

# Collective Dynamics of Dark Web Marketplaces

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## Abstract

Dark web marketplaces are websites that facilitate trade in illicit goods, mainly using Bitcoin. Since dark web marketplaces are illegal, they do not offer any user protection, and police raids and scams regularly cause large losses to marketplaces participants. However, the uncertainty has not prevented the proliferation of dark web marketplaces. Here, we investigate how the dark web marketplace ecosystem re-organises itself following marketplace closures. We analyse 24 separate episodes of unexpected marketplace closures by inspecting 133 million Bitcoin transactions among 38 million users. We focus on users who move their trading activity to a different marketplace after a closure. We find that most migrating users continue trading activity on a single coexisting marketplace, typically the one with the highest trading volume. User migration is swift and trading volumes of migrating users recover quickly. Thus, although individual marketplaces might appear fragile, coordinated user migration guarantees overall systemic resilience.

## Introduction

Dark web marketplaces (or “dark markets”) are commercial websites specialised in trading illicit goods. They are accessible via darknets (e.g., Tor) and vary in specialization, technology, and primary supported language. *Silk Road*, the first modern dark marketplace launched in 2011, limited its sales to drugs while other dark marketplaces allow the trading of weapons, fake IDs and stolen credit cards [1, 2]. Most marketplaces simply facilitate transactions between buyers and sellers of illicit goods, however some marketplaces act as sellers and sell directly to buyers. Bitcoin is the universally accepted currency (occasionally together with other cryptocurrencies) on every dark marketplace.

Operating outside of law, dark marketplaces do not offer any protection to customers or vendors. This has led to a proliferation of scam sales and marketplace hacks. Furthermore, marketplaces may be suddenly closed either by the authorities or by its administrators, causing significant losses to users. For example, *Silk Road* was shut down in 2013 by the FBI [3] and in the same year *Sheep Marketplace* marketplace was closed by its administrator, who vanished with 100 million US dollars stolen from its

users [4]. Following these events, dark marketplaces have adopted better technologies to mitigate losses caused by closures and reassure customers [5–7]. However, this has not prevented further marketplace closures, both due to police seizures and scams.

Counterintuitively, such uncertainty has not prevented a steady growth of both users and revenue of dark marketplaces. As of today, there are at least 38 identified active dark marketplaces [8]. Although it is difficult to identify relevant transactions from the Bitcoin blockchain and to quantify marketplace volume [8–11], the European authorities have estimated that between 2011 and 2015 dark marketplace drug sales were 44 million US dollars per year. A subsequent study estimated that, in early 2016, dark marketplaces drug sales have grown to between 170 million and 300 million US dollars per year. [12]. Recently, *Berlusconi*, known mostly for selling stolen IDs, was seized by the Italian police who estimated their annual transactions to 2 million euros [2].

Several papers have attempted to study dark marketplaces. However, the difficulty of identifying relevant transactions [8–11] has forced researchers to rely mostly on user surveys [13,14] and data scraped from dark marketplaces websites [10,15] (even though dark marketplaces administrators actively fight web scraping which is perceived as a threat). Police shutdowns have been shown to correlate with a sudden increase in drug listings in co-existing marketplaces [16,17]. The most comprehensive study on closures among 12 dark marketplaces concluded “that the effect of law enforcement takedowns is mixed as best” [10]. Another recent analysis of a large 2014 police operation identified an impact of closures on the supply and demand of drugs (but not the prices) [15]. Recent research on attributing anonymised Bitcoin addresses to named entities [18,21,38,39] has not yet been applied to the investigation of the dynamics of dark marketplaces.

In this paper, we investigate the dynamics of 24 marketplace closures by looking at 31 marketplaces in the period between June 2011 to July 2019. We do so by analysing a novel dataset of Bitcoin transactions involving dark marketplaces assembled on the basis of the most recent identification methods [22–24]. We are therefore able to quantify the overall activity of the major dark marketplaces, in terms of number of users and total volume traded. We show that the closure of a dark marketplace, due to a police raid or an exit scam, has only a temporary effect on trading volumes, suggesting that dark marketplace ecosystem is resilient. We provide the first systematic investigation of dark marketplace users migration following an unexpected closure, and show that closures mainly affect low-active users, with highly-active users migrating quickly to a new marketplace. Finally, we reveal a striking pattern of post-closure coordination: 66% of migrating users choose to move their activity to the same coexisting marketplace. Moreover, the marketplace that receives the largest number from migrating users tends to have the largest volume and the most users in common with the closed marketplace.

## Methods

Dark marketplaces operate similar to other online marketplaces, such as eBay, Gumtree or Craigslist, on which vendors advertise their products and price and customers request the shipment through the website and vendors are typically responsible for the delivery. Typically, transactions flow from buyers to the dark marketplace that then sends the money to sellers after buyers confirmation of receiving the goods. Consumers may leave reviews that contribute to vendors’ reputation [7]. Dark marketplaces are also supported by search engines and news websites such as Grams, DeepDotWeb and darknetlive which aggregate information on all active dark marketplaces [25]. After multiple scam closures, nowadays dark marketplaces rely often on escrow systems. The dark marketplace does not keep buyers’ bitcoins in local

addresses but instead sends it to an escrow service. Escrow services can be independent from the dark marketplace or integrated to the dark marketplace, either way users can withdraw their money (refund it) if the shipment was not delivered. After the buyer’s confirmation of receipt, the escrow service transfers the money to the seller.

Our analysis relies on a novel dataset of dark marketplace transactions on the Bitcoin blockchain. The ledger of Bitcoin transactions (the blockchain) is publicly available and can be retrieved through Bitcoin core [26] or a third-party API such as Blockchain.com [27]. It consists of the entire list of transaction records, including time, transferred amount, origin and destination addresses. Addresses are identifiers of 26 – 35 alphanumeric characters that can be generated at no cost by any Bitcoin user. Therefore, a single Bitcoin wallet can be associated to multiple addresses. Even though it is called wallet, Bitcoin wallet is better described as a key chain (similar to mac keychain) where users have multiple keys allow them to access multiple addresses where the Bitcoins are stored. In fact, to ensure privacy and security, most Bitcoin software and websites help users generate a new address for each transaction. In order to be useful, therefore, blockchain data has to be pre-processed to map groups of addresses to individual users.

We used data pre-processed by Chainalysis Inc. following the approach detailed in [22–24]. The pre-processing relies on state-of-the-art heuristics [18,21,38–40], including co-spending clustering, intelligence-based clustering, behavioural clustering, and entity identification through direct interaction [23]. These techniques rely on the observation of patterns in the Bitcoin protocol transactions and user behaviour. First, addresses were grouped based on a set of conditions, following some of the heuristics mentioned above and discussed in Supplementary information S1. Addresses meeting all conditions were included as part of a single cluster. Note that this step is unsupervised and, there is no ground truth regarding the mapping between addresses and entities [39]. Then, clusters were identified as specific dark markets, using transaction data collected by Chainalysis (the technique employed for the identification is similar to the one described in [39]). Identification of addresses by Chainalysis Inc. related to illicit activities has been relied upon in many law enforcement investigations [29,41]. Given the potential uses of identified Bitcoin data, rigorous investigation and avoidance of false positives is crucial. If an address does not meet all the conditions required by the clustering and identification heuristic, it will be tagged as “unnamed”. This means that some addresses belonging to a dark marketplace administrator or dark marketplace users, are not included in our dataset (see more information on our dataset in Supplementary Information Section S1).

We considered the entire transaction data of 31 dark marketplaces (see Supplementary Information Section S2) between June 18, 2011, and July 24, 2019. This dataset includes the major marketplaces on the darknet as identified by law enforcement agencies reports [3,31] and the World Health Organization [32]. We also considered transactions of all users who interacted with one of these marketplaces (dark marketplace’s “nearest neighbours”) after their first interaction with a dark marketplace. Thus, each marketplace can be represented as an egocentric network [33] of radius 2, where the marketplace is the central node, its nearest neighbours represent marketplace users, and “other nodes” appear only through their interaction with one of the marketplaces users. A direct edge represents a transaction occurring either between the marketplace and one of its nearest neighbours, or between two nearest neighbours, or between the nearest neighbour and “other node”. We excluded Bitcoin trading exchanges from our list of nearest neighbours since we focus on the users’ direct interaction with the marketplace. Bitcoin trading exchanges are platforms that allow users to trade Bitcoin for other cryptocurrencies or fiat currencies. Fig. 1 shows a schematic representation of our dataset, where transactions within the square are the ones included in the dataset. After removing transactions to/from cryptocurrency ex-

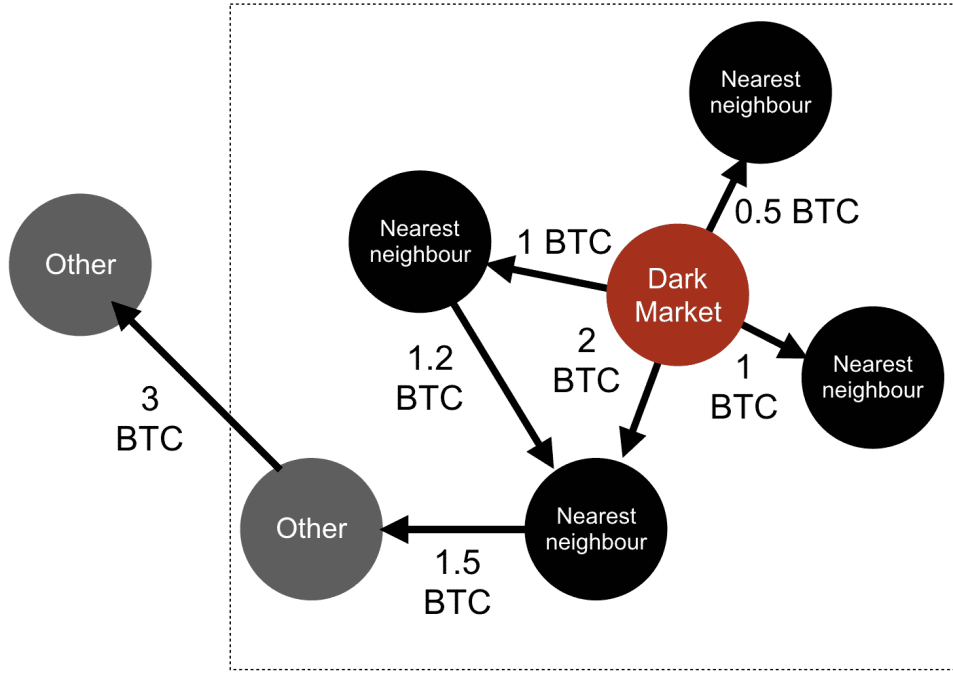


Figure 1: **Dark market ego-network.** Our dataset includes transaction between addresses belonging to a dark marketplace (in red) and its nearest neighbours (in black), as well as the transactions between nearest neighbours and “other” Bitcoin addresses (in grey). Arrows correspond to transactions, and their value in Bitcoin (BTC) is reported. Any transaction between two “other” nodes is excluded from our dataset. In this schematic representation, the dotted square includes transactions present in our dataset.

changes, the dataset contains  $\sim 133$  million transactions among over 38 million distinct users. The total number of addresses which directly interacted with dark marketplaces is  $\sim 8.3$  million. The volume of transactions sent and received by dark marketplaces addresses amount to  $\sim 4.2$  billion US dollars.

In order to gain information on the analysed marketplaces, we collected additional data from the Gwern archive on dark marketplace closures [1]. To compile comprehensive information, we also used law enforcement documents on closures as well as a number of online forums [31,32,34] dedicated to discussing dark marketplaces (see Supplementary Information Section S2). Out of the selected marketplaces, 12 were subject to an exit scam, 9 were raided, 3 were voluntarily closed by their administrators, and 7 are still active. 29 marketplaces operate in English and 2 operate in Russian. Out of the 31 marketplaces, 3 are marketplaces dedicated to fake and stolen IDs and credit cards. The primary currency on these marketplace is Bitcoin. In Fig. 2, we present the lifetime of the selected marketplaces and the reason behind their closure.

## Results

The dataset contains 133,308,118 transactions among 38,886,758 users. The total number of distinct users which directly interacted with a dark marketplace is 8,377,478. The volume of transactions sent and received by dark marketplace addresses amount to 4.210 billion US dollars, while the one received by dark marketplaces address is 1.99 billion US dollar. Note that the conversion between Bitcoins and US dollars is done considering the price of Bitcoin at the time of the transaction. Table S2 in Supplementary Information Section S2 reports characteristics of the 31 marketplaces considered, including overall number

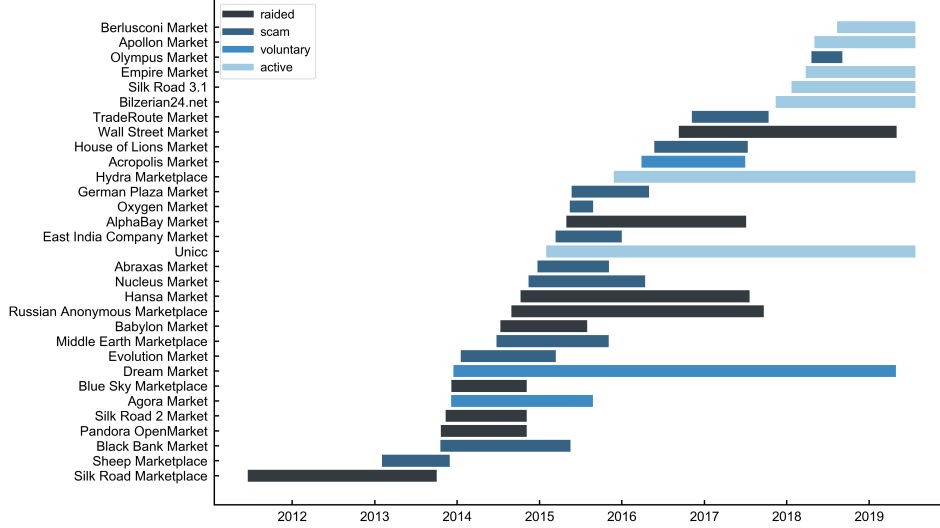


Figure 2: **Dark marketplaces lifetime.** Each bar corresponds to a different dark marketplace (see y-axis labels). Bars are coloured according to the reason behind closure: raided by the police (black), exit scam (dark blue), voluntary closure (blue). Light blue bars correspond to marketplaces that are still active in November 2019.

of users and transaction volume. The most active marketplace in terms of number of users and traded volume is *AlphaBay*, followed by *Hydra*.

## Marketplace resilience

The capacity of the dark marketplace ecosystem to recover following the marketplace closure can be studied by quantifying the evolution of the total volume traded by dark marketplaces over time. Despite recurrent closures, we find that the number of marketplaces has been relatively stable since 2014 as new marketplaces frequently open (see Fig. 3a). In addition, despite closures, the total weekly volume sent/received by dark marketplace addresses has grown from 2014 until the end of 2019 (see Fig. 3b). In fact, Moving Average Convergence Divergence (MACD) analysis [35] reveals that, following each dark marketplace closure, the overall dark marketplace volume drops, but it recovers quickly thereafter, within 9 days on average (median: 3 days, see also Figure S6 in Supplementary Information). Starting from the end of 2018, however, we observe a decrease in the total volume traded (See Fig. 1).

## User migration

The observation that trading volumes recover quickly after unexpected marketplace closure suggests that users may move to other marketplaces [15,36]. We refer to this phenomenon as *migration*.

In fact, migration was observed [37] after the closure of the *AlphaBay* marketplace when other marketplaces, namely *Hansa* and *Dream Market*, experienced an abnormal spike in activity. In this section, we provide the first systematic investigation of dark marketplace users migration, by studying the effects of a series of closures.

We identify migrant users in the following way. For each dark marketplace  $m$  that was shut down, we identify users who started trading on another coexisting marketplace  $m'$  following the closure of  $m$ . If a user was trading on both marketplaces  $m$  and  $m'$  before the closure of marketplace  $m$ , the user is not labelled as a migrant to marketplace  $m'$ . Fig. 4 shows the flows of migrant users between marketplaces.

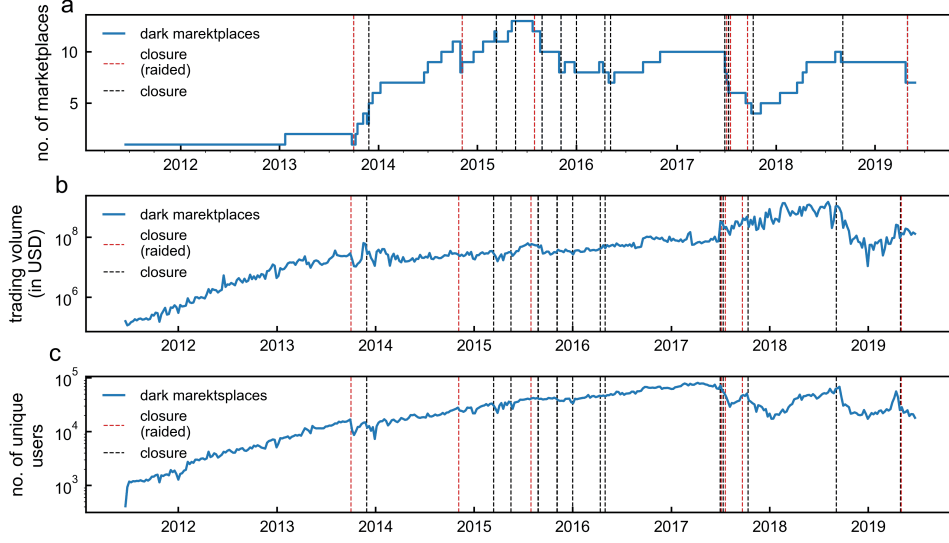


Figure 3: **Dark marketplaces resilience.** (a) The total number of active dark marketplaces across time. (b) The total volume (in US dollars, USD) exchanged by dark marketplaces addresses. (c) The number of unique users interacting with dark marketplaces. Dashed lines represent marketplace closure due to law enforcement raid (in red), or any other reason (in black). Values are calculated using a time window of one week.

But what fraction of users do migrate after a closure? To answer this question we need to consider that  $\sim 38\%$  of all users in our dataset made only one transaction (sent or a received once) - a finding consistent with the evidence that most of the minted Bitcoin were accumulated in addresses which never sent, at least until 2013 [38]). We then need to estimate the expected number of users who would have kept transacting with the market if no closure had occurred. To do so, we focus on the “returning users” over time, i.e., the fraction of all users active (sent or received) in a given week that are active also in the following day. We denote as  $R_t$  the intersection between the set of active users on a given day  $t$ , and the set of users that were active at least once in the preceding week. Thus,  $R_t$  is the set of “returning users”. In order to compare the number of returning users across closures, we normalize the entire time series by the fraction of returning users at the time of closure,  $R_{\hat{t}}$  where  $\hat{t}$  is the day of closure. Thus, the normalized value of returning users on the day of closure is 1. Then, we consider the median across marketplace closures. We find that, 5 days after the closure of a dark marketplace, 85% of the expected number of returning users interact with another marketplace, where the ‘expected’ number is computed by considering the typical number of returning users before closure. This finding indicates that, even though the marketplace closure does affect participation, the vast majority of returning users do migrate to another marketplace following a closure.

## Who is migrating?

The observation that some users stop trading following a dark marketplace closure but the total volume traded in dark marketplaces does not decrease could indicate that migrant users are on average more active than others. We test this hypothesis by computing the activity of migrant users before and after marketplace closure. We refer to the original dark marketplace that a user was interacting with as its *home marketplace*. For all users (migrant and non-migrant), we measure the total volume exchanged with any other user in our dataset including the home marketplace. We find that the median volume



Figure 4: **Migration of users following a dark marketplace closure.** Flows of users migrating to another coexisting marketplace following a closure. The arrowhead points to the direction of migration, and the width of the arrow represent the number of users. Marketplaces are ordered clockwise according to the closing date in ascending order starting from Silk Road Marketplace.

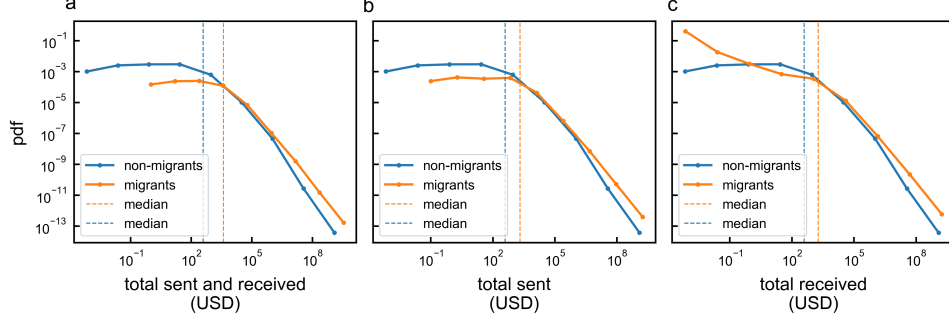


Figure 5: **Migrant vs. non-migrants activity distribution.** (a) The distribution of the total volume sent and received across all closed dark marketplaces for migrants (orange line) and non migrants (blue line). (b) The distribution of the total volume sent across all closed dark marketplaces by migrants (orange line) and non migrants (blue line). (c) The distribution of the total volume received across all closed dark marketplaces by migrants (orange line) and non migrants (blue line). Dashed lines represent the median value for migrant users (orange line) and non-migrant users (blue line).

exchanged by migrant users is  $\sim 10$  times larger than the volume exchanged by non-migrant users (see Fig. 5a), with the median volume exchanged summing to 3,882.9 US dollars across all migrant users and to 387.2 US dollars for non-migrant users. The means are sensitive to high volume users with 71,6441.9 US dollars and 17,529.7 US dollars for migrant and non-migrant users respectively (see Fig. 5). In terms of receiving and sending behaviour migrants users are also more active compared to non-migrants (see Figs. 5b and c) Similar conclusions can be drawn by considering the volume exchanged with the home marketplace only, which has median value of 263 US dollars for migrant users and for non-migrant users 74.3 US dollars and a mean value of 2,725.1 US dollars and 475.9 US dollars for migrant and non-migrant users respectively (see Supplementary Information Section S4).

The activity distribution of migrants is significantly different from the non-migrant users' distribution (using Kolmogorov–Smirnov test,  $p < 0.01$ , see Table S3 in Supplementary Information Section S4).

## Coordination in the dark

We now turn to the analysis of how migrant users decide where to migrate. In our dataset, following every instance of marketplace closure except one, users could migrate to two or more co-existing marketplaces.

Fig. 6(a), we show the evolution of the trading volume shares of the closed marketplace and the top two destination marketplaces in the days preceding and following a closure. Trading volume share for a give market is the normalised trading volume of a market by the total trading volume of all dark marketplaces. We find that the top two destination marketplaces experience an increase in the trading volume share starting 2 days after the closure, and saturating about 6 days after with a share of 27%, approximately more than double the share at the time of closure. The second top destination on the other hand its share increases from 5% to 8.7%.

We investigate the characteristics of the top destination marketplace for migrant users, by ranking coexisting marketplaces according to the total trading volume in US dollars at the time of closure and the total number of common users between the shut down and the coexisting marketplace before closure. We find that, regardless of the reason behind closure, users do not migrate randomly and chose to move to the marketplace with the highest trading volume which, in some cases, is also the marketplace with the highest number of common users.

Focusing on the first week after closure, we find that, on average, one marketplace absorbs  $66.1\% \pm 16.1$



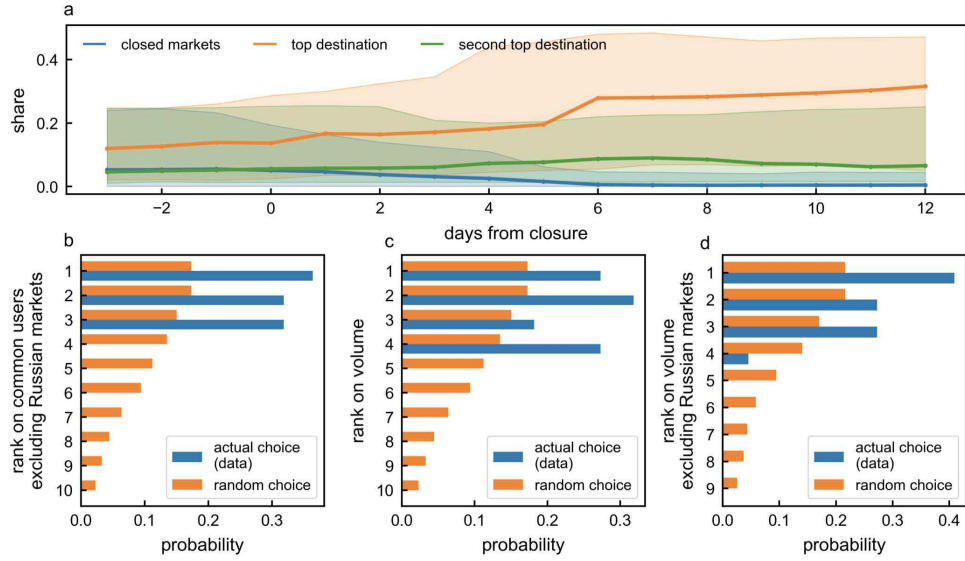


Figure 6: **Migration decision and impact.** (a) The median share (across closures) of a closed marketplace (blue line), the top destination marketplace for the migrant users (orange line) and the second top destination for migrant users (green line). The shaded area represents the 50% interquartile range. Value are computed using a rolling window of one week. Figures (b-d) show the probability of a marketplace to be chosen for migration (becoming the top destination for migration) given its rank at the time of coexisting marketplace closure in comparison to the random model. Marketplaces are ranked in descending order according to (b) the number of overlapping users they have with the closed marketplaces excluding Russian marketplaces (c) the total trading volume in US dollars and (d) the total trading volume in US dollars excluding Russian marketplaces from the ranking. The random model in the Figures b-d represent a model where users can move to any existent marketplace with equal probability.

of all migrant users. Only 4% of the users migrate to more than one coexisting marketplace simultaneously after the closure. What is this marketplace? Fig. 6b shows that, in 36.4% of the closures considered, it is the one sharing the larger number of common users with the closed marketplace, while the chances that users select the second and the third rank is 31.8%. Users do not choose to migrate to marketplaces with rank lower than the third.

Fig. 6c shows that, when marketplaces are ranked according to the volume of their transactions, the second-largest marketplace is preferred in the majority of cases (31.8%). However, a closer look at the data reveals that the Russian marketplace occupies often the top ranks in terms of volume but it tends not to be the preferred migration harbour, probably due language and geographical barriers. Excluding the Russian marketplace from the ranking, in fact, we find that the largest marketplace by volume is selected 41% of the times (see Fig. 6d).

We compare the users' decisions with a null random model, where at each closure users move with equal probability to any of the existent marketplaces. The probability  $P_i$  of the  $i^{\text{th}}$ -ranked marketplace to be chosen for migration uniformly at random after  $m$  closures is equal to

$$P_i = \frac{\sum_{j=1}^m 1/c_j}{m},$$

where  $c_j$  is the number of coexisting marketplaces at the time of closure  $j$ . We find that the data different significantly from the uniform random choice model, confirming the presence of coordination between migrating users (see Fig. 6)

## Conclusion

We analysed a novel dataset of Bitcoin transactions on 31 large dark marketplaces and investigated how the darknet marketplace ecosystem was affected by the unexpected marketplace closures between 2013 and 2019. The marketplaces we considered were heterogeneous in many ways and 24 of them were closed abruptly due to police raids and scams. We found that the total volume traded on these dark marketplaces dropped only temporarily following closures, revealing a remarkable resilience of the marketplace ecosystem. We identified the origin of this resilience, by focusing on individual users, and unveiled a swift and ubiquitous phenomenon of migration between recently closed marketplaces and other coexisting ones. We found that migrating users were more active in terms of total transaction volume compared to users who did not migrate. Finally, we found that migrating users tended to migrate predictably to co-existing marketplaces which had the largest overall volume and the most numbers of users in common with the closed marketplace.

Our findings shed new light on the consequences of sudden closure and/or police raids on dark marketplace, which had been previously raised in the literature and among law enforcement entities [12, 15, 31]. Interesting future research directions include the role of marketplace closure on the emergence of new marketplaces, refining the analysis to investigate whether scam closures and police raids may have so-far neglected effects on user migration, delving deeper into the types of user behaviour that can predict migration, and broadening the research to include the effect of online forums on the performance of existing marketplaces as well as on the migration choices after a closure [34]. More broadly, we anticipate that our findings will help inform future research on the self-organisation of emerging online marketplaces.

## Authors contribution

A.E., L.A., A.T. and A.B. designed the research; L.R. acquired the data. L.R. and A.E. prepared and cleansed the data, A.E. performed the measurements. A.E., L.A., D.G., A.T. and A.B. analysed the data. A.E., L.A., A.T. and A.B. wrote the manuscript. All authors discussed the results and commented on the manuscript.

## Data and materials availability

All data needed to evaluate the conclusions in the paper are present in the paper. Additional data related to this paper may be requested from the authors.

## 1 Appendix

## 2 Clustering techniques

In Bitcoin, multiple addresses can belong to one user; grouping these addresses reduces the complexity of the ledger and Bitcoin anonymity [38]. Clustering techniques rely on how Bitcoin’s protocol works, users behaviour on the blockchain, Bitcoin’s transaction graph structure and finally, machine learning. Methods relying on Bitcoin’s protocol specifically exploit what is known as change addresses: Bitcoins available in an address have to be spent as a whole. Fig. 7 shows an example of a change address. User *A*’s wallet has two addresses, one contains 1BTC and another has 2BTC. User *A* would like to transfer 0.25BTC to user *B*, as shown in Fig. 7A. After transferring the 0.25BTC to *B*, the change (0.75BTC) will not stay in the same address. Bitcoin protocol will create another address, also assigned to *A*, where the 0.75BTC change will be stored. By observing this pattern, a heuristic technique proposed in [40] suggests that these addresses can be grouped, as they belong to one user.

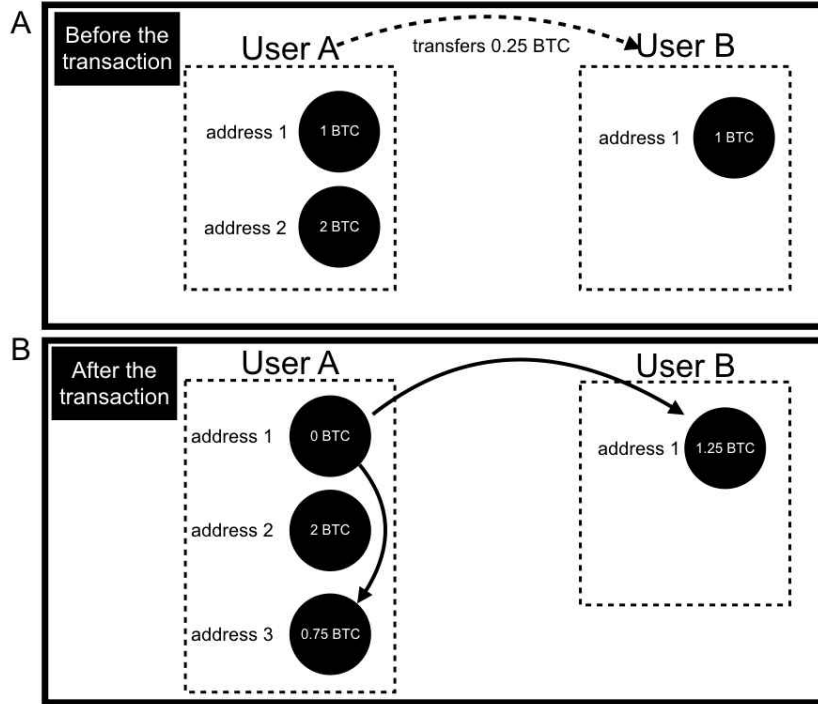


Figure 7: **How Bitcoin's protocol handles transactions with change.** (A) A transaction between users *A* and user *B*, where *A* wants to transfer 0.25 Bitcoins to *B*. User *A* has two addresses, one with 1 Bitcoin and the other with 2 Bitcoins. User *B* has one address, containing 1 Bitcoin. (B) How a transaction is conducted under Bitcoin protocol. User *A* first address transfers 0.25 Bitcoin to user *B* first address. The change of 0.75 Bitcoin does not stay in User *A* first address 1, but appears, instead, as another transaction to a new address. The dotted boundaries in both figures represent a grouping of these addresses, as they belong to one user. A solid arrow represents an executed Bitcoin transaction, while the dotted arrow represents a desired transaction.

Since users can have multiple addresses, they can use multiple of these addresses to transfer Bitcoins in a single transaction. For example, Fig. 8A shows a case where user *A* controls 3 different addresses. Each address has a different amount of Bitcoins, 1, 4 and 2.5 respectively. User *A* wants to transfer 5 Bitcoins to user *B*, and two addresses will be used to complete the transaction as shown in Fig. 8B. This observation allows the grouping of these two addresses as a single user [40].

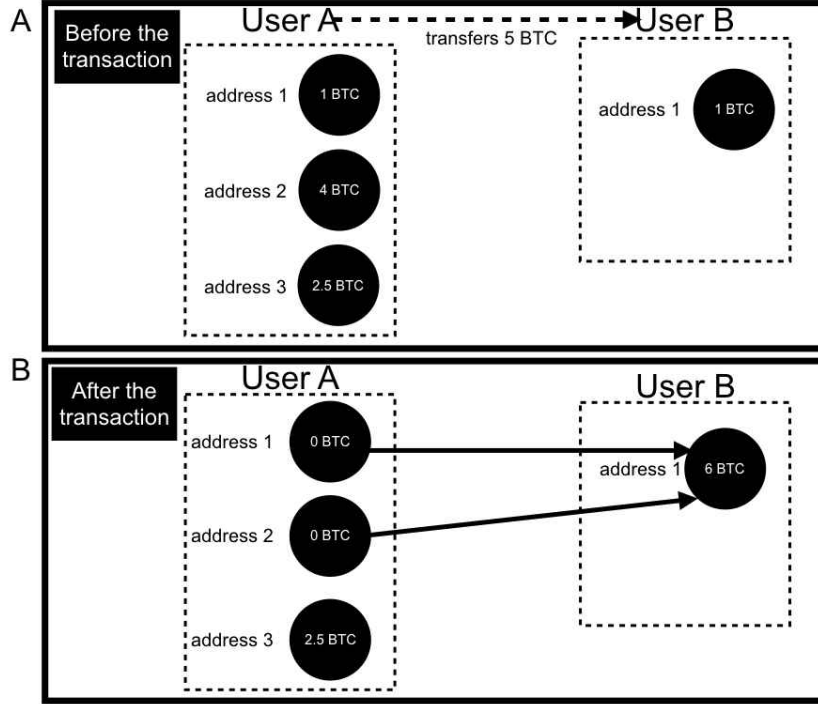


Figure 8: **Sending from multiple inputs in Bitcoin (A)** A desired transaction between users *A* and *B*, where *A* wants to send 5 Bitcoins to user *B*. User *A* has 3 different addresses with 1, 4 and 2.5 Bitcoins respectively. User *B* has one address containing 1 Bitcoin. **(B)** How the transaction will be conducted under the Bitcoin protocol. User *A* will use two addresses to complete the transaction. Both addresses will send to one address belonging to user *B*. The dotted boundaries in both figures represent a grouping of these addresses as they belong to one user. The solid arrows represent an already executed Bitcoin transaction while the dotted arrow represents a desired transaction.

The work in [39] challenged these heuristics, showing the possibility of having false positives and not taking into consideration changes in the protocol. The work suggests instead a manual process, where the behaviour of each entity is investigated. Page rank (network centrality measure [42]) was also used to identify important addresses [43]; however, the addresses were already grouped using the heuristics introduced by [40]. Machine learning was also shown to identify addresses which should be grouped as one with 77% accuracy.

Mapping addresses to an actual identity is more challenging. Some entities already publish their public key for donation and payment, such as Wikimedia Foundation [44]. The only research that introduced a method for mapping a collection of addresses to a real-world identity is [39], through direct interaction with the address. In this work, researchers directly engaged in 344 transactions with different services including mining pools, exchanges, dark marketplaces and gambling websites.

The introduction of these heuristics did not only challenge Bitcoin’s anonymity but also eased the regulation of Bitcoin. Companies specialising in blockchain analytics started to capitalise on these heuristics and provide tools for exchanges and law enforcement entities to facilitate regulatory efforts. For our analysis of dark marketplaces, our data was provided by Chainalysis [45], which is a blockchain analytics company. Chainalysis aided several investigations led by different law enforcement entities, including the United States Internal Revenue Service (IRS) [41].

Our dataset sampling approach (from the entire Bitcoin transactions) deploys a complex network perspective. Transactions on the blockchain can be modelled as a directed weighted graph where a node

represents a user, and a directed edge between two nodes  $A$  and  $B$  represents a transaction from user  $A$  to user  $B$ . Depending on the clustering algorithm, a node can represent one address or multiple addresses. A node can also be labelled as a specific entity or unlabelled (unnamed). Fig. 9 shows a sketch of the network and the different possible meanings of a node. For example in Fig. 9, the black unnamed node on the right side is a representation of two different addresses clustered together, however, they were not attributed to an entity thus remained unnamed.

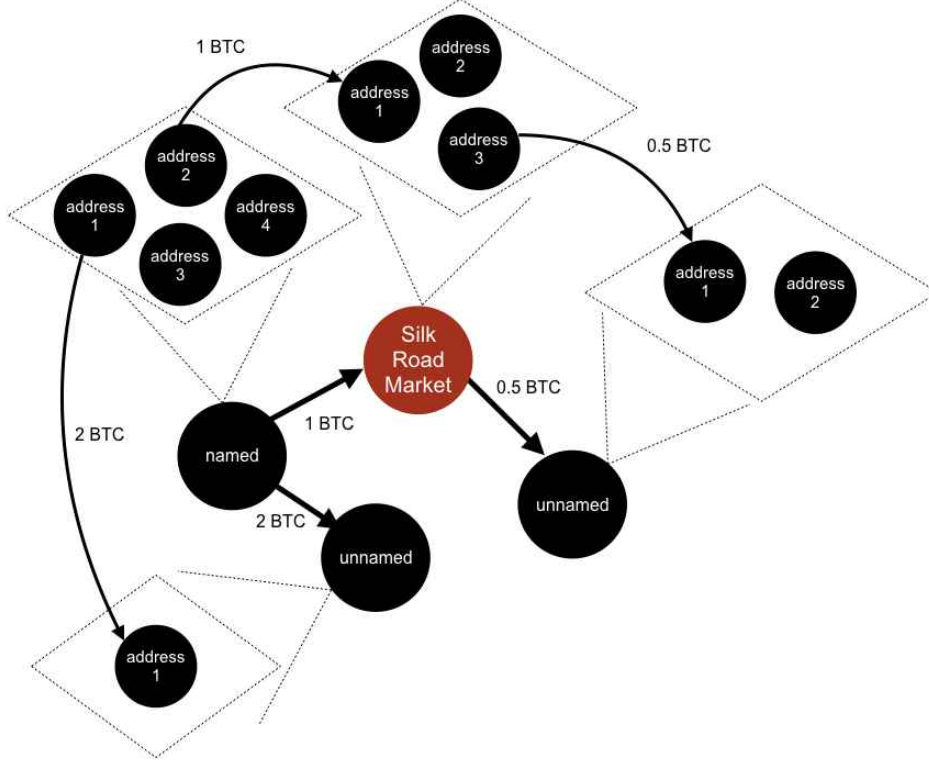


Figure 9: **A dark marketplace’s Bitcoin transaction network.** A schematic representation of our dataset as a complex network. Nodes represent users, and a direct edge between two nodes represents a transaction in the direction of the edge. Nodes can represent different abstractions as shown by the dotted rhombus. Starting from the right side, the unnamed black node represents a cluster of two different addresses which, however, was not attributed to a specific entity. The dark marketplace node (in dark red, Silk Road Market), is a representation of 3 addresses and attributed by the algorithm to the marketplace. The black named node on the left side of Silk Road Market node is a representation of 4 addresses and named to belong to a specific entity. Finally, the black unnamed node at the bottom left side of the figure, represents one address.

### 3 Dark marketplaces information

In this section we provide data on each marketplace under study. Table 1 shows general information on the dark marketplaces included in our dataset.

Table 2 shows the total volume received and sent by the different marketplaces, as well as the number of their users.

Name	Start date	End date	Closure reason	Sales
Abraxas Market	2014 – 12 – 13	2015 – 11 – 05	scam	drugs
Acropolis Market	2016 – 03 – 27	2017 – 07 – 01	voluntary	mixed
Agora Market	2013 – 12 – 03	2015 – 08 – 26	voluntary	mixed
AlphaBay Market	2014 – 12 – 22	2017 – 07 – 05	raided	mixed
Apollon Market	2018 – 05 – 03	active	active	drugs
Babylon Market	2014 – 07 – 11	2015 – 07 – 31	raided	drugs
Berlusconi Market	2018 – 08 – 12	active	active	mixed
Bilzerian24.net	2017 – 11 – 13	active	active	credits
Black Bank Market	2014 – 02 – 05	2015 – 05 – 18	scam	mixed
Blue Sky Marketplace	2013 – 12 – 03	2014 – 11 – 05	raided	drugs
Dream Market	2016 – 03 – 19	2019 – 04 – 30	voluntary	mixed
East India Company Market	2015 – 04 – 28	2016 – 01 – 01	scam	drugs
Empire Market	2018 – 02 – 01	active	active	mixed
Evolution Market	2014 – 01 – 14	2015 – 03 – 14	scam	drugs
German Plaza Market	2015 – 05 – 22	2016 – 05 – 01	scam	mixed
Hansa Market	2014 – 03 – 09	2017 – 07 – 20	raided	drugs
House of Lions Market	2016 – 05 – 23	2017 – 07 – 12	raided	drugs
Hydra Marketplace	2015 – 11 – 25	active	active	mixed
Middle Earth Marketplace	2014 – 06 – 22	2015 – 11 – 04	scam	mixed
Nucleus Market	2014 – 10 – 24	2016 – 04 – 13	scam	mixed
Olympus Market	2018 – 04 – 20	2018 – 09 – 04	scam	mixed
Oxygen Market	2015 – 04 – 16	2015 – 08 – 27	scam	drugs
Pandora OpenMarket	2013 – 10 – 20	2014 – 11 – 05	raided	drugs
Russian Anonymous Marketplace	2014 – 08 – 29	2017 – 09 – 21	raided	mixed
Sheep Marketplace	2013 – 02 – 28	2013 – 11 – 29	scam	drugs
Silk Road Marketplace	2011 – 01 – 31	2013 – 10 – 02	raided	mixed
Silk Road 2 Market	2013 – 11 – 06	2014 – 11 – 05	raided	mixed
Silk Road 3.1	2018 – 01 – 21	active	active	drugs
TradeRoute Market	2016 – 11 – 06	2017 – 10 – 12	scam	mixed
Unicc	2015 – 01 – 30	active	active	credits
Wall Street Market	2016 – 09 – 09	2019 – 05 – 02	raided	mixed

Table 1: **Dark marketplaces information.** Information on the 31 selected dark marketplaces included in our dataset. For each marketplace, the table states the name of the marketplace, the start and end dates of its operation, the closure reason (if applicable) and the type of products sold by the marketplace. “Drugs” indicates that the primary products sold on the marketplace are drugs while “credits” indicates the marketplace specialises in fake IDs and credit cards and “mixed” indicates the marketplace sells both types of products

Name	Volume sent (US dollars)	Volume received (US dollars)	out degree	in degree	Volume tot(US dollars)
Abraxas Market	29,822,178.9	23,044,463.2	21953	96612	52,866,642.1
Acropolis Market	11,196.7	11,407.6	101	201	22,604.3
Agora Market	163,946,119.7	148,224,155.3	122582	468708	312,170,3
AlphaBay Market	605,445,951.5	529,077,614	267818	1590672	1,134,523,565.2
Apollon Market	17,384.5	15,113.6	57	138	32,498.1
Babylon Market	144,292.6	149,257.5	902	1398	293,550.1
Berlusconi Market	230,036.6	239,430.9	514	2153	469,467.5
Bilzerian24.net	22,821,289.6	19,130,767.5	108	240232	41,952,057.1
Black Bank Market	14,841,938.8	13,858,325.9	15805	53260	28,700,264.8
Blue Sky Marketplace	4,294,944.4	3,297,912.5	10210	16275	7,592,856.9
Dream Market	78,031,896.0	60,049,434.3	46648	475260	138,081,330.3
East India Company Market	3,638,096.5	2,942,049.9	4630	1951	6,580,146.4
Empire Market	11,962,986.2	8,975,257.2	1309	66124	20,938,243.4
Evolution Market	55,982,302.9	49,622,433.1	35415	219491	105,604,735.9
German Plaza Market	1,032,802.5	951,757.3	22	10824	1,984,559.9
Hansa Market	62,087,671.5	61,171,541	73496	336045	123,259,212.5
House of Lions Market	705.7	1,018.4	12	97	1,724.1
Hydra Marketplace	426,946,433.7	474,549,308.6	113878	1081883	901,495,742.3
Middle Earth Marketplace	9,861,173.8	8,549,901.3	9503	38506	18,411,075
Nucleus Market	70,112,730.6	58,544,889.4	55522	207791	128,657,619.9
Olympus Market	828,076.9	711,202.93	1877	4230	1,539,279.9
Oxygen Market	42,914.2	37,273.5	278	605	80,187.7
Pandora OpenMarket	9,422,325.0	8,568,086.9	8864	35859	17,990,411.9
Russian Anonymous Marketpl.	131,000,457.9	105,804,257.1	36794	745939	236,804,714.9
Sheep Marketplace	15,624,992.4	11,624,434.9	7718	38612	27,249,427.4
Silk Road 2 Market	85,610,718.5	70,325,928.9	48293	227239	155,936,647.4
Silk Road 3.1	13,310,738.1	9,547,696.8	15574	64205	22,858,434.9
Silk Road Marketplace	172,812,766.4	140,579,172.6	73114	400079	313,391,938.9
TradeRoute Market	18,313,990.6	17,190,084.7	14318	104413	35,504,075.3
Unicc	147,418,817.2	106,581,024.9	443	1301371	253,999,842.1
Wall Street Market	68,596,630.4	52,623,050.2	26522	359656	121,219,680.6

Table 2: **Dark marketplaces overall activity.** The activity of the dark marketplaces as observed in our dataset. For each marketplace, the table reports the total volume sent and received by dark marketplace addresses. It also reports the total number of users who sent (in-degree) and received (out-degree) Bitcoins to/from dark marketplace addresses.



## 4 Moving Average Convergence Divergence Analysis

To further quantify the changes in dark marketplaces traded volume, we calculate the Moving Average Convergence Divergence (MACD) of the weekly trading volume. The MACD is a trading indicator used in stock marketplaces to quantify price movements and fluctuations. It is composed of three time series. Firstly, the MACD, calculated as the difference between the exponential weighted moving average of the trading volume for a period of 12 weeks and the exponential weighted moving average of the trading volume for a period of 26 weeks. Secondly, the signal line, computed as the 9 weeks exponential weighted moving average of the MACD time series. Finally, the last time series, known as the histogram, representing the difference between the MACD and the signal line.

Fig. 10 shows the indicator behaviour across time. For each closure, there is a fluctuation in the MACD line and the histogram line indicates a downward change in the overall dark marketplaces volume. However, an upward change can be observed after the closures indicating that dark marketplaces recover.

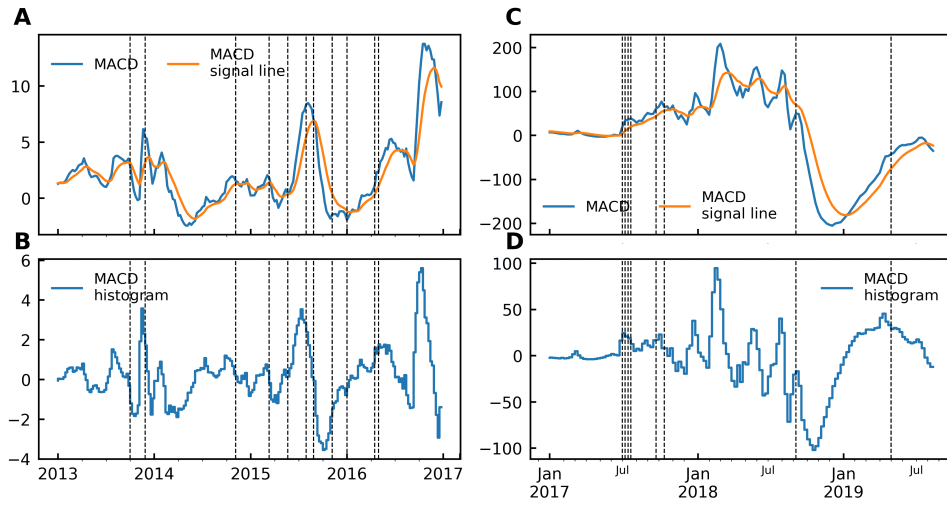


Figure 10: **Moving Average Convergence Divergence (MACD)** (A) The MACD (blue line) and MACD signal line (orange line) for dark marketplaces trading volume from 2013 till 2016. (B) The MACD histogram (blue line) for the dark marketplaces trading volume from 2013 to the end of 2016. (C) The MACD (blue line) and MACD (orange line) signal line for dark marketplaces trading volume from 2017 until July, 2019. (D) The MACD histogram (blue line) for the dark marketplaces trading volume from 2017 until July, 2019. Vertical dashed lines represent marketplaces closure.

## 5 Migrant and non migrants

In the main text we show that for each closed marketplace, migrant users are more active in terms of the total amount they send and received overall, specifically with the closed dark marketplace. In this section, we show the behaviour across each closed marketplaces. Fig. 11 shows that activity for migrants overall is higher than the non-migrants for each closed marketplace.

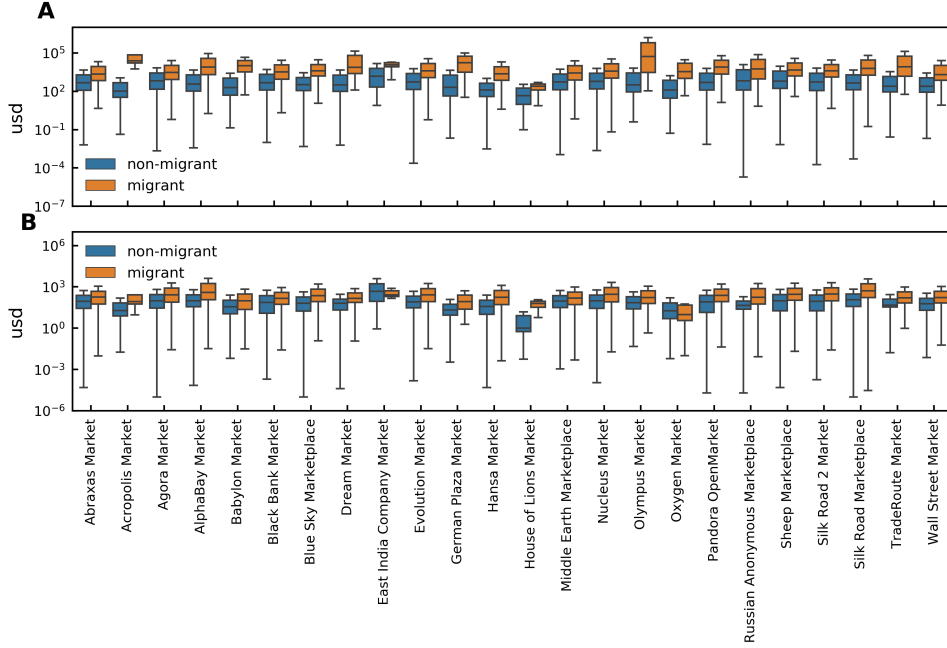


Figure 11: **Migrants are more active than other users.** (A) Total volume exchanged by migrant users (orange box-plots) and non-migrant users (blue box-plots) before the closure of their home marketplace. (B) Volume exchanged by migrant users (orange box-plots) and non-migrant users (blue box-plots) with their home marketplace. The horizontal line in each box represents the median. The lower box boundary shows the first quartile, and the upper one shows the third quartile. The whiskers show the minimum and maximum values within the 1.5 lower and upper interquartile range.

Table 3 shows the results of a Kolmogorov smirnov test between the migrant and non migrant activity distribution.

## References

- [1] Gwern. gwern.net/dnm-survival. <https://www.gwern.net/DNM-survival> (2019). Accessed: 3 July 2019.
- [2] Paganini, P. Italian police shut down darkweb berlusconi market and arrested admins. <https://securityaffairs.co/wordpress/93603/cyber-crime/berlusconi-market-darkweb.html> (2019). Accessed: 8 November 2019.
- [3] United states of america : Vs. ross william ulbricht. <https://www.cs.columbia.edu/smb/UlbrichtCriminalComplaint.pdf> (2019). Accessed: 10 July 2019.
- [4] Coindesk. [www.coindesk.com/sheep-marketplace-track-stolen-bitcoins](https://www.coindesk.com/sheep-marketplace-track-stolen-bitcoins). <https://www.coindesk.com/sheep-marketplace-track-stolen-bitcoins> (2019). Accessed: 28 August 2019.
- [5] Zantout, B., Haraty, R. *et al.* I2p data communication system. In *Proceedings of ICN*, 401–409 (Citeseer, 2011).
- [6] Buterin, V. Bitcoin multisig wallet: the future of bitcoin. *Bitcoin Magazine* URL: <https://bitcoinmagazine.com/11108/multisig-future-bitcoin> (2014).

Dark marketplace	$p$ -value (dark marketplace transactions)	$p$ -value (all transactions)
Abraxas Market	$5.9 * 10^{-85}$	$9.5673 * 10^{243}$
Agora Market	0	0
AlphaBay Market	0	0
Babylon Market	$3.794 * 10^{-04}$	$8.161 * 10^{-17}$
Black Bank Market	$1.632283 * 10^{-42}$	$1.735524 * 10^{-159}$
Blue Sky Marketplace	$1.138519 * 10^{-22}$	$6.731465 * 10^{-67}$
Dream Market	$7.749932 * 10^{-19}$	$1.204320e - 66$
Evolution Market	0	0
German Plaza Market	$9.276236 * 10^{-18}$	$1.049758 * 10^{-44}$
Hansa Market	$4.727538 * 10^{-159}$	0
Middle Earth Marketplace	$9.356239 * 10^{-20}$	$2.203038 * 10^{-83}$
Nucleus Market	$2.538463 * 10^{-174}$	$6.319438 * 10^{-268}$
Olympus Market	$1.453169 * 10^{-03}$	$1.647657 * 10^{-22}$
Pandora OpenMarket	$5.903384 * 10^{-65}$	$1.622666 * 10^{-187}$
Russian Anonymous Marketplace	$3.544511 * 10^{-83}$	$1.673279 * 10^{-48}$
Sheep Marketplace	$4.899846 * 10^{-112}$	$2.234014 * 10^{-231}$
Silk Road 2 Market	0	0
Silk Road Marketplace	0	0
TradeRoute Market	$1.563685 * 10^{-63}$	$3.078314 * 10^{-166}$
Wall Street Market	$8.111283 * 10^{-56}$	$1.109606 * 10^{-123}$

Table 3:  **$P$  values between the migrants and stayers** The table shows the  $p$  value results from the Kolmogorov smirnov test between the migrant and non migrants users distributions. The table report the results for the transactions to/from dark markets and the results for all the transactions.

- [7] Wehinger, F. The dark net: Self-regulation dynamics of illegal online markets for identities and related services. In *2011 European Intelligence and Security Informatics Conference*, 209–213 (IEEE, 2011).
- [8] Christin, N. Traveling the silk road: A measurement analysis of a large anonymous online marketplace. In *Proceedings of the 22nd international conference on World Wide Web*, 213–224 (ACM, 2013).
- [9] Aldridge, J. & Décary-Hétu, D. Not an’ebay for drugs’: the cryptomarket’silk road’as a paradigm shifting criminal innovation. *Available at SSRN 2436643* (2014).
- [10] Soska, K. & Christin, N. Measuring the longitudinal evolution of the online anonymous marketplace ecosystem. In *24th {USENIX} Security Symposium ({USENIX} Security 15)*, 33–48 (2015).
- [11] Dolliver, D. S. Evaluating drug trafficking on the tor network: Silk road 2, the sequel. *International Journal of Drug Policy* **26**, 1113–1123 (2015).
- [12] on Drugs, U. N. O. & Crime. *World drug report 2018* (United Nations Publications, 2018).
- [13] Barratt, M. J., Ferris, J. A. & Winstock, A. R. Use of silk r oad, the online drug marketplace, in the united kingdom, a ustralia and the united states. *Addiction* **109**, 774–783 (2014).
- [14] Van Hout, M. C. & Bingham, T. ‘silk road’, the virtual drug marketplace: A single case study of user experiences. *International Journal of Drug Policy* **24**, 385–391 (2013).
- [15] Décary-Hétu, D. & Giommoni, L. Do police crackdowns disrupt drug cryptomarkets? a longitudinal analysis of the effects of operation onymous. *Crime, Law and Social Change* **67**, 55–75 (2017).
- [16] Van Buskirk, J., Roxburgh, A., Farrell, M. & Burns, L. The closure of the s ilk r oad: what has this meant for online drug trading? *Addiction* **109**, 517–518 (2014).
- [17] Buxton, J. & Bingham, T. The rise and challenge of dark net drug markets. *Policy brief* **7**, 1–24 (2015).
- [18] Tasca, P., Hayes, A. & Liu, S. The evolution of the bitcoin economy: extracting and analyzing the network of payment relationships. *The Journal of Risk Finance* **19**, 94–126 (2018).
- [19] Ron, D. & Shamir, A. Quantitative analysis of the full bitcoin transaction graph. In *International Conference on Financial Cryptography and Data Security*, 6–24 (Springer, 2013).
- [20] Meiklejohn, S. *et al.* A fistful of bitcoins: characterizing payments among men with no names. In *Proceedings of the 2013 conference on Internet measurement conference*, 127–140 (ACM, 2013).
- [21] Harrigan, M. & Fretter, C. The unreasonable effectiveness of address clustering. In *2016 Intl IEEE Conferences on Ubiquitous Intelligence & Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress (UIC/ATC/ScalCom/CBDCCom/IoP/SmartWorld)*, 368–373 (IEEE, 2016).
- [22] Huang, D. Y. *et al.* Tracking ransomware end-to-end. In *2018 IEEE Symposium on Security and Privacy (SP)*, 618–631 (IEEE, 2018).

- [23] Harlev, M. A., Sun Yin, H., Langenheldt, K. C., Mukkamala, R. & Vatrappu, R. Breaking bad: De-anonymising entity types on the bitcoin blockchain using supervised machine learning. In *Proceedings of the 51st Hawaii International Conference on System Sciences* (2018).
- [24] Goldsmith, D., Grauer, K. & Shmalo, Y. Analyzing hack subnetworks in the bitcoin transaction graph. *arXiv preprint arXiv:1910.13415* (2019).
- [25] darknetlive.com.
- [26] Bitcoin. bitcoin-core. <https://bitcoin.org/en/bitcoin-core/> (2019). Accessed: 3 July 2019.
- [27] BLOCKCHAIN. blockchain.com. [www.blockchain.com](http://www.blockchain.com) (2019). Accessed: 3 July 2019.
- [28] Androulaki, E., Karame, G. O., Roeschlin, M., Scherer, T. & Capkun, S. Evaluating user privacy in bitcoin. In *International Conference on Financial Cryptography and Data Security*, 34–51 (Springer, 2013).
- [29] NEWMAN, L. H. How a bitcoin trail led to a massive dark web child-porn site takedown. (2019).
- [30] Chung, Y. Cracking the code: How the us government tracks bitcoin transactions. *ANALYSIS OF APPLIED MATHEMATICS* 152 (2019).
- [31] for Drugs, E. M. C. & Addiction, D. *DRUGS AND THE DARKNET: PERSPECTIVES FOR ENFORCEMENT, RESEARCH AND POLICY* (European Monitoring Centre for Drugs and Drug Addiction, 2017).
- [32] on Drugs, U. N. O. & Crime. *World drug report 2019* (United Nations Publications, 2019).
- [33] Marsden, P. V. Egocentric and sociocentric measures of network centrality. *Social networks* **24**, 407–422 (2002).
- [34] Zamani, M., Rabbani, F., Horicsányi, A., Zafeiris, A. & Vicsek, T. Differences in structure and dynamics of networks retrieved from dark and public web forums. *Physica A: Statistical Mechanics and its Applications* **525**, 326–336 (2019).
- [35] Appel, G. The moving average convergence-divergence method. *Great Neck, NY: Signalert* 1647–1691 (1979).
- [36] Duxbury, S. W. & Haynie, D. L. Building them up, breaking them down: Topology, vendor selection patterns, and a digital drug market’s robustness to disruption. *Social Networks* **52**, 238–250 (2018).
- [37] Dittus, M. [www.oii.ox.ac.uk/blog/a-distributed-resilience-among-darknet-markets](http://www.oii.ox.ac.uk/blog/a-distributed-resilience-among-darknet-markets). <https://www.oii.ox.ac.uk/blog/a-distributed-resilience-among-darknet-markets/> (2019). Accessed: 28 August 2019.
- [38] Dorit Ron and Adi Shamir. Quantitative analysis of the full bitcoin transaction graph. In *International Conference on Financial Cryptography and Data Security*, pages 6–24. Springer, 2013.
- [39] Sarah Meiklejohn, Marjori Pomarole, Grant Jordan, Kirill Levchenko, Damon McCoy, Geoffrey M Voelker, and Stefan Savage. A fistful of bitcoins: characterizing payments among men with no names. In *Proceedings of the 2013 conference on Internet measurement conference*, pages 127–140. ACM, 2013.

- [40] Elli Androulaki, Ghassan O Karame, Marc Roeschlin, Tobias Scherer, and Srdjan Capkun. Evaluating user privacy in bitcoin. In *International Conference on Financial Cryptography and Data Security*, pages 34–51. Springer, 2013.
- [41] YoonJae Chung. Cracking the code: How the us government tracks bitcoin transactions. *ANALYSIS OF APPLIED MATHEMATICS*, page 152, 2019.
- [42] Julia Heidemann, Mathias Klier, and Florian Probst. Identifying key users in online social networks: A pagerank based approach. 2010.
- [43] Michael Fleder, Michael S Kester, and Sudeep Pillai. Bitcoin transaction graph analysis. *arXiv preprint arXiv:1502.01657*, 2015.
- [44] Wikipedia Now Accepts Bitcoin Donations. <https://www.coindesk.com/wikipedia-now-accepts-bitcoin-donations>, 2019. Accessed: 1 October 2019.
- [45] Chainalysis, inc. <https://www.chainalysis.com/>, 2019. Accessed: 10 July 2019.