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Research Paper

Assessing market competition and vendors' size and scope on AlphaBay

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ABSTRACT

Background: Since 2011, drug market participants have traded illegal drugs through cryptomarkets, a user-friendly infrastructure in which drug market participants can conduct business transactions. This study assesses market competition and the size and scope of drug vendors' activities on one of the largest cryptomarkets, AlphaBay, in order to better understand the challenges that drug vendors face when selling on this venue.

Methods: Relying on data collected from AlphaBay, we calculate the degree of competition within the drug market using the Herfindhal-Hirshmann Index (HHI). We then follow a micro analytical approach and assess the size and scope of vendors' accounts. This is done by evaluating each vendor's market share over time using a group-based trajectory model (GBTM). Results from the GBTM are then used to assess vendors' exposure, diversity and experience based on their selling position in the market.

Results: The HHI scores demonstrate that cryptomarkets offer a highly competitive environment that fits in a top-heavy market structure. However, the distribution of vendors' market share trajectories shows that only a small portion of vendors (referred to as high-level vendors) succeed in generating regular sales, whereas the majority of vendors are relegated to being mere market spectators with almost zero sales. This inequality is exacerbated by the aggressive advertising of high-level vendors who post many listings. Overall, product diversity and experience is limited for all market participants regardless of their level of success. We interpret these results through Reuter's work on traditional illegal markets, e-commerce studies and the growing field of cryptomarket research.

Conclusion: We conclude that, while offering a new venue for illegal drug transactions, in many ways, the economics of cryptomarkets for drug dealing are consistent with Reuter's classic assessment of illegal markets and the consequences of product illegality that underlie it. Cryptomarkets conflicting features, a relatively open setting with relatively high barriers to entry and sales, shape the competitive, yet top-heavy market that emerges from our analysis. This creates a challenging environment for cryptomarket drug dealers.

Introduction

Illegal drug markets are dynamic settings where market participants adapt to continually changing constraints and opportunities. This adaptation routinely leads to the displacement of illegal activities and "the relocation of a crime from one place, time, target, offense, tactic, or offender to another" (Guerette & Bowers, 2009: 1333). Tactical displacement is arguably one of the most common forms of displacement and has been analyzed in the past by looking at how offenders adopt new technologies. This study follows the adoption by drug dealers and drug buyers of multiple online anonymizing technologies that have led to the creation of cryptomarkets (Martin 2014a,b), also known as darknet markets (Rhumorbarbe, Staehli, Broséus, Rossy, & Esseiva, 2016) or anonymous online marketplaces (AOMs; see Christin, 2013). Cryptomarkets have all the visual attributes of popular online merchant websites like eBay and Amazon insofar as they present homepages with a grid of listings to buyers who can browse through thousands of ads for illicit drugs (Barratt, 2012). All purchases are then hidden in packages shipped through legal postal services. Cryptomarkets represent a new anonymous and international arena for illegal drugs sales and their impact on the illicit drug business has been the subject of considerable debate

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(Barratt, Ferris, & Winstock., 2013; Martin, 2014a). To better understand the extent to which cryptomarkets shape the drug business, this study assesses market competition and the size and scope of drug vendors' activities on one of the largest cryptomarkets.

In the following sections, we first consider the impact of product illegality on drug markets and how technology influences commerce and sales. We then introduce online illicit markets and the subsequent rise of cryptomarkets in the 2010s. Using data collected on one of the largest cryptomarkets for illegal drugs, we continue by evaluating the degree of competition on the drug market. Then, we assess the size and scope of cryptomarket drug vendors through time, as well as their experience, exposure, and diversity according to their position in the market. These results are used to evaluate the structural challenges that drug vendors must face on cryptomarkets, which are examined in details in the discussion section.

Drug markets

Reuter (1983) found that the illegality of a market commodity affects the way firms[1] undertake production and distribution. Illegality creates constraints that impose high cost-transaction conditions which result in illegal firms remaining small, fragmented, ephemeral and undiversified in their activities and prevent them from gaining an edge in the market. Reuter argued that most costs associated with the supply of illegal goods and services originate from the number of individuals involved and the coordination of group activities. Firms that supply illegal goods and services operate in a risky extra-legal environment in which arrests and asset seizures are a constant risk. To minimize such risks, illegal firms must control the flow of information about their activities, which prevents them from launching advertising campaigns (Kleiman, 1991; Reuter, 1983), thus forcing them to restrict their size and scope.

Much research on illegal drug markets is consistent with Reuter's assessment of the size and scope of illegal firms and the consequences of product illegality. In contrast with the image of large-scale criminal organizations that dominate illegal markets, firms involved in selling illegal drugs have been found to be relatively small, consisting of fewer than 10 participants (Bouchard & Morselli, 2014). In interviews, drug entrepreneurs asserted that smaller groups of individuals are considered more secure than larger groups (Adler, 1993; Jacobs, 1999; Reuter & Haaga, 1989). Drug markets have also been found to be populated by small and flexible networks of free independent entrepreneurs always on the lookout for financial opportunities. Opportunistic entrepreneurs often come together for a limited set of transactions, with the aim of maximizing financial gains, disbanding shortly afterwards (Adler, 1993; Desroches, 2007; Morselli, 2009; Pearson, Hobbs, Jones, Tierney, & Ward, 2001). Arms-length associations between drug entrepreneurs are therefore generally short-lived compared with more enduring ideologically-driven criminal groups (Morselli, Giguère, & Petit., 2007).

While such constraints limit the typical illegal firm's growth, little acumen and investment are required to enter, quit and re-enter drug markets (Adler, 1993; Bouchard, 2007), even at the higher echelons of the drug distribution chain (Reuter & Haaga, 1989). These studies combined suggest that illegal firms participating in drug markets are confronted with a very competitive environment that constrains how they operate. However, the economic environment is constantly changing, especially with the recent use of pseudonymous communication and payment technologies on the rise, providing drug dealers with a new distribution channel: online markets.

Online markets

A substantial amount of research has been devoted to studying the impact of the Internet on licit markets. Some studies have argued that online markets should generate more competitive pressure on online vendors (Ellison & Ellison, 2009; Brynjolfsson, Smith, & Yu Hu, 2003; Brynjolfsson & Smith, 2000). Search costs for buyers (the costs of searching for products and comparing their prices) are lower online because of fast and effective search engines (Brynjolfsson & Smith, 2000; Brynjolfsson et al., 2003). Switch costs for online buyers (costs associated with changing supplier for a specific product or service) are also lower because they can easily find and switch to other vendors when they are dissatisfied with their purchase (Cambini, Meccheri, & Virginia, 2011). Menu costs for vendors (the costs related to a change in how a product is priced) are expected to be insignificant for online markets, allowing retailers to optimally adjust prices to align with market demand with more flexibility (Brynjolfsson & Smith, 2000).

Despite these features, (Cambini et al., 2011) point out that online markets have yet to reach the high level of competition once predicted by economists. Rather, empirical research has shown that market power in online markets is highly concentrated (Brynjolfsson & Smith, 2000; Clay, Krishnan, & Wolff, 2001; Elberse, 2008; Wang & Zhang, 2015). This is a result of consumers' willingness to pay higher prices for goods sold by reputable online vendors compared with goods sold by unrated vendors (Smith & Brynjolfsson, 2001). Branding has also proven to be of great importance for online buyers because they are concerned with unobservable quality control (Latcovich & Smith, 2001). Advertising is perceived as a signal of reliability and security in online shopping. This can increase the market power of vendors who make significant investments in advertising aimed at building a good reputation in online markets while also pushing out smaller competitors with lower advertising budgets. Wang and Zhang (2015) reported that because online markets are large virtual settings where vendors face high fixed costs and low marginal costs, they are motivated to aggressively advertise their products and services.

The literature on e-commerce informs us on the different economic forces that influence the structure of online licit markets. Keeping this in mind, we now look at online illegal markets where illegal goods and services are sold.

Cryptomarkets

Studies investigating the impact of the Internet on markets' structural features are becoming increasingly relevant for criminologists as illegal firms shift their activities online. Past research (Yip, Webber, & Shadbolt, 2013; Wehinger, 2011; Motoyama et al., 2011) has shown that online illicit markets have been active for more than 25 years, including discussion forums and chat rooms dealing in stolen financial information, hacking kits, fake identity papers, stolen account credentials, spam and hacking services. These markets provide convergence settings where participants, either acting alone or in firms, put up listings and transact with one another anonymously. The anonymity of these markets has generated uncertainty among participants because scammers regularly exploit participants with impunity. Thus, to circumvent the risks associated with transaction failures, market

[1] The term *firm* is what Reuter used in his seminal dissertation on organized crime. It refers to any organization, small or big, and is meant as a generic term for all illicit organizations he studied. To remain faithful to Reuter's work, we will use this term as well when referring to illicit organizations and vendor accounts, whether they represent one or more individuals.

administrators act as regulators (Wehinger, 2011). Once trust is established, these markets have been known to be global, competitive and driven by market dynamics (Yip et al., 2013). They are open advertising spaces where vendors advertise and reach a large pool of potential buyers (Chu, Holt, & Ahn, 2010; Holt & Lampke, 2010; Motoyam et al., 2011).

In 2011, a new breed of online marketplaces with a focus on security, anonymity and ease of use was launched. Referred to as a *cryptomarket*, this new type of marketplace shares many of the visual cues of legitimate online markets, such as eBay (Christin, 2013; Barratt, 2012). By implementing two novel technologies, these markets provide a safer environment than previous markets hosted on forum discussion and chat rooms. The first technology, the *Tor network*, is an anonymizing network that routes its users' Internet traffic through a series of relays that build a buffer between the users and the website they wish to visit (Dingledine, Mathewson, & Syverson, 2004). Websites can only trace back the connection to the last relay, making it very difficult to pinpoint the geographical location of the visitors of a website. The Tor network also allows cryptomarket administrators to conceal the location of their website servers, increasing the difficulty for law enforcement to localize the servers and to shut them down. The second technology, cryptocurrencies (the preferred one so far is the Bitcoin) also contributes to the security of marketplaces by providing a pseudo-anonymous means to make payments (Nakamoto, 2008). Bitcoin is a digital currency that only tracks users through a unique identifier called a 'wallet'. With good money laundering techniques, such as Tumblers that mix bitcoin together (Moser, Bohme, & Breuker, 2013), individuals can limit the risks of identification before converting their cryptocurrencies to fiat currencies.

Both digital and physical products are sold on cryptomarkets. When attempting to deliver a physical product, vendors commonly disguise the good in a package that resembles a package from large online retailers such as Amazon, and sends it through postal services to the address provided by the buyer (Volery, 2015). Vendors can also use drop shipping for package delivery where "retailers operating in a jurisdiction where a substance is illegal arrange purchases on behalf of their customers from manufacturers or wholesalers instructed to deliver directly to their customers" (Aldridge & Askew, 2017: 102).

The first cryptomarket, Silk Road (SR1), was launched in February 2011 and operated for more than two years with almost total impunity, dealing mainly in illicit drugs that were shipped through the mail to customers. Drugs accounted for 17 of the 20 largest product categories on Silk Road (Aldridge & Décary-Hétu, 2014). Since 2015, cannabis, MDMA (ecstasy) and cocaine-related products have been the most popular drugs sold online, representing about 70% of all sales (Soska & Christin, 2015).

The Federal Bureau of Investigation (F.B.I.) seized the servers hosting Silk Road in October 2013 (Aldridge & Décary-Hétu, 2014), but that did little to deter online drug vendors and buyers. During the weeks following the seizure, vendors and buyers moved to other markets or started their own cryptomarkets (Soska & Christin, 2015). Eventually, these new marketplaces were also disrupted by police operations, but the impact of the police operations were quite limited as cryptomarket activity recovered very quickly (Soska and Christin, 2015; Décary-Hétu and Giommoni, 2016). This could be due to participants' strong appreciation for the platforms.

Indeed, vendors reported that they enjoy 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 & Bingham, 2014: 183). They also reported appreciating the possibility for "professional advertising of quality products, professional communication and visibility on forum pages [. . .]" (Van Hout & Bingham, 2014: 183). Yet, Christin (2013) found that most Silk Road vendors disappeared within three months of market entrance and only 9% of Silk Road vendors (112 vendors) were present for the entire period of his eight month study. The overall lifespan of listings was also found to be quite short, at less than three weeks, with a very low survival rate of listings (Christin, 2013). Following the fall of Silk Road, Soska and Christin (2015) conducted a two-year observation on multiple cryptomarkets, between 2013 and 2015, and found that the number of vendors 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 vendors sold less than \$1000 worth of products and only 2% sold more than \$100,000. High achieving vendors had trusted reputation in the market (Tzanetakis, Kamphausen, Werse, & von Laufenberg, 2016). The same study found that the total volume of sales across all cryptomarkets was stable between \$300,000-\$500,000 USD per day, with peaks around \$650,000 USD. However, since the methodology of Soska and Christin (2015) does not consider listings with a price over \$1000 USD, the numbers mentioned above may be undervalued.

On the demand side, customers noted that transactions were more convenient, professional and safer, avoiding face-to-face meetings with dealers (Barratt et al., 2013; Van Hout & Bingham, 2013a,b). 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). Moreover, participants' strong appreciation goes beyond economic arguments: several studies found that cryptomarkets hosted an active community in which participants shared drug consumption experiences, information about drug use and argued against dominant discourses on drug prohibition (Maddox, Barratt, Allen, & Lenton, 2016; Van Hout & Bingham, 2013a,b; 2014). Cryptomarkets were also found to be characterized by libertarian philosophical discourses (Maddox et al., 2016), especially in the case of Silk Road (Munksgaard & Demant, 2016). Thus, cryptomarkets do not only have an economic purpose, they also gather a living community of individuals who share a marginal sub-culture (Maddox et al., 2016), a characteristic that was also found in the traditional drug trade research (Sandberg, 2012a, 2012b; Hammersvik, Sandberg, & Pedersen, 2012).

Overall, the resilience of cryptomarkets (Soska & Christins, 2015), their growth (Aldridge & Décary-Hétu, 2016) and participants' strong appreciation (Barratt, Ferris, & Winstock, 2016, Barratt et al., 2013; Van Hout & Bingham, 2013a,b) strongly suggest that such online markets fill a void in the illegal drug business and they are not expected to disappear anytime soon. Thorough understanding of their inner-working is thus needed.

Competition and cryptomarket drug vendors

Cryptomarkets represent new distribution channels through which illicit goods can be bought and sold. Past researchers have argued that cryptomarkets could potentially disrupt the illicit drug business (Barratt et al., 2013; Martin, 2014a). The online anonymous environment of cryptomarkets removes some of the constraints mentioned by Reuter (1983). For instance, vendors openly advertise their products and thus expose themselves. Each listing is an advertisement in and of itself and vendors can use discussion forums linked to cryptomarkets to further promote their business activities. Cryptomarkets also oversee the ordering process, which consequently frees vendors from having to invest time and resources in processing orders which are received automatically by cryptomarkets who also handle payments thereby relieving vendors from accounting responsibilities. Finally, cryptomarkets are international by nature in that they host vendors across multiple countries (Décary-Hétu, Paquet-Clouston, & Aldridge, 2016). Police investigations may be more difficult given the diffuse nature of cryptomarkets and the inability to establish with any degree of certainty the precise location of drug dealing offenses (in the vendor's country, in the country hosting the cryptomarkets servers and/or even in the buyer's country). Pseudo-anonymous technologies used for drug transactions, such as the Tor network and cryptocurrencies, also pose great challenges to law enforcement agencies. Thus, the unique features of cryptomarkets, such as advertising possibilities, payment systems, international customers and pseudo-anonymous technologies seem to offer interesting economic opportunities for drug vendors.

At the same time, Reuter's (1983) research on the impact of product illegality on market structure still provides an important foundation for researchers trying to understand competition in this new area. Reuter's research indicates that illegal drug markets are competitive and populated by small and ephemeral firms whose growth is constrained by the driving forces of product illegality. The important presence of such transitory firms on cryptomarkets has already been revealed by Soska and Christin (2015) who found that most listings were ephemeral and most vendors small-scale. Research on online markets has also shown that certain characteristics of cryptomarkets could foster competition, such as lowering search and switch or menu costs (Cambini et al., 2011; Brynjolfsson et al., 2003). Cryptomarkets could consequently be a very competitive environment for drug dealing. Yet, cryptomarkets are also anonymous and the risks of transaction failures are higher than in licit online markets (Wehinger, 2011). To counter such risks, multiple trust building systems are established, such as automated feedback systems and escrow services (Martin, 2014a,b, Tzanetakis et al., 2016), but just like online licit markets (Wang & Zhang, 2015; Cambini et al., 2011), the competitive prospects for cryptomarkets may be limited by the unwillingness of consumers to risk making purchases with new and less reputed vendors. In this sense, the possibility to advertise at the international level would confront Reuter's initial limits for illegal market trading, because it would favor established suppliers who are able to brand their products while keeping smaller competitors at bay. Such a scenario would result in a top-heavy competitive market.

This research goes beyond previous studies that evaluated vendors' characteristics (i.e. Christin, 2013; Soska & Christin, 2015) by following a novel approach to understand the structural features of drug cryptomarkets and by providing a theoretical grounding of the results based on Reuter's work on traditional illegal markets, e-commerce studies and the growing field of cryptomarket research. We first assess market competition using the Herfindhal-Hirshmann Index (HHI – Diallo & Tomek, 2015; Hindriks & Myles, 2006). Then, we follow a micro-level approach and assess cryptomarket vendors' market share distribution through time using a group-based trajectory model (GBTM) (Nagin, 2005, 1999). Inspired by Reuter's assessment on the size and scope of firms, we, moreover, evaluate vendors' experience, exposure and diversity characteristics based on similar market share trajectory groups that emerged from the GBTM model. We take these three characteristics from Reuter's (1983) theoretical framework (assessing firms' diversification, longevity and advertising capabilities) because they are good and reliable proxies to evaluate whether a vendor's activity is significant on the market. A vendor with high exposure –has many listings compared to others- is considered a strong advertiser in the market. A diversified vendor has a large size and scope, dealing in many sub-markets. A vendor with experience is a vendor that has been on the market for an extended duration, compared to others. These analyses, when put in relationship with past research, contribute to a better understanding of the market's inner-working by illustrating some of the structural challenges that drug vendors face on cryptomarkets.

Methodology

Data collection

Our data was collected using the DATACRYPTO software tool developed by Décary-Hétu and Aldridge (2015). It is a web crawler that was used in a number of published research to collect data on cryptomarkets (Décary-Hétu et al., 2016; Aldridge & Décary-Hétu, 2016; Kruithof et al., 2016; Décary-Hétu & Aldridge, 2015). Once launched, it starts by downloading the home page of a cryptomarket and parses that page for hyperlinks to other content on the same cryptomarket. It then fetches that content iteratively, looking for more pages to download. When this is completed, DATACRYPTO switches to its scraping mode and extracts all the relevant information from each web page.

DATACRYPTO was used to collect information on Alphabay at six successive points in time: at the end of September, October, November and December of 2015, as well as January and February 2016. Alphabay was, at the time of data collection, one of the largest cryptomarkets available, as well as one of the most stable. All listings posted in the drug sections of the cryptomarket and the related vendors' pages were saved and analyzed. Listings that offered drug paraphernalia such as smoking pipes or syringes were removed. The final dataset is presented in Table 1.

Table 1 shows an expansion of the cryptomarket, as the number of drug listings, vendors and feedbacks increases over time. However, since listings can be taken down by vendors anytime, there is a possibility that the number of listings and feedbacks captured in the dataset are under-estimated. This means that the further we go back in time to consider vendors' feedbacks, the less accurate the comparative analysis among vendors is, since some vendors could have deleted their listings with feedbacks. Since this research considers feedbacks as a reliable metric to estimate a vendor's number of sales (just like Kruithof et al., 2016), we consider only the feedbacks left two weeks prior to the data collection for the subsequent analyses. We limit the period to two weeks because using one week of feedbacks is too short as a spike

Table 1
Distribution of Sample over the Period of Study.

Month of data collection	Cumulative Number of vendors	Cumulative Number of listings	Cumulative Number of feedbacks	Number of feedbacks two weeks before data collection
September 2015	692	6923	21,749	2176
October 2015	813	10,734	34,303	3462
November 2015	1210	16,139	51,972	5356
December 2015	1369	20,112	87,616	4389
January 2016	1416	22,040	121,708	7312
February 2016	1582	25,395	153,331	6134

in the sales of a vendor may artificially increase the vendor's market share and not be representative of the true state of the cryptomarket. Using three or even four weeks of feedbacks has been a common practice in past works (see for example Décary-Hétu et al., 2016), but this extended coverage period reduces the accuracy of the analyses in our study. Indeed, we found in our datasets that 20% of listings did not remain online for more than two weeks. By considering only the feedbacks from the past two weeks, we thus guarantee that our analyses are based on at least 80% of all listings that were active at some point during those two weeks.

To develop variables for market shares, exposure, experience and diversity, we extracted from each vendor's page the date the vendor started to sell on the cryptomarket and from each listings' page the title, product description and drug category.

Variables

Market shares

"Market share" refers to a vendor's sales compared to the total amount of sales in a market. Market share shows a vendor's relative power in a market compared to all vendors (Hindriks & Myles, 2006). For this study, market share indicates a vendor's relative success on a cryptomarket and is based on the number of feedbacks posted on a vendor's total listings two weeks prior to each data collection. Just like Kruithof et al. (2016), we consider that the number of feedbacks is a good proxy to assess the level of transactions a vendor does on a platform, relative to others. A vendor's relative power in a market could also be measured by a vendor's volume of sales (ex. in kilograms of drugs sold) or in revenues (in US dollars). Both metrics are valuable but susceptible to be affected by extreme numbers. Indeed, a vendor could make a single sale for a large volume of drugs at a very high price. This single sale would credit the vendor with a sizeable portion of the market share for volume and revenue but would fail to make the vendor a power player in the ecosystem given the vendor's limited track record. Vendors with many sales are much more likely to have name recognition and to be considered as established members of the community. We encourage future studies to test the models with measures of volume and revenue, but such analyses fall outside of the scope of this study.

Consequently, we consider below that vendors with more sales are more active on the market and are therefore more successful. A vendor's market share is the percentage of a vendor's total sales divided 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. The market share variable is calculated for each vendor and at each period of the study. Vendors who have no market share due to nil sales are considered part of the drug supply because they are willing to conduct online drug transactions. The descriptive statistics of the market share variable is provided in Table 2.

Table 2 illustrates that the maximum market share owned by a vendor is 3.13% and the minimum share is 0.00%. Throughout the six months, the mean ranges between 0.06% and 0.14% and the median ranges between 0.01% and 0.05%. Table 2 suggests that the drug market is not concentrated around a few market players.

Exposure

Vendors on a cryptomarket can expand their exposure on the market by posting more listings. The number of drug listings is considered as a proxy for advertisement because listings increase a vendor's visibility on a cryptomarket. The descriptive statistics around the exposure measure is presented in Table 3.

Table 2
Descriptive Statistics on Market Shares.

	Number of vendors	Min	Max	Mean	S.D.	Median
September 2015	692	0.00%	3.13%	0.14%	0.27%	0.05%
October 2015	813	0.00%	2.98%	0.12%	0.28%	0.03%
November 2015	1210	0.00%	2.45%	0.08%	0.17%	0.02%
December 2015	1369	0.00%	2.12%	0.07%	0.16%	0.03%
January 2016	1416	0.00%	2.48%	0.07%	0.16%	0.01%
February 2016	1582	0.00%	1.87%	0.06%	0.14%	0.02%

Table 3 shows that the maximum number of listings posted by a vendor is 383. The average number of listings ranges from 10 to 16 listings with large standard deviations, suggesting that there are large differences among vendors' exposure. The median ranges between 6 and 9. Table 3 suggests that the number of listings posted by vendors increases, on average, over the period of study.

Diversity

Vendors who sell many types of drugs are involved in several drug submarkets and therefore have a larger size and scope in the market. The diversity measure is calculated based on the types of drugs advertised by a vendor. Vendors who advertise two types of drugs must have the capacity to supply both. For this measure, we categorize a listing based on the drug category in which it was posted on the cryptomarket. Seven large drug categories were available on the cryptomarket: (1) ecstasy; (2) cannabis; (3) psychedelics; (4) stimulants; (5) prescriptions; (6) opioids; and (7) others. Table 4 illustrates the specific drugs included in the seven broader categories.

We manually validated the drug categorization of the January dataset, yielding a 95% accuracy rate. This specific categorization has also been used by other scholars (Kruithof et al., 2016). Using these seven categories, the diversity measure is calculated with the Diversity Index developed by Agresti and Agresti (1978). 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 & Agresti, 1978). It is defined as:

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

Where k represents the number of categories associated to a vendor and p_i is the proportion of listings in the ith category ($i = 1, \ldots k$). We standardized the index ($SDI = [\frac{k}{k-1}]D$) to facilitate interpretation of the results. SDI ranges from 0 for no diversity to 1 for perfect vendor diversification. Table 5 shows the descriptive statistics for the diversity variable.

Table 5 illustrates that vendors' maximum diversity score is 0.96 for high diversification, and the minimum is zero for perfect specialization. The mean diversity score ranges from 0.22 to 0.27, illustrating that for the vendors sampled there is, on average, between a 22% and 27% probability that two listings, taken at

Table 3
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	1210	1	343	13	19	8
December 2015	1369	1	367	15	22	8
January 2016	1416	1	369	16	24	8
February 2016	1582	1	383	16	24	9

Table 4
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

Table 5
Descriptive Statistics on Vendors' Diversity.

	Number of vendors	Min	Max	Mean	S.D.	Median
September 2015	692	0.00	0.94	0.23	0.29	0.00
October 2015	813	0.00	0.93	0.26	0.30	0.00
November 2015	1210	0.00	0.94	0.25	0.30	0.00
December 2015	1369	0.00	0.96	0.25	0.31	0.00
January 2016	1416	0.00	0.92	0.22	0.29	0.00
February 2016	1582	0.00	0.96	0.27	0.31	0.00

random in a vendor's listing, are in two different categories. According to the median, half the vendors have a perfect specialization score. Table 5 statistics suggest that vendors are much more specialized than diversified in terms of the types of drugs advertised.

Experience

Vendor experience is assessed according to the number of days a vendor has been selling on the marketplace, based on the date of the data collection. Vendors with experience on the cryptomarket have greater online size and scope because they are likely to be known by other market participants. The descriptive statistics around the experience variable is presented in Table 6.

Table 6 shows that by February 2016, the most experienced vendor had been on the market for about 15 months or 439 days. The minimum experience ranges between zero and five days, indicating that new vendors entered the market at each data collection. On average, vendors had been on the market for about three to six months or between 110 and 162 days. The increase in average experience suggests that vendors tend to stay on the market. The median ranges between 93 and 133 days and indicates that half the vendors had less than four months of experience.

To ensure exposure, diversity and experience were not correlated with each other (which would mean that only one variable could be used as a proxy for all three), we computed bivariate correlations between the three variables for each period of study. We found that the three variables are not highly correlated: the highest significant bivariate coefficient was 0.277.

One limit of the research is our consideration that an account is related to a single vendor. This is because many accounts can be held by a single individual. This limit has existed, and will continue to exist in many studies on online illegal markets. Yet, Décary-Hétu and Eudes (2015) showed that only 8.9% of individuals used many accounts on an illegal carding forum. Also, Motoyam, McCoy, Levchenko, Savage, and Geoffrey, 2011 responded to this criticism by emphasizing the fact that serious and high-level traders were highly unlikely to use many accounts on one forum, due to the difficulty of building a reputation in online markets. Like Motoyam et al. (2011)'s assumption, we consider that the costs of building a reputation on cryptomarkets are high, due to the many challenges that arise from the anonymity and illegality features of cryptomarket drug transactions presented below. Also, if a vendor uses many accounts to distribute the risks of being detected by law enforcement, then that vendor will need to avoid making clear statements that the accounts are related. The extent to which the benefits of having multiple accounts to distribute the risks of being detected offset the costs of building many highly-reputed accounts is unknown. Thus, more qualitative-based research on vendors' tendency to open many accounts on one cryptomarket should be conducted in order to overcome this limit.

Table 6
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	1206	3	342	119	88	93
December 2015	1365	2	373	130	94	109
January 2016	1412	0	400	146	99	122
February 2016	1578	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.

Analyses

Market competition

To estimate drug market competition, we use the Herfindahl-Hirshmann Index (HHI). This index originates from the theory of oligopoly and is one of the most commonly used measures of competition in the literature (Diallo & Tomek, 2015; Hindriks & Myles, 2006). Precisely, the HHI characterizes the distribution of a variable of interest according to its concentration across units (Dorian, Ryan, & Weatherston., 2007). It is defined as:

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

Where MS represents the market share of vendor i in a market with n vendors. The HHI is bound $\sum_{i=1}^{n} MS_i = 1$ between $1/n$ and 1 because market share is distributed between $0 \leq MS_i \leq 1$ and

An Index result close to 1 represents a pure monopoly market whereas a result near $1/n$ represents a highly competitive market (Dorian et al., 2007).

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 can encompass some vendors who do not compete against each other because they sell different types of drugs. 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 ecstasy pills. By assessing the whole market for drugs, we can consider a vendor's relative power compared with other vendors, regardless of the types of illegal drugs advertised. Second, a large variety of products are available on cryptomarkets and easily accessible through a few clicks, which increases the range of choices for buyers. This wide range of products offered has been reported as one major reason why buyers shop on these platforms (Barratt et al., 2013; Van Hout & Bingham, 2013a). Thus, vendors could compete against one another on the platform even though they do not sell the same types of product. Third, studying the whole market for illegal drugs allows a global perspective that considers all drug market players instead of only a fringe. Future studies should more closely examine the submarkets of the larger illegal drug market.

Group-Based trajectory modeling

The second analysis involves assessing the distribution of vendors' size and scope through time. To begin, we evaluate whether clusters of market share trajectories emerge among drug vendors by computing a group-based trajectory model (GBTM) on market shares using the STATA statistical software along with the TRAJPLOT plugin (Jones & Nagin, 2013, 2012). To compute group trajectories, GBTM uses maximum likelihood estimation (Nagin, 2005). Three forms of likelihood estimation functions are possible: censored normal (CNORM), Poisson and logit (Nagin, 2005). The choice of the likelihood functions depends on the distribution of the outcome variable in the model. For this model, the outcome variable is the market share of each vendor at the six periods of study. It spans from zero to one hundred and clusters at zero since more than half of the vendors have nil market share (as shown in the descriptive statistics). The best likelihood function is the censored normal (CNORM) function, because it accounts for distributions that tend to cluster at the maximum or minimum scale (Jones, Nagin, & Roeder, 2001). In the CNORM model, 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 (Nagin, 2005). We consider that vendors with no sales have a potential to make some sales if, for example, there was an increased demand for drugs on cryptomarkets. Thus, the CNORM model considers vendors' censored market shares and allows us to assess vendors' potential to start making transactions. The reference to "censored normal" comes from the idea that the latent variable distribution –of its observed and censored (potential action) counterpart- is assumed to be normally distributed.

The objective of GBTM is to identify groups of individuals with similar trajectories through time. However, 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, which is the maximum allowed by the TRAJPLOT plugin (Jones & Nagin, 2013, 2012). The most appropriate GBTM model can thus be found through a formal procedure, developed by Nagin (1999, 2005), which is based on comparing models according to the Bayesian Information Criterion (BIC) statistical reference. The steps taken in this study to select the most appropriate model follow Nagin's (1999, 2005) procedure and are available in Paquet-Clouston (2017). The model's strength was also evaluated with the model diagnostics developed by Nagin (2005). These diagnostics are explained in the result sections, along with the model's scores.

Group comparison with ANOVA analyses

Once the best model was identified, we looked at the size and scope of vendors in each market share trajectory group in terms of exposure, diversity, and experience with an analysis of variance (ANOVA). The ANOVA analysis estimates whether there are significant differences in exposure, diversity and experience means among the group trajectories 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.

Also, Nagin (2005) mentions that an individual's group membership probability (the probability that an individual belongs to the specified group) needs to be considered when comparing group characteristics to account for the uncertainty that an individual belongs to another group trajectory. Considering group-membership probabilities when comparing group characteristics 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).

Following Nagin's (2005) suggestion, we weight the results of vendors' exposure, diversity and experience according to their group membership probabilities before conducting the ANOVA analysis.

Market competition

The descriptive market share 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 7 supports this inference by illustrating the results of the HHI on the concentration of market shares for the drug market.

Results in Table 7 show that the online drug market is highly competitive throughout the period of study and is not concentrated among a few important market players. They indicate that the structure of the drug market is much closer to perfect competition ($HHI = 1/n$) than to a monopoly ($HHI = 1$). Moreover, the last three months show a marginal decrease in market share concentration compared to the first three months.

Market share trajectories

The group-based trajectory model aims at finding group trajectories on vendors' market share between September 2015 and March 2016. Through the model selection process, we first predetermined the polynomial functions to be linear and added one group at the time in the model, comparing model fits according to Nagin's (1999, 2005) procedure. We found that the best model is a three-group model with a vendor population distribution of 90%, 9%, and 1%. This is the best model based on the BICs statistics and because when we added new groups, the other models only divided the 1% group into smaller fractions. We then looked at the polynomial function forms and tried all possibilities up to the cubic form. The model with the highest BICs is the three groups model that has one group with a constant trajectory and two groups with linear trajectories. The model estimates are presented in Table 8 followed by Fig. 1 illustrating the three trajectories found with 95% confidence intervals.

All estimates of the model are significant. The low-level group accounts for 90% of the population. The trajectory is constant and negative, which is the result of our censored data that cluster at a minimum of zero and the latent variable that accounts for the

Table 7
Results on the Concentration of Market Share.

	Number of vendors	Total market feedbacks	HHI
September 2015	692	2176	0.006614
October 2015	813	3462	0.007397
November 2015	1210	5356	0.004366
December 2015	1369	4389	0.001832
January 2016	1416	7312	0.001871
February 2016	1582	6134	0.001343

Table 8
Results of the Group-based Trajectory Model on Vendors' Market Shares.

	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		

potential of vendors to start making some sales. The potential of vendors to start making sales is therefore negative. We see in Fig. 1 that this group represents vendors who make very few to no sales throughout the period of study. The mid-level group accounts for 9% of the population. Its intercept is positive at 0.49 and the slope is negative at −0.06. Fig. 1 places the mid-level group at the mid-range, making individually between 0 and 0.5% of the total market share. The high-level group accounts for 1% of the population and is composed of 25 vendors that were identified at some point across the six data collection periods. The intercept for the high-level group is positive, with vendors earning an average 1.24% of market shares at the beginning of the period. Fig. 1 shows that individual vendors in this group earn between 0.5 and 1.5% of the total market share throughout the period of study. All slopes are negative, suggesting that individual vendors earn, on average, less in proportion of the market's total sales. Looking at group statistics, we found that the low-level group averages 16% of market shares, the mid-level group averages 36% of market shares, and the high-level group averages 49% of market shares throughout the period of study.

Model diagnostics, such as the average posterior probability (AvePP) and the odds of correct classification (OCC), can be used to ensure the model fits the data, beyond the BIC statistical reference (Nagin, 2005). The AvePP is an average of the posterior probability of group membership, which 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 low, mid and high-level groups respectively. The three AvePPs greatly surpass Nagin's (2005) rule of thumb. Another diagnostic is the odds of correct classification (OCC). Nagin (2005)Nagin's (2005) personal rule of thumb is OCC > 5. The OCCs for the mid-level (OCC = 81.81) and the high-level (OCC = 3233) groups are well above Nagin's criteria. However, the OCC for the low-level group (OCC = 2.67) 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: 88). With an OCC at 2.67 and the low-level group accounting for 90% of the population, the predictive capacity of the OCC is beyond one, which is more than expected.

Size and scope of drug VENDORS' activities

Vendors' score on exposure, diversity and experience is compared below between each trajectory group. First, we conducted the ANOVA analysis on experience, diversity and exposure scores between the three groups 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 conciseness, we present in Table 9 the results of the analysis based on vendors' mean scores for the six-month period.

For the exposure measure, the results of the ANOVA analysis illustrate that there are significant differences in exposure among the three groups. Vendors in the high-level group have more

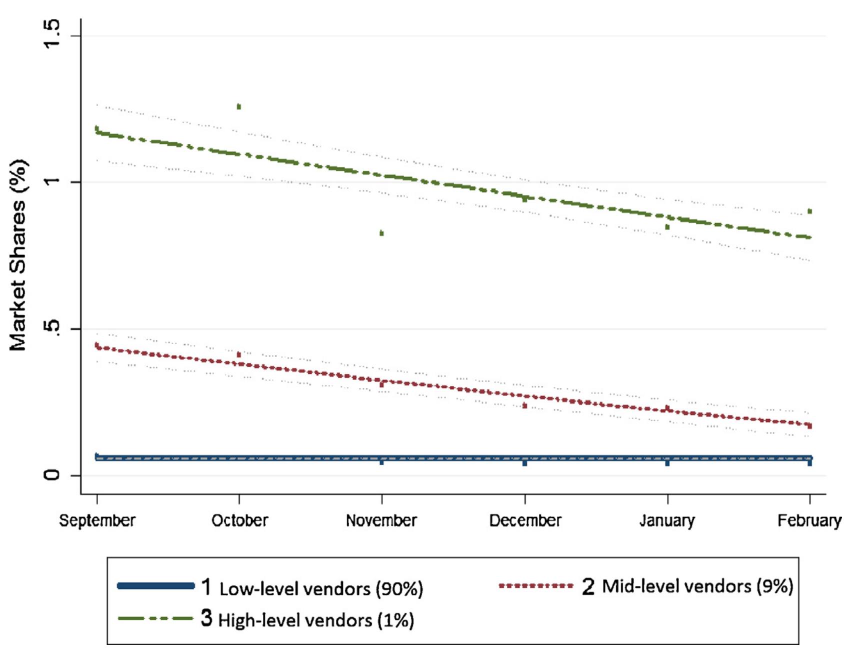

Fig. 1. Group Trajectories of Vendors' Market Share.

Table 9
Group Comparison on Vendors' Size and Scope.

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

exposure than vendors in the two other groups and vendors in the mid-level group have more exposure than vendors in the low-level group. Low-level vendors post, on average, 10 listings whereas mid-level vendors post, on average, 20 listings. High-level vendors surpass the other two groups and post, on average, 38 listings, which is almost twice as much as the mid-level and four times as much as the low-level vendors.

The results are not significant for the diversity measure and thus, we cannot say that there are significant differences in the means of the three groups. The low, mid and high-level vendors are not more or less diversified in terms of the types of drug listed. From the descriptive statistics, we found that most vendors were specialized. The third dimension of the size and scope of vendors is experience. The results of the one-way ANOVA analysis suggest that there are significant differences in the experience mean scores between the low-level vendors and the other two groups. There is, however, no significant difference in the experience mean score between the mid-level and the high-level vendors. High-level vendors have, on average, 167 days of experience, whereas mid and low-level vendors have, on average, 105 and 135 days of experience. This illustrates that drug vendors on the market have, on average, less than six months of experience during the period of study.

Discussion

This study assesses market competition and the distribution of the size and scope of drug vendors' activities on Alphabay. HHI score findings on market competition suggest that this is a highly competitive environment. Consistent with Soska and Christin (2015), the results also show that most vendors reach minimal performance levels and that there is considerable inequality among them. The distribution of vendors' market share trajectories illustrates that only a small portion of vendors succeed in generating regular sales (referred to as the high-level vendors), whereas most vendors are relegated to being market spectators with almost zero sales. The experience measure also suggests that most vendors or, more precisely, most vendor profiles survive less than six months in the market. This may be due to the volatile nature of cryptomarkets, which requires that vendors reinitiate their profile whenever a platform shuts down (Soska & Christin, 2015; Décary-Hétu & Giommoni, 2017). Still, the high-level group stands out above less experienced competitors, while also having more exposure than the other groups by posting, on average, more listings. Finally, most vendors are specialized. Based on these findings, we assess below the structural challenges faced by cryptomarket drug vendors.

Competitive drug cryptomarkets

We found that the drug market is highly competitive on cryptomarkets. Competition may extend from low search, switch, and menu costs. Other online illegal markets hosted on discussion forums and chat rooms have been known to be driven by market dynamics and found to be competitive as well (Holt, 2013; Holt & Lampke, 2010; Yip et al., 2013). Cryptomarkets are even more sophisticated than discussion forums and chat rooms as they are designed to allow buyers to shop through listings and compare prices in a user-friendly manner (Christin, 2013; Barratt, 2012). While the lack of advertising in traditional street markets makes it more difficult for customers to compare the prices of different products (Kleiman, 1991), customers in cryptomarkets can easily compare prices through advertised listings. Buyers' search costs are therefore decreased on cryptomarkets due to the efficient design of the platform. The benefits of such features were also raised in studies surveying cryptomarket buyers (Barratt et al., 2013; Van Hout & Bingham, 2013a,b). Also, vendors can instantly change their listing prices with no menu costs. Thus, just like licit online markets (Ellison & Ellison, 2009; Brynjolfsson et al., 2003; Brynjolfsson & Smith, 2000), specific characteristics of cryptomarkets may foster competition.

Yet, we find that because drug cryptomarkets are a highly competitive environment, high-level vendors seem to advertise aggressively by posting many listings of the same drugs. Indeed, the results on the exposure of vendors illustrate that high-level vendors post many more listings than other vendors. The diversity measure also illustrates that most vendors adopt specialized selling profiles'. Combined, these results suggest that high-level vendors offer multiple listings of the same type of drugs, in different quantities or in different alternative products. A study on online markets found that in these virtual settings, customers seem to respond more to advertising than low prices (Latcovich & Smith, 2001). Also, large online vendors tend to invest more resources on advertising to prevent other niche vendors with smaller advertising budgets to conduct sales (Wang & Zhang, 2015). Aggressive advertising by high-level cryptomarket vendors could be a strategy to help them maintain their position in the market while pushing out smaller vendors. Such an advertising strategy could explain why the drug market is highly unequal, with only a few vendors making sales and the majority of them acting as mere spectators in the market. The arid economic environment found in our results could also emerge from high barriers to entry and barriers to sales found on cryptomarkets, as explained below.

Barriers to entry and barriers to sales

Research on street markets suggests that entering drug markets as a vendor is easy because there are few barriers to entry either at low or high levels of drug dealing (Bouchard, 2007; Reuter & Haaga, 1989). On cryptomarkets, however, one may argue that drug vendors also face limited barriers to entry insofar as they can easily register on a cryptomarket and begin posting drug listings. According to what is advertised on the site, vendor registration on Alphabay costs $200 (US), which can be considered minimal. However, vendors still need to gain knowledge of how the marketplace and the technologies related to it work in order to successfully conceal their identity. Moreover, they need to learn how to successfully conceal and ship the product without attracting attention from law enforcement agencies. Altogether, these challenges can result in high barriers to entry. Also, when advertising their products, vendors are active in drug supply, but supplying does not guarantee that they will conduct actual sales. Indeed, our results indicate that most vendors who post drug listings on cryptomarkets do not make any sales. This suggests that such drug vendors also face barriers to sales. This results in a top-heavy market environment, in which a high number of start-up firms compete only at minimal performance levels and only a few vendors achieve some level of establishment.

Barriers to sales may be due to buyers' tendency to avoid the risks of transaction failures in online markets and opt for safer and reputable suppliers. Moreover, online licit buyers are known to be willing to pay higher prices to reputable vendors for products with strong branding (Smith & 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 (Wehinger, 2011; Yip et al., 2013). Anonymity features of online drug transactions may exacerbate the tendency of buyers to favor branding and reputation over prices to minimize their risk of transaction failures. Buyers have indeed reported to carefully choose the vendors with whom they conduct business (Van Hout & Bingham, 2013a). High and mid-level vendors were found to be more experienced than low-level vendors. Buyers could likely perceive experience as an important characteristic of vendor reliability and credibility. Such a characteristic cannot be faked and can only be acquired through time, and most vendors entering the market do not benefit from the luxury of time. This means that even though markets are volatile (Soska & Christin, 2015; Décary-Hétu & Giommoni, 2017), the experience signal on vendors' profile could still be quite important. Altogether, the high barriers to entry and barriers to sales may greatly increase vendors' challenges to sell online and could explain their limited size and scope.

Limited size and scope of cryptomarket drug vendors' activities

Throughout the study, we also found that the online size and scope of cryptomarket drug vendors are small. At the individual level, product diversification is low, experience is short, and market shares do not raise above 3%. Much of the explanation that accounts for the small size and scope of vendors' activities is likely due to the embeddedness of cryptomarket drug vendors in the physical world. Even though many transactions are conducted online, the products being sold still need to be produced or bought, packaged, and shipped. Drug vendors must therefore perform offline activities when selling on cryptomarkets, making their virtual world business directly reliant on physical illegal drug markets. Offline activities will most likely remain small in size and scope due to the risky and extra-legal environment in which they are undertaken (Reuter, 1983). For cryptomarket drug vendors, expansion and diversification would require an increase in labor-intensive offline activities. Packaging and shipping activities especially require extensive management by vendors to prevent detection. Thus, vendors who sell drugs online most likely face the same constraints as traditional drug dealers.

There is a possibility that vendors play an intermediary role in which they advertise drugs and when they conduct a sale, they buy from another vendor and require the package to be shipped to the buyer's address. In this case, they would not need to conduct offline activities. However, someone down the chain would still need to package and ship the product, facing the driving forces of product illegality.

Moreover, negative market share trajectories were identified even though drug sales increased during the period of study. This does not mean that vendors made fewer sales, but instead that they earned gradually less in proportion to the size of the market. Cryptomarkets for illicit drugs therefore face limits to growth because most participants need to deal with the consequences of product illegality which are similar to those of traditional street markets and limit their selling capacities.

The small size and scope of vendors' activities may also be due to vendors' reliance on independent actors. Most of the drug distribution is subcontracted to legal postal services which participate unwillingly in drug distribution. To some extent, these services control the packages that flow through their network and they would likely notice the suspicious activities of relatively large vendors. Vendors can also use drop shipping for package delivery. Aldridge and Askew (2017) found evidence of this technique on cryptomarket's forums. However, even with this technique, vendors would still rely on a subcontracted third-party for delivering their products. Moreover, the extent to which the third-party can quickly and efficiently deliver the product, without using postal services, is unknown. Vendors must also rely on the platforms for their revenues and advertising insofar as cryptomarket administrators are responsible for designing and maintaining the marketplace, establishing secure payment systems, and reaching the largest possible customer base. Cryptomarkets provide a service that is cost efficient for drug vendors, but over which vendors have no control. Dysfunctionalities in cryptomarket features (e.g., compromised escrow payment), as well as scam exits from administrators, and law enforcement shut-downs can abruptly terminate the activities of drug vendors. Such problems have been documented in the past (Soska & Christin, 2015) and they prevent vendor profiles from developing experience signals; and consequently, growing drug vendors' illicit business over time.

Conclusion and policy implications

This study illustrates how cryptomarket drug dealing is consistent with Reuter's assessment of illegal markets and the consequences of product illegality. Most cryptomarket drug vendors have a limited online size and scope, small market shares, little experience, and limited diversity. This could be a consequence of the drug cryptomarkets' challenging structural features. The combination of opposing features shapes the competitive, yet top-heavy market that emerges from our analysis. Such features are marked by: 1) a relatively open setting, yet with high barriers to entry and barriers to sales; 2) high advertising opportunities, yet high constraints extending from anonymity and the need, in most cases, to participate in the street market to complete one's role as a supplier; and 3) the potential to reach a large pool of consumers, while not controlling part of the supply process, such as mail delivery. This creates an arid environment for cryptomarket drug vendors to conduct business.

Yet, despite these challenges, the resilience of drug cryptomarkets is impressive (Soska & Christin, 2015). Such resilience could emerge from the idea that these platforms are more than an economic market: they host a living community that shares a marginal subculture. Cryptomarket participants use these platforms not only for economic purposes, but also to openly discuss stigmatized behaviors, such as drug consumption experiences (Maddox et al., 2016; Van Hout & Bingham, 2013a,b, 2014). The resilience could also be explained by vendors not respecting a profit maximizing behavior. Some studies have found that drug vendors sell to cover their own drug use (Sandberg, 2012b), to help friends (Sandberg, 2012a, 2012b) or want to stay small to stay in line with their anti-capitalist values (Hammersvik et al., 2012).

Moreover, the results of this study open the discussion toward the relative importance of these platforms for more general illegal drug markets. It shows that the number of listings –the amount of products and services offered- is not a good proxy to assess the size of a cryptomarket, since most vendors do not conduct any sales. Thus, policy makers should consider these findings when assessing the importance of cryptomarket platforms relative to the global drug trade. Just as an increase in the number of arrests does not mean that crime levels are rising, an increase in the number of listings does not mean that cryptomarket activities are on the rise. Specific data on sales will always trump the number of listings.

Also, this study finds that drug vendors face many challenges while selling online which limits their business expansion. Conducting successful sales online is not an easy endeavor as only few vendors manage to conduct constant sales through time. This implies that large vendors could be targeted to disrupt the cryptomarket ecosystem. Given the large proportion of sales that cluster around a few vendors, it is likely that many buyers are also clustered around these same vendors. Buyers may be more reticent to continue to purchase online when their main supplier is taken down by law enforcement. Yet, due to the high degree of competitiveness, targeting high-level vendors may only create an opening for middle and low-level vendors to replace the arrested vendors. This is reminiscent of a tournament setting where leaders are inevitably replaced by others looking to profit from a leadership position (Levitt & Venkatesh, 2000; Lazear & Rosen 1981). Policy makers may therefore be more effective at disrupting cryptomarkets by removing the desire of individuals to become leaders in this community. One way of achieving this is by damaging vendors' reputation and the trust in the online ecosystem. However, the potential harm-minimizing effects of cryptomarkets on health and transnational conflicts should be considered before doing so (Aldridge, Stevens, & Barratt, 2017). Also, it is likely that offenders will adapt to these disruptions, finding ways to improve the trust and reputation mechanisms established in these marketplaces.

Finally, regulators and policy makers reading this study now possess a better idea of the economic inner working of cryptomarket, which can lead to better-informed decisions on the matter.

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