*Original Article*

Journal of Drug Issues
2022, Vol. 0(0) 1–24

DOI: 10.1177/00220426221133030
journals.sagepub.com/home/jod
SAGE

# Are Illicit Drugs a Driving Force for Cryptomarket Leadership?

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## Abstract

Cryptomarkets, i.e., illicit online marketplaces, have gained considerable attention from the media, law enforcement agencies, and researchers. An increasing number of studies have revealed various aspects of these cryptomarkets; however, whether drugs play a major role for competing cryptomarkets to be the market leader, has not been addressed. Weekly sales and the number of listings for the major products on three leading cryptomarkets (Silk Road 2, Agora, and Evolution) were examined using Granger causality tests and interrupted time series analysis. Not only drugs trading on cryptomarkets played a pivotal role in the growth of each cryptomarket, but also a higher increase in drug supply than in competing marketplaces is crucial to become market leaders. The relative supply of drugs plays a larger role when leading marketplaces disappear. Law enforcement agencies should focus on monitoring marketplaces with a larger increase in drug supplies than on competing marketplaces.

## Keywords

drug economy, cryptomarkets, cybercriminal, policing effort, time series analysis, illicit drugs

## Introduction

Online illicit marketplaces known as cryptomarkets have received a great deal of attention since Silk Road, the first successful dark web marketplace, was launched in February 2011. Since then, numerous dark web marketplaces have been launched and shut down by either international law enforcement operations or voluntary exits. After Silk Road 2.0—the successor of Silk Road—was shut down by the international law enforcement operation known as Operation Onymous, Agora, Evolution, and AlphaBay, in turn, became the largest dark web marketplaces that were later shut down. Even after AlphaBay was taken down by an international law enforcement operation called Operation Bayonet, new marketplaces were repeatedly launched and closed one after another, thus exhibiting resilience to law enforcement operations. These online marketplaces focused on anonymity and security to limit the risk of identification of both vendors and buyers. Three online anonymizing technologies—the Tor network,[1] cryptocurrency,[2] and encrypted communication

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(e.g., PGP)[3]—led to the creation of cryptomarkets. Administrators of dark websites can conceal their website servers' locations and website visitors' information, and thus avoid law enforcement agencies. Therefore, various illicit goods and services, including illicit drugs, counterfeit passports and currency, fraud items (e.g., stolen identity documents (IDs) and bank accounts), malware, hacking tools and services, and weapons and firearms have been traded on cryptomarkets (Copeland, Wallin, & Holt, 2020; Grossman & Newton-Small, 2013; Meland, Bayoumy, & Sindre, 2020). In addition to drugs, digital goods on cryptomarkets have attracted media and researcher attention. They can be considered major cybercrimes that harm online activities. They include hacking tools and services, personal information, and stolen financial information.

## *Research on Cryptomarkets*

Studies have provided evidence of these marketplace ecosystems, including sales volume estimates and numbers of listings, vendors, and product categories, via scraping methods that collect information on product listings offered by vendors and feedback received by them. The vendors and listings on cryptomarkets have increased, and trade and purchase volumes have increased steadily (e.g., Broséus, & Morelato, Tahtouh, & Roux, 2017a; Christin, 2013; Demant, Munksgaard, & Houborg, 2018; Rhumorbarbe et al., 2016; Soska & Christin, 2015) regardless of the observed periods or marketplaces. Several studies indicate that the most popular products on cryptomarkets are illicit drugs (e.g., Aldridge & Décary-Hétu, 2014; Broséus et al., 2016; Broséus et al., 2017a; Christin, 2013; Soska & Christin, 2015; Tzanetakis, 2018). The listed drugs are primarily for personal use or social networks including friends and colleagues, although most revenue comes from business-to-business dealings (Aldridge & Décary-Hétu, 2016; Barratt, 2012; Barratt et al., 2016; Demant et al., 2018). Some studies have investigated the geography of the vendors' countries of origin and their destination countries, and revealed that cryptomarkets have primarily manifested in the Anglo-Saxon world and Western Europe (Christin, 2013; Demant et al., 2018; Dolliver, 2015; Morelato et al., 2020; Norbutas, 2018; Van Buskirk, Naicker, Roxburgh, Bruno, & Burns, 2016). The buyer-seller network is highly fragmented across geographical borders to reduce the risk of inspection (Aldridge & Askew, 2017; Broséus, Rhumorbarbe, Morelato, Staehli, & Rossy, 2017b; Kruithof et al., 2016; Norbutas, 2018). Furthermore, Décary-Hétu, Paquet-Clouston, & Aldridge (2016) provided evidence that vendors ship small quantities to reduce the risk of interception. Reputation mechanisms ensure that vendors with good user ratings can price their drug products higher (Bhaskar et al., 2019; Espinosa, 2019; Hardy & Norgaard, 2016). Van Wegberg et al. (2018) comprehensively studied leading cryptomarkets from Silk Road to AlphaBay and found that commoditization of digital goods on these marketplaces was spottier than previously assumed. Cryptomarkets are not restricted to economic exchange by users; they often entail scams, hacks, and threat (Masson & Bancroft, 2018; Tzanetakis, Kamphausen, Werse, & von Laufenberg, 2016). Moeller, Munksgaard and Demant. (2017) explored various types of theft and fraud on cryptomarkets using multiple sources, including forum posts, and revealed that cryptomarkets fall prey to hacking attempts and that the sites' administrators often abscond with users' funds.

Studies have focused on the impact of police intervention because international policing efforts toward closing cryptomarkets are increasingly important against illicit drug trading and cybercrime. International law enforcement operations, named Operation Onymous and Operation Bayonet, revealed that cryptomarkets are resilient to law enforcement as new platforms rapidly replace those eradicated by users' migration to other cryptomarkets (e.g., Aldridge & Décary-Hétu, 2016; Barratt, Ferris, & Winstock, 2016; Bhaskar et al., 2019; Décary-Hétu & Giommoni, 2017; Tzanetakis, 2018; Van Buskirk et al., 2017; Van Wegberg & Verburgh, 2018). Childs, Coomber, Bull, and Barratt (2020) showed that direct dealing using encrypted messaging applications beyond the provided platforms are more likely to occur during instances of law enforcement crackdowns. According to the literature, the lifetime of a cryptomarket is summarized as follows: After the birth of a cryptomarket, it remains a small marketplace where few transactions are traded. For a while, there are no significant changes; a little growth at most. It then grows rapidly due to the shutdown of other major cryptomarkets and user migration. Finally, it is seized or exited.

To overcome web crawling drawbacks, other studies have focused on cryptocurrency transaction records. Bitcoin transactions on cryptomarkets provide transaction times because records are publicly available. Lee et al. (2019) estimated the market size of cryptomarkets between January 2017 and March 2018, and revealed that Bitcoin accounted for 99.8% of the collected cryptocurrency addresses, and 80% was used for illegal purposes. Foley et al. (2019) found that Bitcoin worth approximately USD 76 billion per year was used in cryptomarkets, and accounted for 46% of all Bitcoin transactions by investigating Bitcoin transactions between January 2009 and April 2017. Hiramoto and Tsuchiya (2020) estimated the sales volumes of seven leading cryptomarkets between 2013 and 2016, and showed when the leading positions changed between the marketplaces, which was consistent with those studies with web-crawling that provide evidence on their evolution and the limited impact of policing efforts. Tsuchiya and Hiramoto (2021) found clear patterns of transaction activity on the marketplaces at night in countries where the cryptomarket drug trade is most active, and provided evidence that the retail drug trade accounts for a large part of the cryptomarkets.

### *Motivation and Objective*

However, the role of drug trading in the overall growth of cryptomarkets has not yet been explored; this includes the role of drugs and digital goods in the growth of cryptomarkets, how drugs affect competition between cryptomarkets, and the role they play when a leading cryptomarket shuts down and users migrate. Studies are lacking because of the scraping method's limitations, which precludes sufficiently large observations for statistical analysis. First, the scraping method may provide incomplete information of transactions because scraping is subject to data collection interval; in other words, scraping is only implemented at the frequency of one scraping per several days to a few weeks. Second, because scraping identifies transactions based on buyers' feedback, it cannot capture exactly when a transaction occurs. Third, actual prices and quantities can differ from those listed. Finally, feedback may not be timely, and scraping cannot cover the lifetime of a particular dark web market. Several studies on scraping methods report less accurate timing of sales, and less frequent observations of sales, despite capturing details of vendors, items and products on cryptomarkets (e.g., Christin, 2013; Soska & Christin, 2015; Tzanetakis, 2018; Van Wegberg et al., 2018).

Therefore, this study uses data from two bodies of literature to examine whether illicit drug trading on cryptomarkets is the main driver of cryptomarket growth in two respects: First, drug trading is a major engine of each cryptomarket. Second, drug trading is a key influence of relative growth among competing cryptomarkets along with the impact of policing efforts. By integrating data from the two streams, weekly sales data and the number of listings for the major products on three leading cryptomarkets (Silk Road 2, Agora, and Evolution) were obtained. Weekly sales represent the development and growth of each cryptomarket over time. The weekly number of listings for major products represent their supply over time. Using time-series of sales and supply, we can address the two unrevealed questions. Despite the limited analysis of these three cryptomarkets, there are a few advantages. First, we examine the impact of international law enforcement operations—is this case Operation Onymous—which led to the closure of Silk Road 2. Second, we analyze the competitive relationship between two cryptomarkets that eventually adopted leading positions when the former leader, Silk Road 2, was closed. If many cryptomarkets compete for leadership, it is difficult to examine their complex relationships. During our sample period, other cryptomarkets were very small; thus we focused on the two relatively larger cryptomarkets. To draw implications that can be used to guide and support agencies' monitoring efforts, our study analyzes the factors driving the development and growth of leading cryptomarkets.

This study uses time series analysis techniques: Granger causality tests and interrupted time series analysis based on the autoregressive distributed lag (ARDL) model. Otterstatter, Amlani, Guan, Richardson, and Buxton (2016) used Granger causality tests to show that illicit drug overdose deaths are attributed to income assistance payment. Granger causality implies that the cause occurs before the effect; thus, if an event $X$ is the cause of another event $Y$, then $X$ should precede $Y$ (Granger, 1969). Granger causality does not identify a specific causal mechanism because it requires experimental settings. However, Granger causality provides a rigorous test of whether variables directly impact each other. A significant test result indicates that (relative) drug supply is predictive of temporal patterns in cryptomarkets' (relative) sales, and is not simply an association in time. Martin, Culliffe, Décary-Hétu, and Aldridge (2018) used a simple interrupted time series analysis to examine opioid trade, through cryptomarkets, with the US Drug Enforcement Administration's ruling in 2014 to reschedule hydrocodone combination products. They revealed that prescription opioids sales through US cryptomarkets increased after the schedule change, with no statistically significant change other prescription drugs' or illicit opioids' sales.

The remainder of this paper is organized as follows. Section 2 provides an overview of the data, and Section 3 describes the methodologies for analysis. Section 4 presents the results, while Section 5 discusses the implications and limitations of the study and concludes.

## Data

This study uses two data sources: sales data on cryptomarkets from Tsuchiya and Hiramoto (2021) and the number of listings on cryptomarkets from the Darknet Market (DNM) archives[4] in Branwen et al. (2015). The former provides hourly sales volumes for seven cryptomarkets between 2012 and 2016 from Bitcoin transactions using methods proposed by the two previous studies.[5] The former study uses three heuristics, which are based on the characteristics of Bitcoin transactions (Androulaki, Karame, Roeschlin, Scherer, and Capkun, 2013; Meiklejohn et al., 2013; Reid & Harrigan, 2013) and a feature of Bitcoin transaction management shared by those cryptomarkets (Hiramoto & Tsuchiya, 2020) to identify transactions. The methodology provides accurate records of sales volumes and dates for each purchase to establish a comprehensive picture of the transactions for any frequency (e.g., hourly, daily, monthly, and the overall active period) over the established method of web-scraping, assuming that addresses owned by cryptomarkets are correctly identified. The most crucial limitation is the correctness of Bitcoin addresses of cryptomarkets. Another drawback is that it is impossible to determine product categories. However, the method broadly provides consistent estimates of sales volumes and consistent time-series paths with those studies based on web-scraping. Further, the misdetection rate is not likely to be large because a large proportion of Bitcoin addresses on the dark web were used with illegal purposes (Lee et al., 2019).

The latter provides information on item listings offered by vendors by scraping for all existing English-language dark web marketplaces between 2013 and 2015. The scraping method is the most widely used tool to obtain information from cryptomarkets. Particularly, this dataset has been used in various studies.[6] It is noteworthy that the number of listed items in each category may not be accurate because vendors may place their products in the wrong category or list items in multiple categories. However, the misclassification rate is not likely to be high, because Broséus et al. (2017b) provide supporting evidence for similar classification rates[7] of listed items with ours (as described below) for Evolution.

This study aggregates data to weekly frequency to avoid the following issues: First, hourly sales data is subject to a day-of-the-week seasonality (i.e., that there are larger or smaller sales on specific days of the week) (Tsuchiya & Hiramoto, 2021). This seasonality causes difficulty in time-series analysis with daily data because the effects of the seasonality need to be removed. Second, data on item listings have not been observed frequently or regularly, that is, they are observed on certain days of the week (e.g., every Monday) or at a given interval (every 5 days). To apply time-series analysis, intervals of time periods should be fixed.

Matching the sales volumes and the number of listings with sufficiently large observations for statistical analysis restricts our analysis to the three leading cryptomarkets (Silk Road 2, Agora, and Evolution) for the sample period November 2013 to May 2015. Table 1 provides a brief overview of three cryptomarkets: Silk Road 2, Agora, and Evolution. Approximately a month after the FBI arrested the operators of the first successful cryptomarket, Silk Road, and it was shut down in October 2013, Silk Road 2.0 was launched, and closed by an international law enforcement operation known as Operation Onymous[8] on November 6, 2014, coordinated by the FBI and the European Police Office (EUROPOL, 2017). Among several other marketplaces, Agora, which operated between December 2013 and September 2015, and Evolution, which operated between January 2014 and March 2015, overtook Silk Road 2.0. Evolution closed via an exit scam[9] (EUROPOL, 2017), and Agora closed voluntarily.

## *Sales Volumes*

Figure 1 shows the weekly sales volumes for the three marketplaces. Silk Road 2.0 grew rapidly after the original Silk Road was shut down, with a sharp decline in February 2014.[10] Agora steadily increased its sales until they were exceeded by those of Evolution near the end of November 2014. Earlier, Evolution's sales were relatively small. The presence of Evolution increased sharply in the latter half of 2014 and it assumed the lead until February 2015. Evolution's rapid growth can be attributed to a growth phase of all cryptomarkets in 2014 (Hiramoto & Tsuchiya, 2020; Soska & Christin, 2015), and partly to Operation Onymous, as it helped in closing many cryptomarkets and led to the migration of users. Agora's sales did not increase significantly for several months after Operation Onymous. A sharp increase in Evolution's sales and several irregular declines in Agora's sales after Operation Onymous and around the exit of Evolution, were because of Agora's accidental downtimes.[11] Agora went offline because of traffic surges caused by user migration from Silk Road 2. Evolution had better uptime than Agora.

## *Item Listings*

The number of listings within their categories is calculated on each date it was scraped because when vendors offer goods and services, they categorize them. Multiple observations in a week

**Table 1.** Summary of Active and Sample Periods.

| Marketplace | Active period | Sample period | Weeks of observation |
|---|---|---|---|
| Silk road 2 | Nov 2013–Nov 2014 | Nov 2013–Nov 2014 | 45 |
| Agora | Dec 2013–Sep 2015 | Jan 2014–May 2015 | 77 |
| Evolution | Jan 2014–Mar 2015 | Jan 2014–Mar 2015 | 59 |

*Notes.* Active periods are taken from EUROPOL (2017). Active period indicates active periods for each marketplace. Sample period specifies sample periods covered in this study, and Weeks of observations indicate the number of weeks of observation in this study.

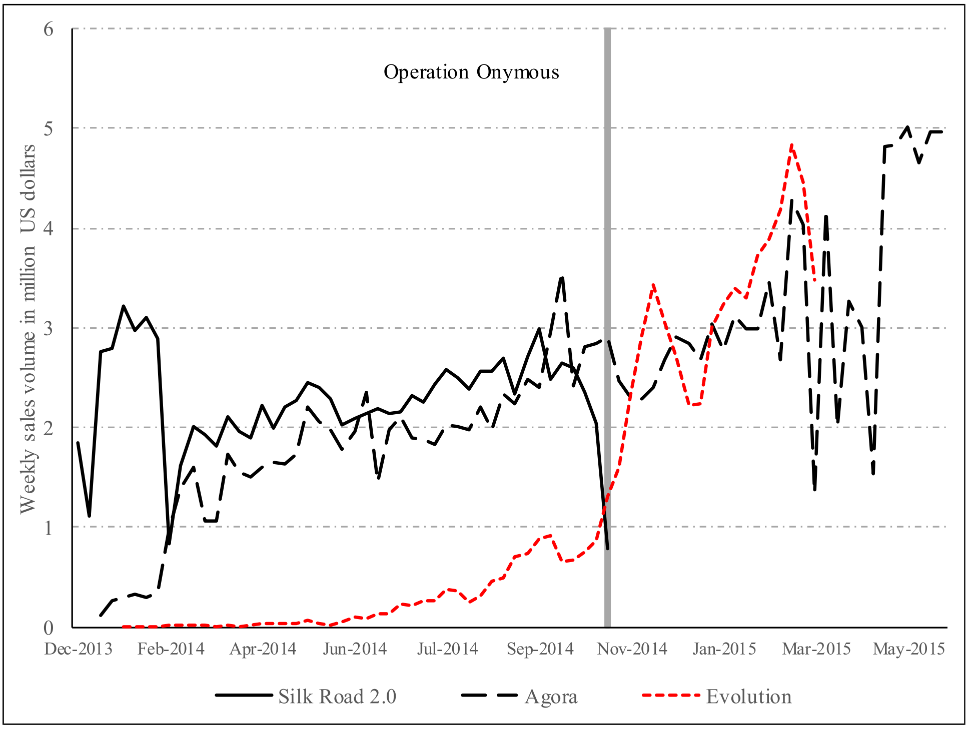


**Figure 1.** Weekly sales volumes.

were averaged. Some missing values of the number of listings during the observation period due to a lack of scraping, were linearly interpolated.

These categories and the number of them differ among marketplaces.[12] To examine whether drugs are associated with growth in cryptomarkets, this study considers three major item categories: drugs, digital goods, and others. Our category definitions are based on our modification of those of Broséus et al. (2017b). They constructed three major categories (drugs, fraud-related, and others), and found that digital fraud-related items (e.g., hacking services or materials related to financial fraud, manuals, and IDs or legitimation documents) showed a clear difference from physical fraud-related items (e.g., counterfeit goods and firearms). Therefore, our definition of digital goods attempts to measure digital products, and physical items other than drugs are categorized as others. In this way, this study highlights the relative importance of drugs and digital goods on cryptomarket growth from the perspective of illicit drug trades and cybercriminals on cryptomarkets. Drugs include illicit and licit drugs, and drug paraphernalia, with illicit drugs as the major items. Because names of item listings related to those cybercriminals differ among cryptomarkets, two definitions were used: One uses a direct indicator of digital goods. Alternative definitions include a broad category. In particular, categories strongly related to cybercriminals, including erotica, services, custom listings, fraud, guides, and tutorials are used. Others include the remaining categories for the two definitions.

Table 2 shows shares of three major categories for each marketplace. It indicates that drugs constitute the major category on all marketplaces with varying magnitude. Drug shares are above 70% on Silk Road 2 and Agora, while the share on Evolution exceeds 50%.[13] Shares of digital goods are not large; between 4% and 9%. For alternative definitions, shares of digital goods listed on Agora and Evolution increased to 18% for Agora, and 40% for Evolution whereas for Silk

**Table 2.** Share of Major Listing Items over Sample Period.

| | Silk road 2 | Agora | Evolution |
|---|---|---|---|
| Drugs | 80.5 | 73.4 | 52.5 |
| Digital goods | 4.2(5.8) | 3.4(17.6) | 8.9(39.5) |
| Others | 15.3(13.7) | 23.2(9.0) | 38.6(8.0) |

*Notes.* The numbers and names of categories of listing items vary among marketplaces. Drugs include drugs and drug paraphernalia in all marketplaces. Digital goods include digital goods for all marketplaces, except Agora. Digital goods include data for Agora. Others are the remaining categories for each marketplace. Share is according to the alternative definition of digital goods, and Others are in parentheses. Digital goods are included in all marketplaces; erotica and services for Silk Road 2. Services for Agora. Custom listings, erotica, fraud, tutorials, and services for Evolution.

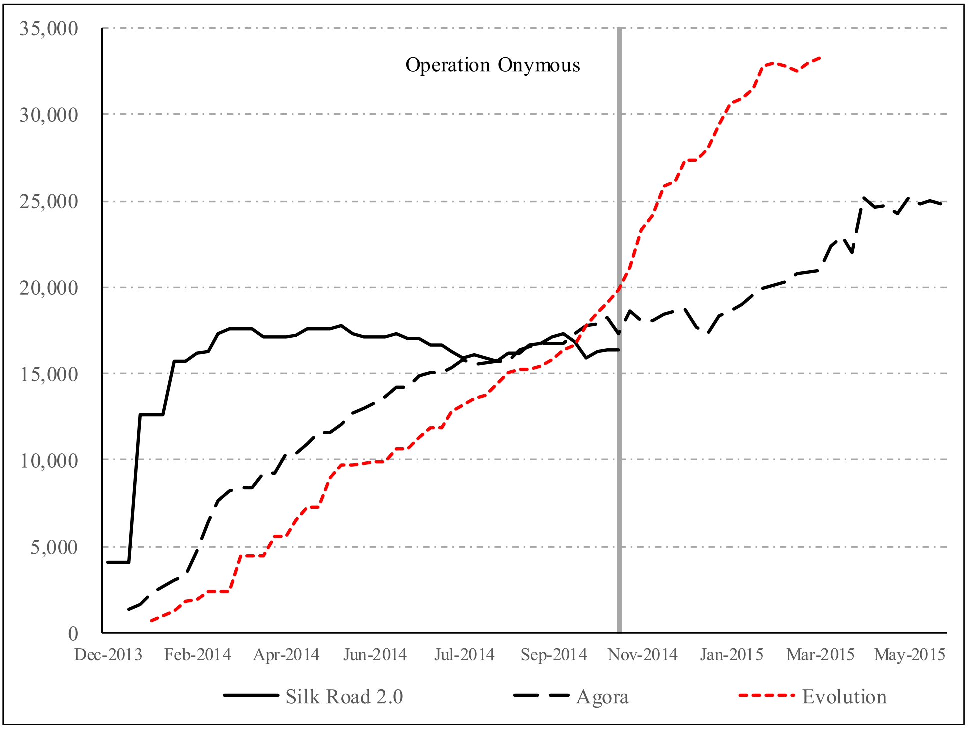


**Figure 2.** Weekly average total listing numbers.

Road they increase slightly to 6%. These suggest that the newer the marketplace, the lower the percentage of drugs and the higher the percentage of digital products.

Figure 2 shows the total weekly number of listings per cryptomarket. It indicates that listings increased with sales. The listings on Evolution increased sharply and surpassed Agora's a few weeks before Operation Onymous, which contrasts with the stagnation in Agora. Vendors seemed to frown upon the unstable access. Figure 3 illustrates that the number of drug listings paralleled the development of overall listing numbers. Drug listings on Agora decreased sharply after Operation Onymous, and took 2 months to revert to the pre-operation level. Drug listings on Evolution increased further 5 weeks before Operation Onymous and increased at a higher rate thereafter. This suggests that Agora's downtimes after Operation Onymous are not only attributed

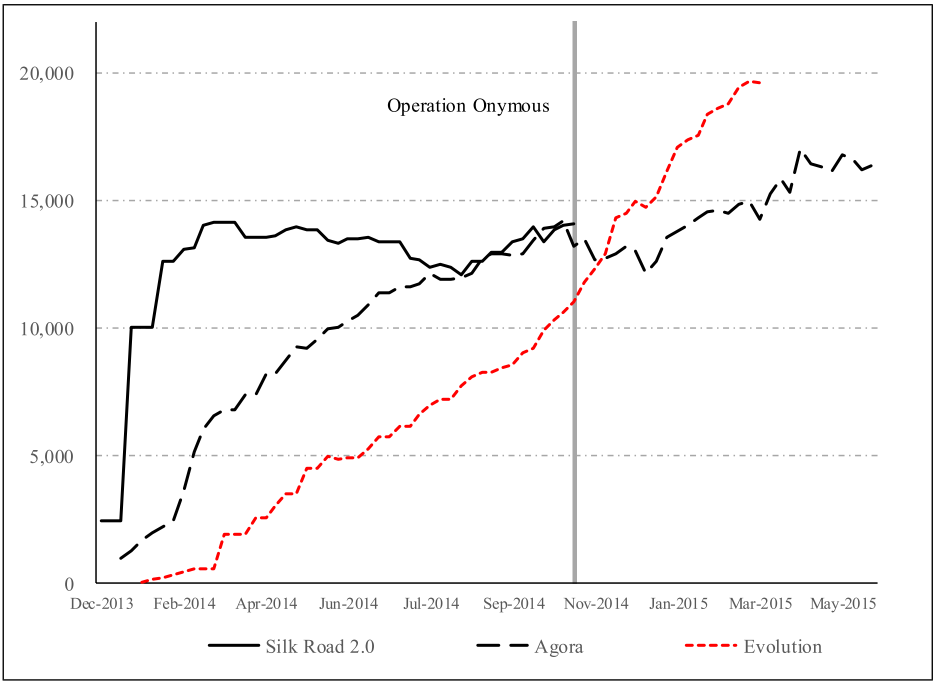


**Figure 3.** Weekly average listing numbers of drugs.

to the rapid growth in sales at Evolution after Operation Onymous but to Evolution attaining market leadership.

## Method

### *Granger Causality Test*

First, Granger causality tests are used to examine whether the drug supply in cryptomarkets is a major engine of their respective growth. To test whether certain types of supply Granger-cause sales of cryptomarkets in the bivariate case, the following equation is used

$$\Delta S_t = a_0 + \sum_{i=1}^{p} a_{1i}\Delta S_{t-i} + \sum_{i=1}^{p} a_{2i}\Delta L^j_{t-i} + \varepsilon_t \tag{1}$$

where $S_{t-i}$ represents the log of sales of a cryptomarket at week $t-i$, and $L^j_{t-i}$ represents the log of the number of average listings for product category $j$ at week $t-i$, and $\varepsilon_t$ represents an identically and independently distributed error term with mean zero and constant variance. $\Delta$ represents the difference in $S_t$ between the weeks $t$ and $t-1$, implying that the differenced series of log variables represent the percentage change in that variable. Product category $j$ is $Dr$ for drug, $Dig$ for digital goods, and $O$ for others. $p$ represents lags for the dependent and independent variables.The optimal lag order was selected using the Akaike information criterion (AIC).

The percentage change in each variable is used because stationarity of variables is required to use Granger causality test, VAR analysis, and ARDL model. If those variables are not stationary, conventional OLS-based statistical inferences, included performing a hypothesis test using t-statistics, cannot be used. To test whether the variables used were stationary, the augmented Dickey–Fuller unit root test with and without time trend was conducted. The augmented Dickey–Fuller tests[14] indicate that almost all of level variables, $S_t$ and $L^j_{t-i}$ , exhibit non-stationarity, whereas the differenced series, $\Delta S_t$ and $\Delta L^j_{t-i}$ , exhibit stationarity.

The Granger causality test precisely examines the hypothesis that the coefficients of all the values of one of the variables in equation (1) are zero. This null hypothesis implies that these regressors have no predictive content for the independent variable $\Delta S_t$ beyond that in the other regressors. Failure to reject the null hypothesis is equivalent to failing to reject the hypothesis that one of the variables in equation (1) does not Granger-cause the independent variable, whereas rejecting the null hypothesis implies that one variable Granger-causes the sales. The results are interpreted as follows: When the test statistic is not significant at the standard significance level (1, 5, 10%), it can be concluded that the coefficients on lagged values of the number of listings for product category *j* are effectively (jointly) zero in the regression, and indicate that the supply has no impact on cryptomarket sales. In contrast, a significant test statistic indicates that the lagged values of the number of listings (jointly) impact cryptomarket sales.

When one variable Granger-causes another, another variable may simultaneously Granger-cause a variable, indicating a feedback effect between the two variables. To examine whether the reverse relationships are observed, that is, sales Granger-causes certain types of products, the following equation that interchanges the dependent and independent variables is considered

$$\Delta L^j_t = a_0 + \sum_{i=1}^{p} a_{1i}\Delta L^j_{t-i} + \sum_{i=1}^{p} a_{2i}\Delta S_{t-i} + \varepsilon_t \tag{2}$$

The Granger causality test with equation (2) investigates whether growth in cryptomarkets attracts more vendors to list certain products. The interpretations of test results are same as those of equation (1).

Furthermore, this study uses an extension of the bivariate Granger causality test to the multivariate Granger causality test because cryptomarkets' sales and drug listings may interrelate to other cryptomarkets' product categories. In this case, a significant bivariate relationship may disappear when additional variables are included in the analysis because the additional variables could have more relevant information and higher predictive power than an independent variable in the bivariate regression. This is performed using the straightforward extension of equation (1) to the vector autoregressive model of order , known as VAR($p$), as follows

$$y_t = \Phi_1 y_{t-1} + \cdots + \Phi_p y_{t-p} + \varepsilon_t \tag{3}$$

where $y_t = (S_t, L^{Dr}_t, L^{Dig}_t, L^O_t)$, $\Phi_i$ are $4 \times 4$ coefficient matrices, $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}, \varepsilon_{4t})$ where each $\varepsilon_{jt}$ is white noise. The Granger causality test is conducted in a manner similar to the bivariate case. In each equation and each endogenous variable that is not the dependent variable, the test statistics that the coefficients on all the lags of an endogenous variable are jointly zero are computed. For each equation in VAR, the hypothesis that each of the other endogenous variables does not Granger-cause the dependent variable in that equation is tested.[15] The interpretations of test results are similar to the bivariate case. A significant test statistic of a certain variable indicates that it impacts the rest of the variables. In contrast, a non-significant test statistic of a certain variable indicates that it has no impact on the rest of the variables.

## *ARDL Model*

Second, the ARDL model is used to examine whether drug trading is a driving force for market leadership among competing cryptomarkets. The ARDL model has the advantage of capturing the complex time-series nature between the variables. To closely examine whether marketplace shutdowns affect the relationship between their sales and certain listings in competition between them, the following ARDL model with an interaction term between dummy variables of marketplace shutdowns and the number of listings are considered

$$\Delta\widehat{S_t} = a_0 + \sum_{i=1}^{p_1} a_{1i}\Delta\widehat{S_{t-i}} + \sum_{i=1}^{p_2} a_{2i}\Delta\widehat{L_{t-i}^{Dr}} + \sum_{i=1}^{p_3} a_{3i}\Delta\widehat{L_{t-i}^{Dig}} + \sum_{i=1}^{p_4} a_{4i}\Delta\widehat{L_{t-i}^{O}} + \sum_{i=1}^{p_2} b_{2i}\Delta\widehat{L_{t-i}^{Dr}}D_t + \sum_{i=1}^{p_3} b_{3i}\Delta\widehat{L_{t-i}^{Dig}}D_t + \sum_{i=1}^{p_4} b_{4i}\Delta\widehat{L_{t-i}^{O}}D_t + \varepsilon_t \tag{4}$$

where $D_t$ takes a value of unity when Silk Road 2 is taken down by Operation Onymous and takes zero otherwise. According to previous studies, the impact of marketplace shutdown lasts less than a month, and the dummy takes a value of unity for 3 weeks after the shutdown (including the shutdown week). Note that $\Delta\widehat{S_t}$ is the difference in percent changes of sales between two competing marketplaces, Evolution and Agora, that is, $\Delta S_t^{Evolution} - \Delta S_t^{Agora}$. The remaining variables, with ˆ are defined similarly. This is motivated by the relative growth in sales between competing marketplaces possibly relating to the relative supply of respective listing categories. Using this equation, Agora and Evolution are examined with the effects of Operation Onymous. $\varepsilon_t$ has a standard assumption.[16] Similar to Granger causality tests, the augmented Dickey–Fuller tests are performed and the differenced series are used.[17] The optimal lag order was selected using the AIC. Hansen (2017) states that heteroscedastic robust standard errors are appropriate if the number of lags is sufficiently large so that the errors are serially uncorrelated. Moreover, influences on the dependent variables that are not captured by the model are collected in the error term, which is likely to violate the assumption of white noise. The Ljung–Box test of white noise is used to confirm the validity of our model specification because the assumption of white noise is likely to be violated if other cryptomarkets excluded from our analysis affected Agora and Evolution significantly.

This enables us to examine whether there are any impacts of Operation Onymous from each category. For example, the coefficients related to the drug during the operation become $\sum_{i=1}^{p_2}(a_{2i} + b_{2i})\Delta\widehat{L_{t-i}^{Dr}}$, and its slope is $a_{2i} + b_{2i}$ $(i = 1, \cdots, p_2)$ and that without the effect of operation is $a_{2i}$ $(i = 1, \cdots, p_2)$. $a_{2i}$ $(i = 1, \cdots, p_2)$ captures the impact of the drug. A significantly positive $a_{2i}$ indicates that relatively higher growth in the drug category is associated with relatively higher growth in cryptomarket sales, indicating that drug trading is a driving force for market leadership among competing cryptomarkets. $b_{2i}$ $(i = 1, \cdots, p_2)$ captures the impact of the operation. Similar interpretations of the parameters for digital goods and others are possible. A significant $b_m$ indicates that certain product categories affect cryptomarket sales differently when Silk Road 2 is shut down than when it operates. The coefficients in the ARDL model can be interpreted as multipliers (Hansen, 2017), who showed that the long-run impact of each listing is calculated as $\sum_{i=1}^{p_m} a_{mi}/(1 - \sum_{i=1}^{p_1} a_{1i})$. The coefficients $a_{m1} + b_{m1}$ and $\sum_{i=1}^{p_m}(a_{mi} + b_{mi})/(1 - \sum_{i=1}^{p_1} a_{1i})$ are multipliers with operational effects.

## Results

### Granger Causality Tests

First, a bivariate analysis was performed.[18] The upper panel of Table 3 shows results of the Granger causality tests[19] i.e., whether the respective supply category Granger-causes sales for each cryptomarket. For all, except Silk Road 2, each supply category (listings of drugs, listings of digital products, and listings of others) Granger-causes sales. For example, the null hypothesis that

**Table 3.** Granger Causality test: Bivariate Analysis.

| | Silk road 2 | Agora | Evolution |
|---|---|---|---|
| $\Delta L \nrightarrow \Delta S$ | | | |
| Drugs | 2.91(.406) | 25.9***(.000) | 37.7***(.000) |
| Digital goods | .74(.389) | 20.0***(.001) | 10.5***(.005) |
| Others | .03(.868) | 18.2***(.001) | 39.2***(.000) |
| $\Delta S \nrightarrow \Delta L$ | | | |
| Drugs | 8.38**(.039) | 8.81*(.066) | 20.6***(.000) |
| Digital goods | 3.18*(.075) | 11.5**(.022) | 12.8***(.002) |
| Others | 13.1***(.000) | 34.0***(.000) | 18.6***(.001) |

*Notes.* $\chi^2$ -statistics of Granger causality tests are provided, and *p*-values are in parentheses. The lag order for each model was between 1 and 4, which was selected by the AIC. $\Delta L \nrightarrow \Delta S$ indicates the null hypothesis that the number of item listings in product category, $\Delta L$, does not Granger-cause total sales volume, $\Delta S$. $\Delta S \nrightarrow \Delta L$ indicates the null hypothesis that total sales volume, $\Delta S$, does not Granger-cause the number of item listings in product category, $\Delta L$. ***, **, and * indicate 1%, 5%, 10% significance, respectively.

**Table 4.** Granger Causality test: Multivariate Analysis.

| | Silk road 2 | Agora | Evolution |
|---|---|---|---|
| $\Delta L \nrightarrow \Delta S$ | | | |
| Drugs | 28.1***(.000) | 8.43*(.077) | 23.1***(.000) |
| Digital goods | 56.7***(.000) | 7.42(.116) | .02(.879) |
| Others | 7.21(.125) | .58(.965) | 11.0***(.001) |
| $\Delta S \nrightarrow \Delta L$ | | | |
| Drugs | 13.4***(.010) | 8.63*(.071) | 2.72*(.099) |
| Digital goods | 4.68(.322) | 6.71(.152) | 12.8***(.000) |
| Others | 2.89(.577) | 15.8***(.003) | 4.25**(.039) |

*Notes.* $\chi^2$ -statistics of Granger causality tests are provided, and *p*-values are in parentheses. The lag order for each model was between 1 and 4, which was selected by the AIC. $\Delta L \nrightarrow \Delta S$ indicates the null hypothesis that the number of item listings in product category, $\Delta L$, does not Granger-cause total sales volume, $\Delta S$. $\Delta S \nrightarrow \Delta L$ indicates the null hypothesis that total sales volume, $\Delta S$, does not Granger-cause the number of item listings in product category, $\Delta L$. ***, **, and * indicate 1%, 5%, 10% significance, respectively.

drugs do not Granger-cause sales is rejected at the 1% significance level for Agora. In contrast, no product category Granger-causes sales on Silk Road 2. The lower panel shows that sales Granger-cause each product category for all cryptomarkets. Hence, there are feedback effects between sales and supply on Agora and Evolution; an increase in sales increases the growth of Silk Road 2. Although respective categories have predictive power for sales, it may be absent when considering the other categories because they can have stronger predictability. Therefore, Granger causality tests in the multivariate framework are performed as follows.

Table 4 illustrates results of the multivariate Granger causality tests to investigate each category's impact. This shows that the drug supply Granger-causes sales on all cryptomarkets, even when considering the remaining two variables. Digital goods on Silk Road 2 and others on Evolution also Granger-cause sales. Sales Granger-cause drugs supply regardless of the cryptomarkets, indicating feedback effects between sales and drug supply. Sales Granger-cause other categories on Agora and digital goods, and other categories on Evolution. There is a feedback effect between sales and others on Evolution. These results suggest that drugs are pivotal in the growth of cryptomarkets because drugs Granger-cause sales and sales further Granger-cause drugs and other categories.

Our result that drugs are a major driving force for respective cryptomarket growth is consistent with the findings of previous literature (e.g., Broséus et al., 2017b; Christin, 2013; EUROPOL, 2017; Soska & Christin, 2015). The minor role of digital goods in cryptomarket growth might be attributed to lower commoditization that requires specialized knowledge and higher prices, although purchasing them is less risky because no physical delivery is required. Although users' identities are concealed when ordering drugs, they risk being arrested when receiving them because the postal service is used to send the drugs.

## ARDL Model

Table 5 presents results of the ARDL model that show that contemporaneous and the lagged order of drugs and digital products are associated with sales, whereas others are not[20]. This result is broadly consistent with Granger causality. Contemporaneous drugs have a negative coefficient, but lagged drugs have a positive coefficient. For example, the coefficient of $\Delta\widehat{L_{t-1}^{Dr}}$ at 1.6 indicates that a 1% point relative increase in drug listings leads to a 1.6% point relative increase in sales. Contemporaneous digital products have a positive coefficient; lagged digital products have a negative coefficient. For both drugs and digital products, the magnitude of positive coefficients is larger than that of negative coefficients. Drug supplies have a lagged impact on sales, whereas the

**Table 5.** Impacts of Market Shutdowns by Operation Onymous.

| Dependent variable | $\Delta\widehat{S_t}$ |
|---|---|
| $\Delta\widehat{S_{t-1}}$ | −.268**(.113) |
| $\Delta\widehat{L_t^{Dr}}$ | −.844***(.269) |
| $\Delta\widehat{L_{t-1}^{Dr}}$ | 1.552***(.209) |
| $\Delta\widehat{L_t^{Dig}}$ | .699**(.330) |
| $\Delta\widehat{L_{t-1}^{Dig}}$ | −1.134***(.266) |
| $D_t \times \Delta\widehat{L_t^{Dr}}$ | −.289(.701) |
| $D_t \times \Delta\widehat{L_{t-1}^{Dr}}$ | 5.467***(1.786) |
| $D_t \times \Delta\widehat{L_t^{Dig}}$ | .346(.705) |
| $D_t \times \Delta\widehat{L_{t-1}^{Dig}}$ | −2.567**(1.120) |
| Constant | .065(.047) |
| Lung–box test | 1.28(.864) |
| Adjusted $R^2$ | .688 |
| Observations | 59 |
| Long-run impact | |
| Without operation | |
| Drug | .558 |
| Digital | −.343 |
| With operation | |
| Drug | 4.643 |
| Digital | −2.089 |

*Notes.* The coefficient estimates are provided, and the standard errors are in parentheses. ***, **, and * indicate 1%, 5%, 10% significance, respectively.

supply of digital products impacts sales immediately. This difference in timing of positive impact is likely attributed to user caution to reduce the risks of potential vendor and administrator scams. The prior studies revealed that drug users look for information, including the reputations of vendors and marketplaces on forums on the dark web (e.g., Espinosa, 2019; Hardy & Norgaard, 2016; Masson & Bancroft, 2018; Moeller et al., 2017).

Long-run impacts were calculated for drugs and digital goods.[21] Drugs have a positive long-run impact above .5 on sales. This indicates that a 1% point relative increase in drug listings leads to a .5% point relative increase in sales. In contrast, digital goods have a negative impact, although the magnitude is not large. This indicates that drugs enhance the relative growth of cryptomarkets and work as a driving force in becoming the market leader. To examine the validity of our model specification, the Ljung–Box test for white noise of error terms was performed and the statistic is not rejected at the 10% significance level, indicating model validity. This justifies the exclusion of other factors related to the development of Agora and Evolution. For example, the effects of other small competing cryptomarkets are negligible.

Next, we examine the impact of the shutdown of Silk Road 2. The interaction terms between product categories and the dummy of Operation Onymous are statistically significant at least at the 5% significance level for lagged drugs and digital goods. The sign is positive, and the magnitude is larger for drugs, whereas it is negative for digital goods. Long-run impacts with the effect of the operation are even larger than 4 for drugs, and smaller, below −2, for digital goods. This suggests that drug listings plays an even larger role when the leading cryptomarket shuts down and users migrate to other cryptomarkets. A cryptomarket with a larger increase in drugs after the shutdown of leading markets is likely to exhibit higher growth in its sales, and eventually become a leading marketplace. Considering the fact that a large fraction of vendors simultaneously sold their products on multiple cryptomarkets (Soska & Christin, 2015), a cryptomarket that succeeds in

**Table 6.** Granger Causality test: Alternative Categorization.

| (a) Bivariate analysis | Silk road 2 | Agora | Evolution |
|---|---|---|---|
| $\Delta L \nrightarrow \Delta S$ | | | |
| Digital goods | .81(.367) | 16.0***(.003) | 9.23**(.026) |
| Others | .01(.942) | 28.4***(.000) | 21.3***(.000) |
| $\Delta S \nrightarrow \Delta L$ | | | |
| Digital goods | 2.53(.112) | 20.5***(.000) | 7.18*(.066) |
| Others | 13.1***(.000) | 11.4**(.023) | 4.73**(.030) |
| **(b) Multivariate analysis** | **Silk road 2** | **Agora** | **Evolution** |
| $\Delta L \nrightarrow \Delta S$ | | | |
| Drugs | 16.8***(.002) | 5.94(.204) | 34.4***(.000) |
| Digital goods | 59.2***(.000) | 4.34(.362) | 8.73*(.068) |
| Others | 14.1***(.007) | 5.04(.283) | 20.9***(.000) |
| $\Delta S \nrightarrow \Delta L$ | | | |
| Drugs | 18.7***(.001) | 11.2**(.024) | 5.58(.233) |
| Digital goods | 4.88(.300) | 10.7**(.030) | 5.90(.207) |
| Others | 2.82(.589) | 10.03**(.040) | 14.4***(.006) |

*Notes.* $\chi^2$ -statistics of Granger causality tests are provided, and $p$-values are in parentheses. The lag order for each model was between 1 and 4, which was selected by the AIC. $\Delta L \nrightarrow \Delta S$ indicates the null hypothesis that the number of item listings in product category, $\Delta L$, does not Granger-cause total sales volume, $\Delta S$. $\Delta S \nrightarrow \Delta L$ indicates the null hypothesis that total sales volume, $\Delta S$, does not Granger-cause the number of item listings in product category, $\Delta L$. ***, **, and * indicate 1%, 5%, 10% significance, respectively.

listing more drug products from vendors than other cryptomarkets are likely to attract more buyers who have already done business with those vendors, thereby exhibiting higher growth in its sales.

Hence, drugs play a major role not only in the growth of each market, but in their competitiveness. Furthermore, its role expanded when the leading marketplace was taken down. Markets with high drug growth attract more users and become market-leaders. At the time of Operation Onymous, the largest alternative Silk Road 2.0 marketplaces were Agora and Evolution. Agora led, followed by Evolution. The sharp increase in Evolution's sales around Operation Onymous may be attributed to buyer migration from Silk Road 2.0 and other seized markets, and possibly reflects higher growth in drugs in Evolution than in Agora. Evolution led over Agora approximately a month after Operation Onymous.

Our results are not mainly driven by Agora's downtimes after Operation Onymous because drug listings on Evolution had started to increase at a higher rate than Agora's 5 weeks before Operation Onymous (Figure 3). This suggests that an increase in available drugs is attributed to a gradual increase in recent sales. Moreover, as anecdotal evidence shows, vendors review information on forums to avoid risk and enjoy higher privacy levels and secure trading; it is likely that vendors observed that Evolution would be a good business platform before the operation.

**Table 7.** Impacts of Market Shutdowns by Operation Onymous: Alternative Definition.

| Dependent variable | $\widehat{S_t}$ |
|---|---|
| $\widehat{\Delta S_{t-1}}$ | −.231(.141) |
| $\widehat{\Delta L_t^{Dr}}$ | −.950***(.310) |
| $\widehat{\Delta L_{t-1}^{Dr}}$ | 1.479***(.256) |
| $\widehat{\Delta L_{t-2}^{Dr}}$ | −.507**(.240) |
| $\widehat{\Delta L_t^{Dig}}$ | .411(.411) |
| $\widehat{\Delta L_{t-1}^{Dig}}$ | −1.369*(.726) |
| $D_t \times \widehat{\Delta L_t^{Dr}}$ | 2.298***(.522) |
| $D_t \times \widehat{\Delta L_{t-1}^{Dr}}$ | .440(.580) |
| $D_t \times \widehat{\Delta L_{t-2}^{Dr}}$ | 1.642***(.400) |
| $D_t \times \widehat{\Delta L_t^{Dig}}$ | .830(.694) |
| $D_t \times \widehat{\Delta L_{t-1}^{Dig}}$ | 1.337***(.491) |
| Constant | .083(.051) |
| Lung–box test | 1.86(.762) |
| Adjusted $R^2$ | .681 |
| Observations | 58 |
| Long-run impact | |
| Without operation | |
| Drug | .024 |
| Digital | −.779 |
| With operation | |
| Drug | 3.585 |
| Digital | .983 |

*Notes.* The coefficient estimates are provided, and the standard errors are in parentheses. ***, **, and * indicate 1%, 5%, 10% significance, respectively.

### Robustness

To check the robustness of our results, Granger causality tests and interrupted regression of the ARDL model are performed using alternative definitions of digital goods.

Table 6 shows the results of the Granger causality tests. These are broadly consistent with the main results. However, drugs no longer Granger-cause sales on Agora in the multivariate analysis. Table 7 provides results of the ARDL model that are broadly consistent with the main results. Drugs have a longer lag of up to 2. Moreover, the impact of drugs in the long term is positive and much larger than that of digital goods. Furthermore, their long term impact with the effects of the operation is larger than that of digital goods; however, the long-run impact of digital goods with the operation effect is positive.

## Discussion and Conclusion

Finally, this section discusses the role of drugs compared to other types of products available on cryptomarkets and the implications of our results for law enforcement activities. First, the significant role of drugs on cryptomarkets may be historical. The first successful cryptomarket, Silk Road, was designed for drug trades (Christin, 2013; Ormsby, 2016). Although other types of illegal products and services can be offered for sale on cryptomarkets, the sale of digital products (e.g., Van Wegberg et al., 2018), firearms (e.g., Copeland et al., 2020), and new psychoactive substances (e.g., EUROPOL, 2017) still accounted for a much smaller proportion than that of drugs. Thus, drugs in cryptomarkets continue to play a major role. This major role of drugs on cryptomarkets has also been strengthened by media coverage. Considerable attention from major worldwide media has focused on illegal drugs available on cryptomarkets (e.g., Bugge, 2017; Grossman & Newton-Small, 2013; Kanno-Youngs & Whalen, 2017). Therefore, potential buyers are likely to associate cyrptomarkets with drugs. However, note that there was a recent increase in incidents of stolen data from public institutions being posted on the dark web,[22] and the presence of digital products may increase if there is more media coverage on such incidents.

Next, the implications for law enforcement are discussed. Kruithof et al. (2016) summarized four broad categories of strategies available to law enforcement in the detection and intervention of drug trades on cryptomarkets: (1) traditional investigation techniques, (2) postal detection and interception, (3) online detection (e.g., big data techniques, monitoring of cryptomarkets, and tracking money flows), and (4) online disruption (taking down online marketplaces). Our findings provide a new implication for the third category, particularly the monitoring of cryptomarkets. To effectively use capacity, resources, and technical capabilities, law enforcement agencies should focus on and monitor marketplaces with relatively larger increases in drug supply than on relatively small competing marketplaces. As in anecdotal evidence in the previous studies, monitoring cryptomarket forums as the third strategy would be effective policing. Soska and Christin (2015) argued that policing efforts for cryptomarkets should be reconsidered because law enforcement seizures of individual cryptomarkets, which are categorized in the fourth strategy, are ineffective at reducing sales across their broad ecosystem.

This study has some limitations. First, our analysis is restricted to the period between 2013 and 2015 and to three cryptomarkets, and thus our findings and implication are subject to a relatively early stage of cryptomarkets when illicit drugs was a major product category, and temporal and market-specific heterogeneity. However, although ecosystems of cryptomarkets including most actively traded product categories, procedures and standards of trades have changed rapidly recently (Van Wegberg et al., 2018), our findings are likely to provide implications that law enforcement agencies focus on a product category traded most actively across cryptomarkets and monitor cryptomarkets that show larger increases in that product category than other cryptomarkets. Furthermore, generally, it is necessary to investigate the characteristics of cryptomarkets that subsequently grow to become leading marketplaces and develop a model that predicts which cryptomarkets grow more rapidly when leading marketplaces are shut down. Analyses of numerous and recent cryptomarkets is a future agenda.

Second, this study focuses on the number of major product listings. However, other factors may influence the sales of cryptomarkets and their competition. It would be fruitful to examine how communication between users on cryptomarkets' forums affects cryptomarkets' growth and competition. Considering the first point, the legal context of cannabis that has been changing over the decade might be another factor that affects activities on cryptomarkets (e.g., Van Buskirk et al, 2016). In the U.S., where the cryptomarkets are most active, some states legalize cannabis, while others have progressively decriminalized cannabis possession and consumption or legalized it for medicinal purposes. Jardine and Lindner (2020) reported evidence that interest in cryptomarkets is associated with increased cannabis use in the U.S. between 2011 and 2015, and its effect is concentrated in states with more frequent cannabis users and those where recreational cannabis use is legalized.

This study investigated whether drug trading on cryptomarkets is a major engine for cryptomarket growth using weekly data on three leading cryptomarkets (Silk Road 2, Agora, and Evolution) obtained from the two strands of the literature based on time series analysis techniques. As reported in prior literature, this study showed that drug trading on cryptomarkets plays a pivotal role in the growth of each cryptomarket. Furthermore, this study revealed new findings that drug trading on cryptomarkets plays a crucial role in the relative growth between competing cryptomarkets, and that the relative supply of drugs plays an even larger role when leading marketplaces disappear and users migrate. Our contributions provide policy implications for the monitoring of cryptomarkets. It can be more effective for law enforcement agencies to monitor marketplaces with more rapid growth in drug supply than competing marketplaces with lesser growth. Further, law enforcement agencies should more closely monitor cryptomarkets with a larger increase in drugs after the shutdown of leading markets, because it is likely to become a leading marketplace among the surviving marketplaces.

# Appendix

**Table A1.** Major Listing Items and Their Shares over the observation Periods.

| Silk road 2 | | Agora | | Evolution | |
|---|---|---|---|---|---|
| Alcohol | 2.2 | Counterfeits | 3.7 | Counterfeits | 2.9 |
| Apparel | 3.1 | Data | 3.4 | Custom listings | 3.1 |
| Books | 3.0 | Drugs | 73.4 | Digital goods | 8.9 |
| Custom orders | 1.3 | Forgeries | 1.5 | Drugs | 52.5 |
| Digital goods | 4.2 | Information | 11.2 | Erotica | 1.6 |
| Drugs | 80.5 | Services | 3.1 | Fraud | 10.2 |
| Money | 1.8 | Other | 3.8 | Guides & tutorials | 12.6 |
| Services | 1.1 | | | Services | 4.6 |
| Other | 2.8 | | | Other | 3.4 |

*Notes.* Items for which the share is less than 1% are included as Other. These include art, computer equipment, electronics, erotica, forgeries, hardware, jewelry, laboratory supplies, lotteries and games, medical, money, packaging and writing for Silk Road 2, electronics, jewelry, tobacco, and weapons for Agora, electronics, jewelry, laboratory supplies, miscellaneous, and weapons for Evolution.

**Table A2.** Augmented Dickey–Fuller test.

| Silk Road 2 | Model | Test statistics | | Model | Test statistics |
|---|---|---|---|---|---|
| Level | | | Percent change | | |
| Sales | I | −2.64 | Sales | I | −3.27* |
| | II | −2.76* | | II | −3.28** |
| Drugs | I | −2.00 | Drugs | I | −7.36*** |
| | II | −2.11 | | II | −7.49*** |
| Digital goods | I | −.41 | Digital goods | I | −3.61** |
| | II | −1.40 | | II | −3.21** |
| Others | I | −1.21 | Others | I | −3.75** |
| | II | −1.89 | | II | −3.45*** |
| Digital goods | I | −.39 | Digital goods | I | −3.78** |
| | II | −1.28 | | II | −3.27** |
| Others | I | −1.58 | Others | I | −3.67** |
| | II | −2.15 | | II | −3.52*** |
| **Agora** | **Model** | **Test statistics** | | **Model** | **Test statistics** |
| Level | | | Percent change | | |
| Sales | I | −3.41* | Sales | I | −6.52*** |
| | II | −.91 | | II | −6.18*** |
| Drugs | I | −3.21* | Drugs | I | −2.88 |
| | II | −3.57*** | | II | −2.67* |
| Digital goods | I | −.44 | Digital goods | I | −4.33*** |
| | II | 1.58 | | II | −4.47*** |
| Others | I | −2.40 | Others | I | −4.22*** |
| | II | −.48 | | II | −4.13*** |
| Digital goods | I | −.64 | Digital goods | I | −3.97*** |
| | II | 1.15 | | II | −4.05*** |
| Others | I | −2.47 | Others | I | −5.12*** |
| | II | −1.11 | | II | −5.12*** |
| **Evolution** | **Model** | **Test statistics** | | **Model** | **Test statistics** |
| Level | | | Percent change | | |
| Sales | I | −1.85 | Sales | I | −5.57*** |
| | II | −.06 | | II | −5.47*** |
| Drugs | I | −1.20 | Drugs | I | −3.94** |
| | II | 1.24 | | II | −3.49*** |
| Digital goods | I | −2.61 | Digital goods | I | −5.46*** |
| | II | −.33 | | II | −5.01*** |
| Others | I | −1.68 | Others | I | −4.60*** |
| | II | −.32 | | II | −4.05*** |
| Digital goods | I | −1.93 | Digital goods | I | −3.65** |
| | II | −.68 | | II | −3.41** |
| Others | I | −1.88 | Others | I | −4.91*** |
| | II | .07 | | II | −4.77*** |

*Notes.* The auxiliary regression includes a constant and time trend (I), and a constant (II). Test statistics shows Dickey–Fuller test statistics. Lag length of 3 is chosen according to the AIC for all specifications. ***, **, and * indicate that the null hypothesis can be rejected at the 1%, 5%, 10% significance, respectively.

**Table A3.** Augmented Dickey–Fuller Test of Difference in Percentage Changes Between Evolution and Agora.

| | Model | Test statistics |
|---|---|---|
| Sales | I | −4.64*** |
| | II | −4.68*** |
| Drugs | I | −6.42*** |
| | II | −5.65*** |
| Digital goods | I | −5.03*** |
| | II | −4.59*** |
| Others | I | −4.98*** |
| | II | −4.84*** |
| Alternative categorization | | |
| Digital goods | I | −4.06*** |
| | II | −3.83*** |
| Others | I | −5.32*** |
| | II | −5.38*** |

*Notes.* The auxiliary regression includes a constant and time trend (I), and a constant (II). Test statistics shows Dickey–Fuller test statistics. Lag length of 3 is chosen according to the AIC for all specifications. ***, **, and * indicate that the null hypothesis can be rejected at the 1%, 5%, 10% significance, respectively.

**Table A4.** Bivariate Granger Causality Tests Between Each Major Item and Sales Volumes.

| Silk road 2 | | | |
|---|---|---|---|
| $\Delta L \nrightarrow \Delta S$ | | $\Delta S \nrightarrow \Delta L$ | |
| Item | Test statistic | Item | Test statistic |
| Alcohol | 2.08(.556) | Alcohol | 6.82(.078) |
| Apparel | .61(.433) | Apparel | 1.53(.216) |
| Books | 1.19(.275) | Books | 3.55(.059) |
| Custom orders | 14.0(.003) | Custom orders | 3.05(.384) |
| Digital goods | .76(.385) | Digital goods | 3.11(.078) |
| Drugs | 43.9(.000) | Drugs | 2.92(.571) |
| Money | 8.05(.045) | Money | .91(.822) |
| Services | 1.15(.283) | Services | 3.34(.068) |
| Other | .70(.402) | Other | 4.66(.031) |
| **Agora** | | | |
| $\Delta L \nrightarrow \Delta S$ | | $\Delta S \nrightarrow \Delta L$ | |
| Item | Test statistic | Item | Test statistic |
| Counterfeit | .01(.938) | Counterfeit | .30(.581) |
| Digital products | 1.62(.444) | Digital products | 23.04(.000) |
| Drugs | 24.36(.000) | Drugs | 7.46(.114) |
| Forgeries | .12(.727) | Forgeries | 2.29(.130) |
| Information | 26.41(.000) | Information | 4.61(.329) |
| Services | 1.06(.329) | Services | 20.61(.000) |
| Other | 20.61(.000) | Other | .19(.659) |

*(continued)*

**Table A4.** (continued)

| Evolution | | | |
|---|---|---|---|
| $\Delta L \nrightarrow \Delta S$ | | $\Delta S \nrightarrow \Delta L$ | |
| Item | Test statistic | Item | Test statistic |
| Counterfeits | 41.26(.000) | Counterfeits | 17.27(.002) |
| Custom listings | 70.29(.000) | Custom listings | 43.32(.000) |
| Digital goods | 11.22(.024) | Digital goods | 20.56(.000) |
| Drugs | 50.45(.000) | Drugs | 15.24(.004) |
| Erotica | 18.60(.000) | Erotica | .19(.661) |
| Fraud | 12.63(.002) | Fraud | 17.37(.000) |
| Guides & tutorials | 6.36(.174) | Guides & tutorials | 11.23(.024) |
| Services | 12.76(.000) | Services | .81(.367) |
| Other | 6.17(.046) | Other | 16.48(.000) |

**Table A5.** The Lag order for Granger Causality Tests.

| | | Silk road 2 | Agora | Evolution |
|---|---|---|---|---|
| Bivariate analysis | Drugs | 3 | 4 | 4 |
| | Digital goods | 1(1) | 4(4) | 2(3) |
| | Others | 1(1) | 4(4) | 4(1) |
| Multivariate analysis | | 4(4) | 4(4) | 1(4) |

*Notes.* The lag order, which is selected by the AIC, is shown for each model. The lag order selected by the AIC for alternative categorization is shown in parentheses.


## Acknowledgments

We are grateful for the helpful suggestions from anonymous referees. The opinions expressed herein are those of the authors and do not necessarily reflect those of Mercoin Inc.

## Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

## Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.



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## Notes

1. Users' messages are routed through a series of relays that serve as a buffer between users and visited websites (Dingledine et al., 2004).
2. The most notable is Bitcoin that is a fully decentralized digital currency based on blockchain (Nakamoto, 2008).
3. The most common message encryption software is PGP, used by cryptomarket administrators, vendors, and buyers. PGP stands for "Pretty Good Privacy." See, for instance, Cox (2016).
4. https://www.gwern.net/DNM-archives
5. See Hiramoto and Tsuchiya (2020) and Tsuchiya and Hiramoto (2021) for details.
6. See https://www.gwern.net/DNM-archives for the list of those studies using this dataset.
7. Broséus et al. (2017b) investigated Evolution between January and March 2015, and showed that drug-related items accounted for 63% of all item listings, and the rest accounted for 37%. As shown in Table 2, the category of drugs in this study accounted for 52.5%.
8. See EUROPOL (2014) for details.
9. Exit scam refers to administrators of cryptomarkets running off with Bitcoins deposited in escrow and shutting down the marketplaces. Those cryptomarkets use the escrow system to manage their transactions. First, users transfer their Bitcoins to the sites' Bitcoin addresses. The Bitcoins sent by users are held in escrow until the transactions are completed. After an ordered product is completed, the marketplace sends the Bitcoins to the vendor.
10. In February 2014, Silk Road 2 was subject to a major hack and withdrew its escrow service. This hacking incident affected its reputation and contributed to a slowdown (e.g., Bhaskar et al., 2019).
11. See Soska and Christin (2015) for details.
12. See Appendix Table A1 for each major item and respective share of each cryptomarket.
13. The relatively lower share on Evolution is consistent with the fact that Evolution has emerged from the carding scene unlike other marketplaces (Martin et al., 2019).
14. See Table A2 in Appendix.
15. See Hamilton (1994) for details on Granger causality test and VAR analysis.
16. The assumption is essential serially uncorrelated white noise. Normality needs are not necessarily assumed because asymptotic theory proves that under a moderately large number of observations, estimated coefficients distribute normally (e.g., Greene, 2018; Stock & Watson, 2019). A sample size with 30 observations might suffice for valid asymptotics. Unbiasedness and consistency of OLS are not affected by heteroscedasticity or serial correlation, however, the standard errors are. This indicates that the OLS estimators are no longer efficient. For efficiency, heteroskedastic robust standard errors are used. Using these standard errors, all inferences and other tests are valid.
17. See Table A3 in Appendix. It indicates that the differenced series exhibit stationarity.
18. See Appendix Table 2A for results of bivariate Granger causality tests for each major item. The results that drugs and items related to digital goods Granger-cause sales are consistent with results reported in the main text.
19. See Appendix Table 3A for optimal lag selection. The table provides results of optimal lag selection for multivariate Granger causality tests and the ARDL model described below (Tables 4A and 5A).
20. Contemporaneous or any lag order for others are not included in the ARDL model because AIC indicated poor performances of those models.
21. Long-run impacts of "others" cannot be calculated because related variables are not included in the model.
22. See, for example, Fox (2022), regarding health data that were stolen and posted on the dark web.

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