets still subsists and many market participants conduct transactions on the platform. Some studies have argued that online illegal markets avoid failure due to the trust mechanisms developed by market participants or imposed by market administrators (Yip et al., 2013; Wehinger, 2011). This study shows that, even with these trust mechanisms, cryptomarkets are a difficult environment in which to sell drugs, but drug transactions still take place. An understanding of how and why these online drug markets subsist is needed, but is beyond the scope of this research. The relative resilience of the online drug market hosted on cryptomarkets may be due to the subculture that motivates participants, as discussed in Maddox et al. (2015). These authors found that Silk Road was not simply a market, but also a place to discuss and exchange on subjects that are usually stigmatized in today's society, such as drug consumption. The drug market may also be relatively resilient because some drug vendors have few alternative economic opportunities, living in poorer countries or in difficult economic situations. In any case, there is something fascinating about the drug market hosted on cryptomarkets because, although economically difficult for drug vendors, it still resists and subsists.

Finally, cryptomarkets are a new and constantly evolving setting. These marketplaces, in the past years, have appeared and disappeared due to law enforcement take-downs or administrators scam-exits. Yet, despite these risks, market participants continue to conduct transactions online, constantly adapting to new settings. Cryptomarkets are stable in their instability. This makes them a fascinating setting to study, but also an uncertain one. Continuous studying of these markets is the only solution we have to better understand this new and constantly evolving criminal phenomenon.

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Annex I

Correlation Matrix

	Market Shares	Exposure	Diversity	Experience
September				
Market Shares	1	-	-	-
Exposure	-0.261**	1	-	-
Diversity	0.027	0.240**	1	-
Experience	0.053	0.175**	0.048	1
October				
Market Shares	1	-	-	-
Exposure	0.226**	1	-	-
Diversity	0.002	0.224**	1	-
Experience	0.117**	0.143**	0.068	1
November				
Market Shares	1	-	-	-
Exposure	0.199**	1	-	-
Diversity	0.049	0.178**	1	-
Experience	0.087**	0.144**	0.097**	1
December				
Market Shares	1	-	-	-
Exposure	0.277**	1	-	-
Diversity	0.060*	0.254**	1	-
Experience	0.069*	0.177**	0.069*	1
January				
Market Shares	1	-	-	-
Exposure	0.253**	1	-	-
Diversity	0.040	0.238**	1	-
Experience	0.075**	0.148**	-0.025	1
February				
Market Shares	1	-	-	-
Exposure	0.249**	1	-	-
Diversity	0.057*	0.257**	1	-
Experience	0.056*	0.165**	-0.001	1

**. Correlation is significant at the 0.01 level (2-tailed).