



European Monitoring Centre
for Drugs and Drug Addiction

Analysis of the supply of drugs and new psychoactive substances by Europe-based vendors via darknet markets in 2017-18

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This background paper was produced under contract no CT.18.SAS.0023.1.0 and we are grateful for the valuable contribution of the authors. The paper has been cited within the EDMR 2019 and is also being made available online for those who would like further information on the topic. However, the views, interpretations and conclusions set out in this publication are those of the authors and are not necessarily those of the EMCDDA or its partners, any EU Member State or any agency or institution of the European Union.

Executive summary

Online anonymous marketplaces are a relatively recent technological development that enables sellers and buyers to transact online with far stronger anonymity guarantees than are available on traditional electronic commerce platforms. This has led certain individuals to engage in transactions of illicit or illegal goods.

We investigated how commerce on online anonymous marketplaces evolved after the takedown of the AlphaBay marketplace. Namely, we studied, over the summers of 2017 and 2018, a collection of marketplaces – Dream Market, TradeRoute, Berlusconi, and Valhalla. In this report, we present an analysis of sales, with a focus on the drug supply coming from the European Union (EU). Keeping in mind the limitations inherent to such data collection, we found that, for the period and the marketplaces considered:

- The overall ecosystem appears to have (slightly) grown again since the combined takedown of the AlphaBay and Hansa marketplaces, and now exceeds EUR 750 000 euros per day. This calls into question the long-term impact of such takedowns on the overall online anonymous marketplace ecosystem.
- Dream Market is overwhelmingly the dominant marketplace, and its daily volume exceeds previous numbers gathered for AlphaBay (Christin, 2017).
- EU-based suppliers represent approximately 43% of all drug sales; this is in line with the 46% for marketplaces previously studied (Christin, 2016) in the 2011-15 period, and a marked increase compared with the roughly 25% observed in the subsequent AlphaBay study (Christin, 2017).
- EU-originating drugs continued to come primarily from Germany, the Netherlands, and the United Kingdom.
- Cannabis, cocaine and other stimulants altogether continued to represent the majority of all EU-based drug sales.
- The supply of new psychoactive substances (NPS) remained modest with revenues below EUR 10 000 per day at market peak, but these slightly increased compared with our previous measurements.
- As in our previous studies, marketplace vendors primarily operated in the retail space, but there was evidence of larger (bulk) sales. Volume-based discounting tended to occur, albeit at relatively modest levels.
- As in our previous studies, half of the vendors specialised in one type of drug, and half of the drug sellers tended to stick to a given weight category.
- Most of the trends observed in this report confirm what we had previously found for other marketplaces in the 2011-17 period (Christin, 2016, 2017). In other words, despite takedowns and scams, the ecosystem, as a whole, appears relatively stable over time, with the fluctuation in the European sales share noted above indicating an exception.

1 Introduction

By using a combination of network-level anonymity technology (Dingledine et al., 2004) and pseudonymous (Nakamoto, 2008) or anonymous (Ben-Sasson et al., 2014; van Saberhagen, 2013) payment systems, online anonymous marketplaces are a relatively recent technological development that enables sellers and buyers to transact online with far stronger anonymity guarantees than on traditional electronic commerce platforms. Unfortunately, as a by-product of this anonymity, certain individuals have been using this technology to engage in transactions of illicit or illegal goods, as exemplified by most transactions on the well-known Silk Road marketplace (Christin, 2013).

This report builds on two previous reports released in 2016 (Christin, 2016) and 2017 (Christin, 2017). In these previous reports, we first analysed data collected by Soska and Christin (2015), spanning several years (late 2011-early 2015) including the ‘early days’ of online anonymous marketplaces (Christin, 2016), and extended our analysis to cover the AlphaBay marketplace (Christin, 2017) throughout most of its existence (December 2014-May 2017). AlphaBay was shut down in July 2017 by law enforcement. All three reports share a significant amount of prose – when discussing background and near-identical results in both the datasets considered in our previous reports (Christin, 2016, 2017) and here – but the data presented in this report are completely new.

As in our previous work, we focus on analysing the drug supply reportedly originating from the European Union (EU), and derive relationships between financial revenues and the actual quantities (weights, volumes, units) of products being sold.

This report is organised as follows. We briefly discuss how online anonymous marketplaces operate and outline their history in Section 2. We move to discussing our methodology, which has many of the same assumptions and limitations as the original study by Soska and Christin in Section 3. We turn to analysing the collected data in Section 4, before drawing brief conclusions in Section 5.

2 Background

Narcotics have been traded on the internet since the advent of the World Wide Web. The earliest trading platforms (e.g., the Hive, Pondman, RACResearch, OVDB, and others) were primarily discussion forums. While quite open, these forums catered to relatively limited numbers of users, and offered very weak anonymity guarantees, leading their patrons to take relatively high risks when ordering drugs online.

The creation of the Silk Road website in 2011 marked a drastic change in the way drugs were traded online (Christin, 2013). The combination of network-level anonymising technology (Tor (Dingledine et al., 2004) or i2p (i2p, 2003)), crypto-currencies, such as Bitcoin (Nakamoto, 2008), with better privacy protection than traditional online financial instruments, and media exposure (Chen, 2011; Greenberg, 2013) ushered in a new era in the online drugs trade. We refer the reader to Christin (2013), Martin (2014), and Soska and Christin (2015), for a thorough description of how modern online anonymous marketplaces (or ‘cryptomarkets’) are designed. In a nutshell, cryptomarkets resemble e-commerce marketplaces such as eBay or the Amazon marketplace; however, the level of anonymity they promise, sometimes a bit too confidently, facilitates the trade of illicit or illegal items.

2.1 A short history of cryptomarkets

Between February 2011 and November 2013, Silk Road (Christin, 2013) was the *de facto* leading cryptomarket. While other cryptomarkets appeared – Black Market Reloaded, Sheep Marketplace, and Atlantis, notably – their revenues were comparatively extremely small (Soska and Christin, 2015). However, in November 2013, the Silk Road operator was identified and arrested, and the site was taken down. This resulted in major changes to the ecosystem: former also-rans (Black Market Reloaded and Sheep Marketplace) experienced a sudden influx of Silk Road customers coming to patronise their markets; numerous short-lived markets (e.g., Black Flag) unsuccessfully tried to fill the gap left by Silk Road’s demise. This chaotic situation stabilised about a month later, with the emergence of Silk Road 2.0, ran by former Silk Road staff, and using an interface visually strikingly similar to Silk Road’s. A number of other marketplaces (Pandora, Hydra, Evolution, Agora, Cloud 9, etc.) had also appeared within a few months, resulting in a diverse ecosystem, that flourished throughout 2014. Indeed, the aggregate revenue of all markets quickly exceeded what Silk Road was generating in its heyday (Soska and Christin, 2015). But, again, law enforcement intervened in November 2014, through Operation Onymous (U.S. Attorney’s Office, Southern District of New York, 2014), which led to the shutdown of Silk Road 2.0, as well as that of a number of lesser-known sites (e.g., Cloud 9). The immediate effect was that traffic primarily migrated to the Agora and Evolution marketplaces from November 2014.

2.2 The AlphaBay marketplace

The AlphaBay marketplace was reportedly designed in mid-2014 (United States District Court, Eastern District of California, 2017). It went online on December 26, 2014, shortly after Operation Onymous took place. Similarly to the Evolution marketplace, AlphaBay was reportedly started by ‘carders’ (i.e., people who had been trading stolen credit card numbers and other banking credentials). However, AlphaBay quickly started offering listings for narcotics as well. AlphaBay was originally a fairly small marketplace, overshadowed by Evolution and Agora. By mid-2015, it started to get considerably increased exposure as Evolution closed its doors, and it reportedly became one of the leading markets later that year. By 2016, it had become the leader in the cryptomarket space (Christin, 2017). A major police operation resulted in its take-down in July 2017.

2.3 The AlphaBay and Hansa combined take-downs

Coincidentally, in June of 2017, the Dutch police seized another large (albeit smaller than AlphaBay) marketplace – called Hansa Market. The Dutch police had actually been operating Hansa Market undercover for a few weeks when AlphaBay was taken down. As is usually the case after a takedown (Soska and Christin, 2015), the patrons of the marketplace taken down, in this case AlphaBay, quickly flock to other large marketplaces, in this case to Hansa Market. In doing so, they inadvertently fell into the waiting arms of law enforcement. This unique situation, compared with previous operations, could have seriously dented consumer confidence in the security of these marketplaces. However, while this was the effect in the short term, as this report will show, revenues and trade volumes, over the long term, do not appear to have been

affected.

2.3.1 2017 and 2018 marketplaces

Following the AlphaBay and Hansa take-downs, a host of second-tier marketplaces grew in importance. In this report, we will focus on Dream Market (which had been active since late 2013), Traderoute (active since mid-2016, exited the ecosystem in October 2017), Valhalla (formerly known as Silkkitie, online between 2013 and 2017), and Berlusconi Market (appeared in late 2017). While there are other markets worth reporting on (e.g., Tochka, Wall Street) our data indicate a very high concentration of sales on Dream Market, and thus other marketplaces appear to be little more than back-ups for vendors and buyers at this point.

3 Collection methodology and data

3.1 Data collection

Our data collection infrastructure is an evolution of the platform we used for other marketplaces, and which we described in previously published work (Soska and Christin, 2015). In short, we devised a special-purpose web crawler, using heavily parallelised connections to gather considerable amounts of online anonymous market web pages in relatively short amounts of time. Specifically, the crawler collects ‘scrapes’, that is, the text content present on each website it visits.

A full exposition of the technical details can be found in a companion paper (Soska and Christin, 2015). The current version of the code is a significant evolution the prototypes described in that paper, which helps us obtain more complete scrapes. Architecturally and conceptually, however, the platform has remained consistent over time.

The scrapes are subsequently fed into a parsing engine, which extracts salient data from each relevant page: vendor name, item price, item description (including shipping origin), feedback left by buyers (and its associated timestamp). These data are stored in an intermediate database of ‘parsed contents’.

An analysis engine works from the parsed content database to derive more complex metrics, such as the revenue generated by each item, the revenue generated by each vendor, or the weight and quantities associated with each offering. As an example, to compute revenue associated with a specific item, the analysis engine correlates every piece of feedback left for that item with the price of the item at the time the feedback was left.

The data presented in this report are the outputs of the analysis engine, complemented by manual analysis when required, when obvious outliers or errors appear as an output of the automated process.

For this report, we use data collected by our research group and summarised in Table 1. Overall, we collected 35 scrapes of four markets – Dream Market, Traderoute, Valhalla, and Berlusconi Market – between summer 2017 and summer 2018. As we will discuss later, we did not obtain any data over the winter 2017-18, primarily due to extensive maintenance operations on our collection infrastructure.

Market name	Number of scrapes	Oldest scrape	Most recent scrape
Dream Market	19	15-07-2017	20-08-2018
Traderoute	5	28-07-2017	11-10-2017
Valhalla	3	28-07-2017	12-06-2017
Berlusconi Market	8	22-11-2017	22-08-2018

Table 1: **Markets collected.** The table shows the number of scrapes (complete or incomplete) collected on the various markets included in the study. Dream Market became the focus of our efforts when its dominant position became clear to us.

3.2 Data classification and processing

As discussed above, once all listings have been parsed and stored into a (PostgreSQL) database, the data need to be further processed to be amenable to analysis. In particular, we need to identify the type of product being sold, the quantities and volumes of product being sold, and the country of origin of the items. We use exactly the same methodology as in previous reports (Christin, 2016, 2017), which, for the sake of completeness, we summarise again here.

Item categories As discussed in the 2015 paper (Soska and Christin, 2015), categories self-reported by sellers (e.g., ‘Stimulants/Cocaine’) are often incorrect (e.g. we have seen weapons being categorised under ‘plants’). Instead, we determine the type of product by performing automated text analysis of the item description. The process is analogous to that described in the 2015 paper (Soska and Christin, 2015), but uses different categories of interest. In an effort to provide a heads-to-heads comparison with other marketplaces, we consider the same following 22 categories as in the previous reports (Christin, 2016, 2017):

1. *Drug categories of primary interest:*

- Cannabis: all forms of cannabis products (resin, herbal, oil, seeds, etc.)
- Cocaine: cocaine products.
- Dissociatives: ketamine, gamma hydroxybutyrate (GHB), gamma butyrolactone (GBL).
- Hallucinogens: LSD and related hallucinogens, but excluding psychedelics.
- Stimulants: all stimulants other than cocaine, including (meth)amphetamine, 3,4-Methylenedioxyamphetamine (MDMA) and 3,4-Methylenedioxyamphetamine (MDA).
- Opioids: Heroin, opium, analgesics (e.g., oxycodone)
- NPS (cannabinoids): synthetic cannabinoids including spice and K2.
- NPS (dissociatives): synthetic dissociatives such as methoxetamine (MXE) and dextromethorphan (DXM).
- NPS (hallucinogens): synthetic hallucinogens including 25i-NBOMe, 4-ACO-DMT and 2C-B.

- NPS (opioids): synthetic opioids (including fentanyl and MT-45).
- NPS (synthetic stimulants): other not classified above (e.g., mephedrone, 4-fluoroamphetamine).

2. *Other drugs:*

- Benzodiazepines: medicines containing for instance Valium, Rivotril, or Xanax as active ingredients, and ‘downers’ that are used as an anti-anxiety muscle relaxant and can be sleep-inducing.
- Prescription: prescription drugs.
- Psychedelics: mushrooms and other psychedelics.
- Sildenafil: viagra and related products.
- Steroids: steroid products.

3. *Non-drugs:*

- Drug paraphernalia: bongos, pipes, scales, etc.
- Digital goods: all forms of digital goods (including forgeries of identification documents, credit card numbers, e-books, etc.).
- Electronics: electronic items and components
- Misc: miscellaneous items not categorised in any other category.
- Tobacco: tobacco products, including e-cigarettes.
- Weapons: all sorts of firearms, weapons, etc.

In the commissioning of a previous report, we evaluated this redesigned classifier using 10-fold cross validation. The overall precision and recall were both (roughly) 0.97, meaning in plain English that the classifier gets things right about 97% of the time, when compared with our baseline. We evaluated the classifier on data from the Agora marketplace when trained with samples from the Evolution marketplace, and vice versa, to ensure that the classifier was not biased to only perform well on the distributions it was trained on.

A key caveat, however, is that the classifier can only perform as well as its training set; that is, if the samples used for training are incorrectly labelled, the classifier will not be able to rectify the error. In the remainder of this report, and similar to previous reports (Christin, 2016; Soska and Christin, 2015), the training set uses Evolution data, which have the advantage of presenting an overwhelmingly large number of correctly labeled items. Unfortunately, there are categories in which classification is inherently ambiguous, even for an expert manually labelling samples.

This is particularly true of NPS, which tend to be bundled with the type of chemicals that they attempt to emulate – a notable exception are NPS hallucinogens, which tend to be properly labeled. On the other hand, opioids are much more muddled. For instance, fentanyl is frequently not labelled as ‘Fentanyl’ (which itself would map to NPS (Opioids)) but as the more general ‘Opioids’ category. As a result, as in the previous reports, it is hard to assess through this automated classification system the actual proportion of NPS, as opposed to heroin and morphine, in opioids. Classification difficulties affect not only NPS, but also other

categories. For instance, oxycodon could be classified as an opioid or as a prescription drug, and both classifications are actually correct.

To improve the quality of the training, we have two options worth considering in future work:

- Manually label a large number of items and use them as training. While this approach should provide a very reliable training set, it does not scale up to very large numbers, and it is unclear whether it will achieve higher performance than our current training. Indeed, consider a 1,000-strong training sample: this would probably take a few hours to label (using multiple experts to ensure agreement), but a single error would have an impact (very roughly) equivalent to 100 errors in a 100 000-strong pre-labelled dataset.
- Inject artificial entries containing strings that are characteristic of entries that may be ambiguous. For instance, we could create synthetic listings for fentanyl, carfentanyl and other NPS of interest, and feed them into our existing training set. This has the advantage of keeping the benefits of our large, mostly well-labelled, training set; on the other hand, it might also bias classification towards expecting certain strings.

We emphasise however, that, by and large, classification is correct. A manual evaluation of classification ‘errors’ revealed that misclassified items were in fact properly classified, only in a category more general than we would have wished for.

Quantities and volumes For a number of the analyses of interest in this report, we also needed to extract quantities and volumes from each listing. We use exactly the same strategy as in previous reports (Christin, 2016, 2017). To summarise, we infer volume and quantities from the item listing titles, based on ‘regular expression matching’. For instance, we scan item titles for number patterns followed by the characters ‘G’ or ‘grams’ to infer how many grams were sold in that specific listing. While, at first glance, this seems like an error-prone heuristic, we discovered in our previous work, that with about 17 regular expressions, we were able to correctly infer most of the item weights and quantities.

As in previous reports, we evaluated the classification algorithms by picking 200 items at random, manually labelling them, and comparing the manual labels with those obtained programmatically. Of those 200 items, 128 were drug related, and were thus useful for our purposes (the others were discarded). All 128 have a volume and or quantity specified, and we could *correctly* infer quantities and volumes for 103 items (i.e. 80 % of the time). We got the volume wrong 19 times (always by failing to extract it when it was present, but never by incorrectly computing it). In this sample, we never overestimated quantities or volumes, which means that all of our estimates were conservative. While performing computations of prices per quantity, shown later in this report, we discovered a handful of overestimations that were easily corrected by hand.

In previous reports, extraction failed when, for instance, certain items consisted of ‘package deals’ such as a (small) dose of MDMA coupled with a (small) dose of cannabis. Interestingly, none of these ‘package deals’ appeared in our random sample this time. We did observe a couple of such ‘package deals’ when inspecting outliers in our price per quantity analysis. Most failures were due to alternative spellings of the associated volume.

Origin countries Last, we also need to identify countries from which products ship ⁽¹⁾. Vendors typically indicate where they are shipping from in a specific field, and they have no incentive to lie, as buyers can verify the postmark when they receive parcels. On the contrary, vendors have a strong incentive to be truthful, so that buyers can properly estimate shipping times. Depending on the marketplace considered, the entries a vendor can provide are constrained (selectable only by a drop-down menu) or unconstrained (free form). We use a manually labelled system to correctly identify the country of origin. When several countries are mentioned, we label the country as ‘Other’.

Currency conversion Some marketplaces list their item prices in bitcoins, while other list them in various currencies (dollars, euros, yens, etc.). Whenever possible, we collect item prices in a traditional currency rather than in Bitcoin (due to the rapid fluctuations of the currency), and then convert the price to euros using the dollar-euro exchange rate at the time of the sale.

3.3 Assumptions and limitations

As discussed in previous work (Christin, 2013, 2016, 2017; Soska and Christin, 2015), a study of this magnitude, on field data, relies on a number of assumptions, and suffers from a number of limitations, which we discuss next.

Lack of buyer information Most marketplaces we look into do not provide any buyer information. As a result, we do not perform any buyer analysis in this study.

Incomplete data coverage As is the case in all studies of this type (Soska and Christin, 2015), coverage is necessarily imperfect, given that it is very difficult to ensure that a ‘scrape’ of an online anonymous marketplace is complete, particularly when that marketplace is large – even with the improvements we made to our crawlers, as discussed in Section 3.1. This can lead to pernicious errors: for instance, Dolliver (2015) appears to have under-estimated sales on Silk Road 2.0 by several orders of magnitude (Soska and Christin, 2015).

Figure 1 shows an interesting quirk in the data we use in this report. The figure represents the number of pieces of feedback that we were able to collect from Dream Market, ranked by their age. The figure clearly shows that there is a sharp drop off at the 150-day mark. In other words, Dream Market apparently deletes feedback older than 150 days. This means that it is impossible to recover some data if more than (roughly) 5 months pass between complete scrapes. This leads us to consider two time intervals – summer 2017 and summer 2018 – separately; the data in between (winter 2017-18) is missing and cannot be used for analysis. The figure also shows that the feedback available decreases extremely quickly with age. This suggests that one needs to scrape often to achieve a clear picture of what is happening. As a result, ‘growth trends’ observed in the absence of scrapes at the corresponding times, should be interpreted with caution.

⁽¹⁾ We discuss in Section 3.3 why it is extremely difficult to determine where products are actually being shipped to.

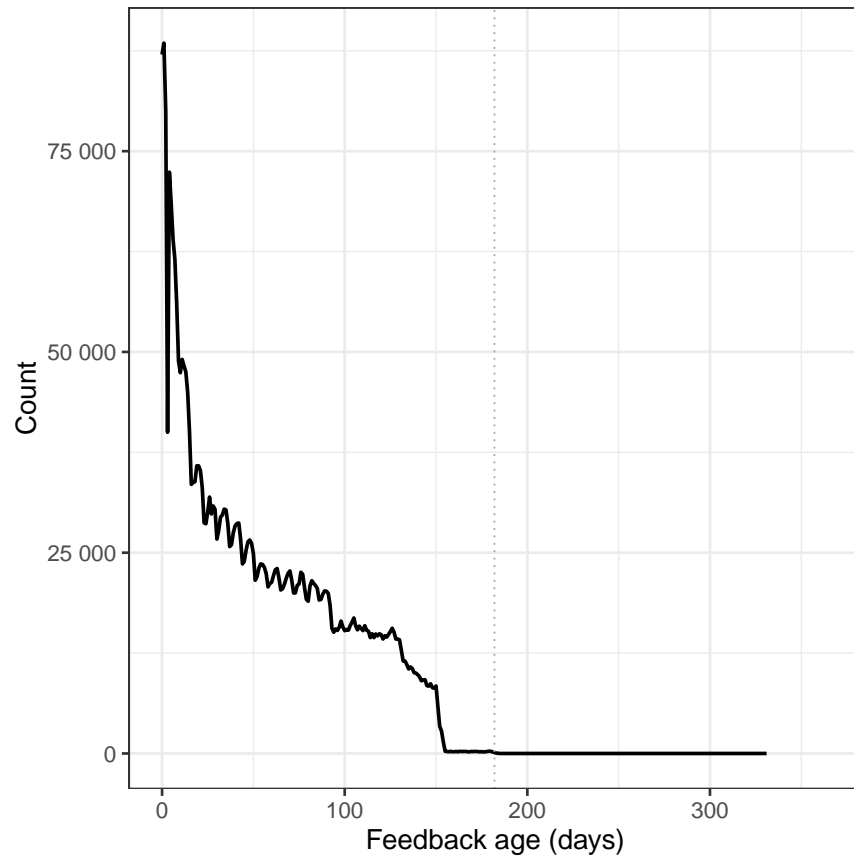


Figure 1: **Distribution of feedback by age on Dream Market.** Quite clearly, a cut-off occurs after 150 days (the point at 151 days may be due to measurement uncertainty), which suggests that Dream Market simply deletes feedback older than 150 days. The dotted line represents the 6-month mark.

Bulk items Inspired by the methodology in previous reports (Christin, 2016, 2017), we filter out all items with a sales price greater than USD 20 000 from the analysis in the next sections (USD 10 000 was used as a threshold in previous reports). The rationale, presented in previous work (Soska and Christin, 2015), is that such items are rare, and tend to reflect a technique used by vendors to discourage customers from buying a specific out-of-stock item, without removing the listing (and thus discarding the reputational data associated with it). However, Aldridge and Décary-Héту found, on the Silk Road marketplace, $n = 52$ high-priced items that were apparently legitimate and corresponded to bulk sales (Aldridge and Décary-Héту, 2016). Such items are eliminated from our analysis, which could bias our work against bulk sales. Manual inspection of the listings confirms the presence of such bulk listings, which leads us to carry out a separate analysis here.

We examine all items with a sales price *consistently* greater than USD 20 000. That is, the price needed to be in the top three quartiles of all prices and should not have been greater than 100 times the minimum price for the item. We found $n = 713$ such items. We then filter out all of the items for which we did not have any records of any sale having taken place: this brings the number of items to consider to $n = 42$ (note, however, that this is a lower bound, as we cannot claim perfect coverage). Finally, we look only at the items shipping from the EU, Norway or Turkey: this brings down the number of items to consider to $n = 34$. We manually inspect these 34 items:

- 22 items are explicitly labelled as ‘out of stock’.
- 9 listings are bulk cocaine sales: 500 g (1 listing, at approximately⁽²⁾ EUR 18 426), 750 g (2 listings, respectively at approximately EUR 24 920 and EUR 27 593), 1 kg (3 listings, at EUR 20 289, EUR 20 456⁽³⁾ and EUR 30 552) and 2 kg (3 listings, at EUR 58 824, EUR 61 318, and EUR 67 583)
- 3 listings are bulk ketamine sales for 1.5 kg (2 listings, at EUR 18 310 and EUR 19 678) and 2 kg (at EUR 25 043).

All of these 12 bulk listings were found on Dream Market. All have only one sale. As everywhere else, the prices given are subject to approximations due to the price of the underlying cryptocurrency and the dollar-euro exchange rate – for instance, the listings evaluated at EUR 58 824 and EUR 61 318 could very plausibly both refer to an actual attempted sales price of EUR 60 000.

In total, we evaluate the revenue from all of these sales at approximately EUR 393 000 – as we will see later, this is quite negligible compared to the overall EU-originating sales (approximately 0.5% of all EU sales).

Automated classification Our scrapes have collected data on a total of 130,897 items, which means that we need to perform automated classification, as any manual processing would not scale to such sizes. As shown above, our algorithms fortunately appear to have good accuracy, and generally err on the side of producing conservative estimates, rather than inflated ones.

⁽²⁾ Subject to variations in the bitcoin-dollar and dollar-euro exchange rates.

⁽³⁾ These two listings are from the same vendor. These prices seem to be substantially below street prices.

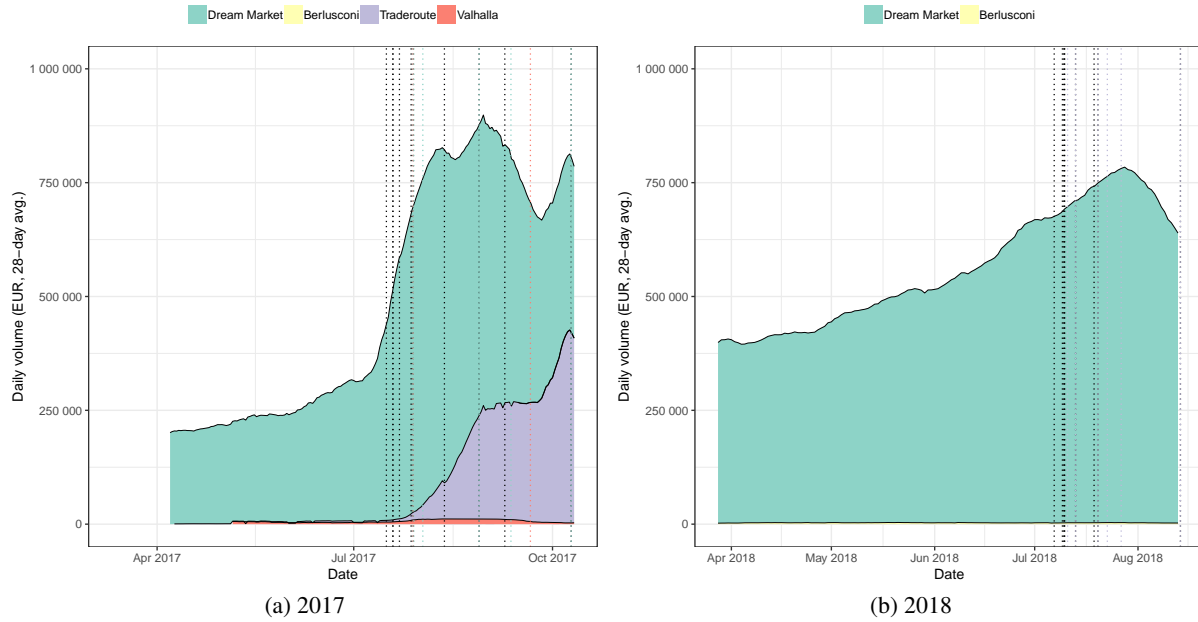


Figure 2: **Evolution of sales in the four markets considered (2017-18)**. Each point is a moving 28-day average. The plot is a stacked plot, meaning that the top line represent the sum of all markets. The vertical dotted lines represent times at which we obtained scrapes of the relevant markets (black dotted lines correspond to Dream Market). The further from a scrape, the less reliable the data are. In particular, we have no data from winter 2017-18 due to unreliable data (no scrapes were performed during that time, and inferences are highly dubious, due to the aforementioned limitations, of, for example, Dream Market removing old feedback). Also, the dip at the end of the plot is an artefact of the lack of future data in the computation of the moving average, rather than an observed decrease.

4 Data analysis

We next turn to analysing the data we collected. We start with an overview of the four marketplaces we monitored before delving into EU specifics.

4.1 Evolution of sales in 2017-18

We start with a generic plot showing the evolution of the four marketplaces considered in 2017-18, shown in Figure 2. Each point is a moving 28-day average of the daily sales, in euros, of each marketplace studied. The figure is a stacked plot, so that the top line represents the sum of all market revenues. The vertical dotted lines correspond to the times we scraped the various markets (described in Table 1); the colour of each line matches the market scraped – except Dream Market, which, for clarity, is in black. As discussed in related work (Soska and Christin, 2015), the further from a scrape, the less reliable the data are. In particular, we do not report data between November 2017 and April 2018: since Dream Market seemingly discards feedback older than 150 days, the points correspond to averages with missing data, resulting in meaningless

inferences. Likewise, the rightmost point of the graph corresponds to 28-day averages over a time interval where points are not yet defined (since they are in the future), which explains the late dip.

We thus recommend focusing on areas where many scrapes were conducted, as the data are inherently far more reliable than for other time intervals. This corresponds to the period immediately before the censored interval (July-October 2017), and to the period just before the end of the plot (roughly, June-August 2018).

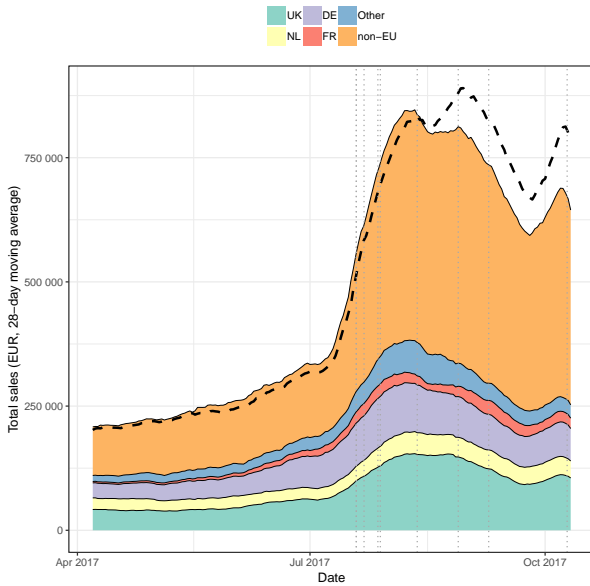
We derive three major findings:

1. We observe a strong increase in revenue on Dream Market and Traderoute starting in July 2017. This corresponds to AlphaBay (and Hansa) being taken down.
2. The overall revenue eventually reaches approximately EUR 800 000 per day on average (our raw data indicates that revenue, on certain days, exceeded EUR 1 million) which is in line with – or even slightly higher – what AlphaBay was grossing in its heyday (Christin, 2017; Möser et al., 2018; van Wegberg et al., 2018). In other words, we can reject the hypothesis that the AlphaBay and Hansa take-downs significantly affected the overall revenue of the ecosystem. This is unsurprising, as similar ecosystem resilience to the Silk Road and Operation Onymous takedowns (Soska and Christin, 2015) had been observed.
3. The ecosystem shows a near monopolistic behaviour, with Dream Market accounting for a disproportionate percentage of all sales. Only Traderoute seems to have challenged this leadership position in late 2017, but Traderoute eventually reportedly ‘exit-scammed’ in October 2017, that is, it abruptly closed its doors, and, in the process, took any money that had been held in escrow. Valhalla, and, more recently, Berlusconi Market, show negligible sales volumes compared with Dream Market. While there are additional markets worth investigating – Tochka/Point Market, for instance, or Wall Street Market – preliminary investigations suggest that their sales volumes are far smaller than Dream Market’s. In other words, Dream Market is clearly the leading player, as were AlphaBay, Silk Road and Silk Road 2, in their respective eras.

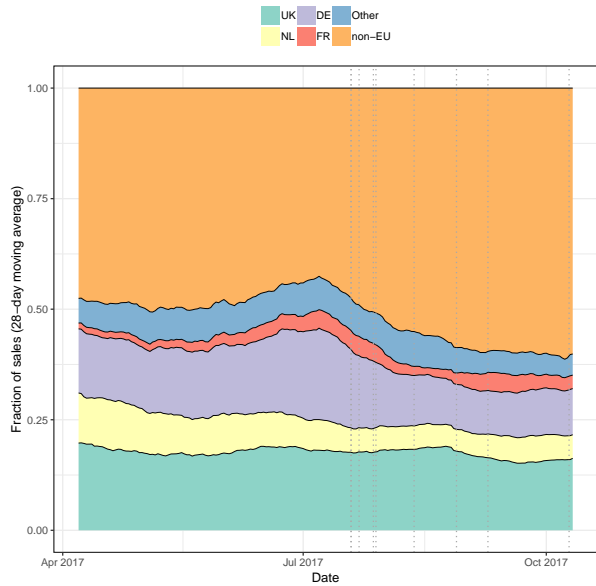
4.2 European and categorical sales

We next turn to a comparison of sales over Europe, and by category. Figure 3 is a stacked plot representing the overall evolution of the cumulative sales across all four markets we study. As before, vertical dotted lines correspond to the times of each of the 35 scrapes we have collected (see Table 1). Each (stacked) curve represents a specific (set of) countries. The United Kingdom is in green, the Netherlands in yellow, Germany in purple, France in red, all other EU countries in blue, and non-EU countries in orange.

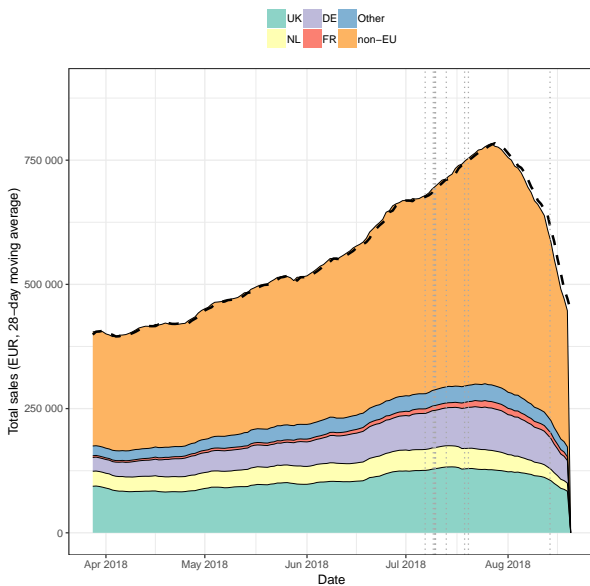
Figures 3(a) and 3(c) represent the evolution of sales in absolute value, over time, in euros, as a 28-day moving average. As in the previous report (Christin, 2017), the thick dashed line denotes the *total* amount of sales. The discrepancy – represented by a white area – between the total amount of sales and the sum of all sales from countries that could be identified is due to partially incomplete coverage. Specifically, we use item feedback to count the number of sales (assuming each piece of feedback corresponds to one sale, which, by and large, has shown to be a reasonable approximation in the past (Soska and Christin, 2015)). On the marketplaces we study, this feedback is displayed in two locations: each *item page* features a list of all



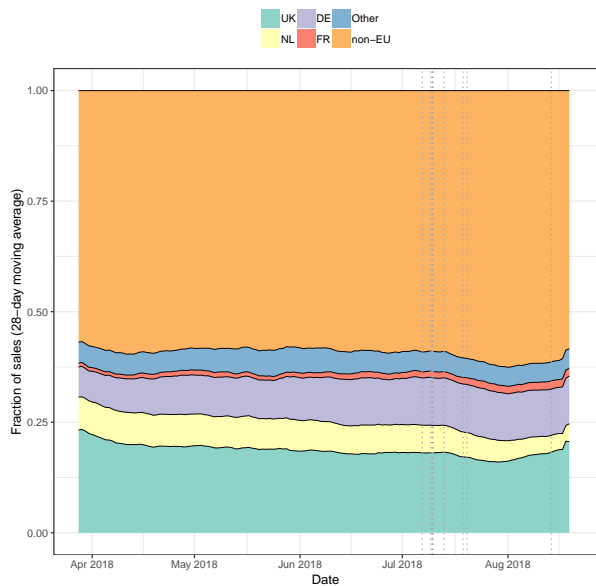
(a) Total sales over time (per-country breakdown), 2017



(b) Relative sales over time (per-country breakdown), 2017



(c) Total sales over time (per-country breakdown), 2018



(d) Relative sales over time (per-country breakdown), 2018

Figure 3: **Evolution of sales over time (per-country breakdown).** The vertical dotted lines represent times at which we obtained scrapes. The left-hand plots represent a breakdown per country. The dashed line represents the total amount of sales. The white area represents sales for which we have a record, but for which we cannot recover the corresponding item listing, and thus cannot infer the country. (Note the slight discrepancies when we are close to full coverage, due to summing of averages.) The orange area depicts non-EU sales. As before, the dip at the end of the plot is an artefact of the lack of future data in the computation of the moving average, rather than an observed decrease. The right-hand plots present the same information, but on a relative scale, excluding items for which we do not have a corresponding listing.

pieces of feedback recorded for that item; each *user page* features a list of all pieces of feedback recorded for that user. Both sets should be consistent – that is, the set of all pieces of feedback for all users, and the set of all pieces of feedback for all items should be the same. However, scraping is rife with practical difficulties: a given scrape may take a couple of days to complete, and in the meantime certain item listings may be removed; the scrape may unexpectedly terminate before having visited every single page of the website, due to the site going down, or the scraper being logged out accidentally or voluntarily. As a result, it may happen that feedback gleaned from a user page is ‘orphaned’, that is, does not have a corresponding item listing that we can refer to. This orphaned feedback is characterised by the white area in Figures 3(a) and 3(c): we know a vendor sold something for a given value on that day, but we do not necessarily have all information for the listing – in particular, we cannot be sure where the item reportedly ships from, and we do not have the listing description, but merely the listing title.⁽⁴⁾ We could potentially infer the shipping origin by looking into shipping information for other items from the same vendor, but certain vendors operate from multiple countries at once; instead, we prefer to adopt the conservative approach of marking these listings as ‘unidentified’. Overall, because our scraping of Dream Market was usually complete, we managed to mostly avoid such gaps – the only time they appeared to be significant was during Traderoute’s heyday. The small glitches, in which the volume of non-EU sales appears slightly higher than the total volumes are due to rounding errors in computing moving averages.

Figures 3(b) and 3(d) show the same information, but expressed as a fraction of total sales. We see that all EU trade is roughly between 40 % and 50 % of the total trade that we could identify, and that this remained roughly constant over time. This result is in line with what had been seen in the 2016 report (Christin, 2016) and is an increase over what had been observed for AlphaBay (Christin, 2017).

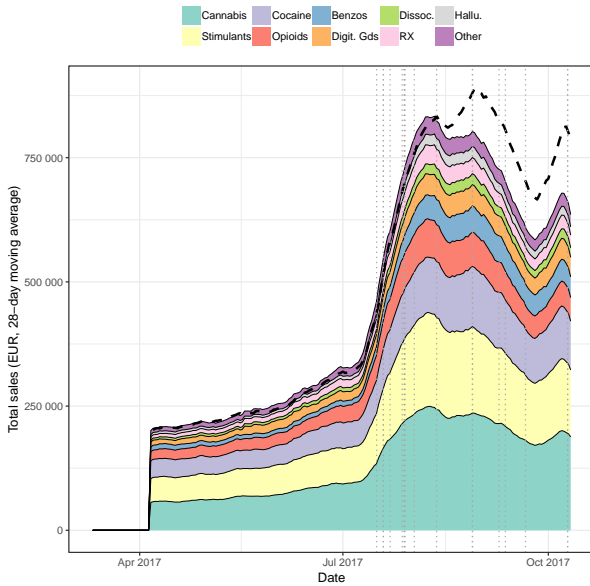
Validating our numbers Validation has been more difficult than in previous attempts – indeed, none of these markets have been seized (and in fact, out of the four markets we study, Dream Market and Berlusconi Market are still active at the time of writing), which means that there is no potential evidence disclosed as part of court proceedings, or criminal complaints, as was the case with AlphaBay, Silk Road or Silk Road 2.

As pointed out earlier, confidence in our results strongly decreases with the distance from a given scrape. In other words, some of the growth trends in the figures may be exacerbated by lack of data. While the large number of scrapes in summer 2017 gives us certainty that there was a large growth in Dream Market (and others) following the fall of AlphaBay, we cannot ascertain that the growth shown in 2018, for instance, was due to economic conditions, as opposed to missing data. We are, however, quite confident of our results when a good number of scrapes are performed.

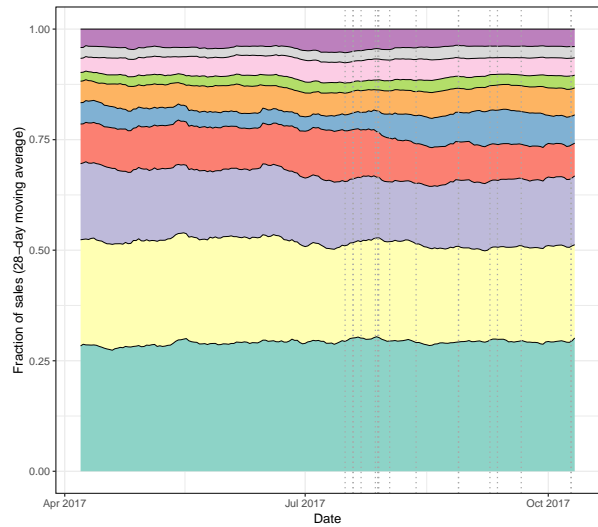
We also do not claim that our numbers represent the entire ecosystem: some potentially important marketplaces such as Wall Street Market are missing from our analysis (due to poor coverage). As such, our estimates should be interpreted as a lower bound on the total amount of transactions conducted.

Categories over time We next provide, in Figure 4, a different graphical representation of the overall sales volume, broken down, this time, by product categories. This plot shows worldwide sales. As before,

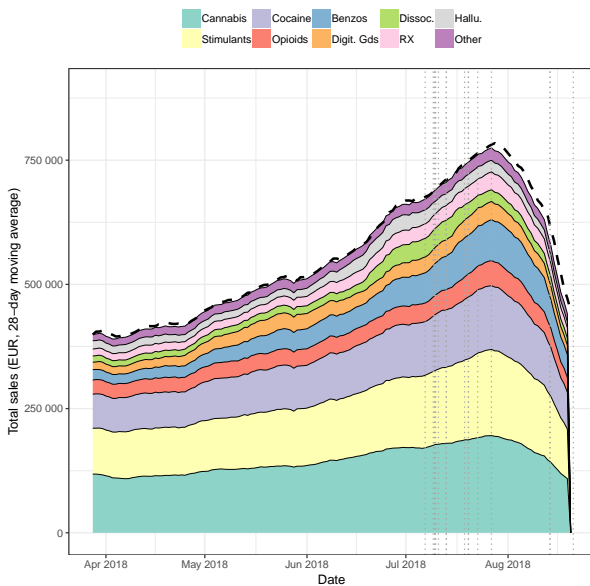
⁽⁴⁾ There are also pieces of feedback gleaned from item pages, that do not have a user page associated with them. However, this is less of an issue, since the item page contains all the information needed to classify a specific listing.



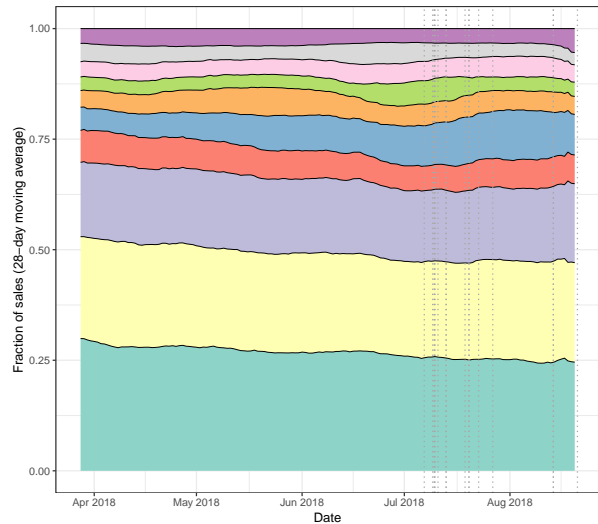
(a) Total sales over time (per-category breakdown), 2017



(b) Relative sales over time (per-category breakdown), 2017



(c) Total sales over time (per-category breakdown), 2018



(d) Relative sales over time (per-category breakdown), 2018

Figure 4: Evolution of sales over time (per-category breakdown). The left-hand plots represent a breakdown per category. The dashed line represents the total amount of sales. The white area represents sales that we have a record of, but for which we cannot recover the corresponding item listing, and thus cannot infer the category. (Note slight discrepancies when we are close to full coverage, due to summing of averages.) As before, the dip at the end of the plot is an artefact of the lack of future data in the computation of the moving average, rather than an observed decrease. The right-hand plots present the same information, but on a relative scale (excluding items for which we do not have a corresponding listing). The vertical dotted lines represent times at which we obtained scrapes.

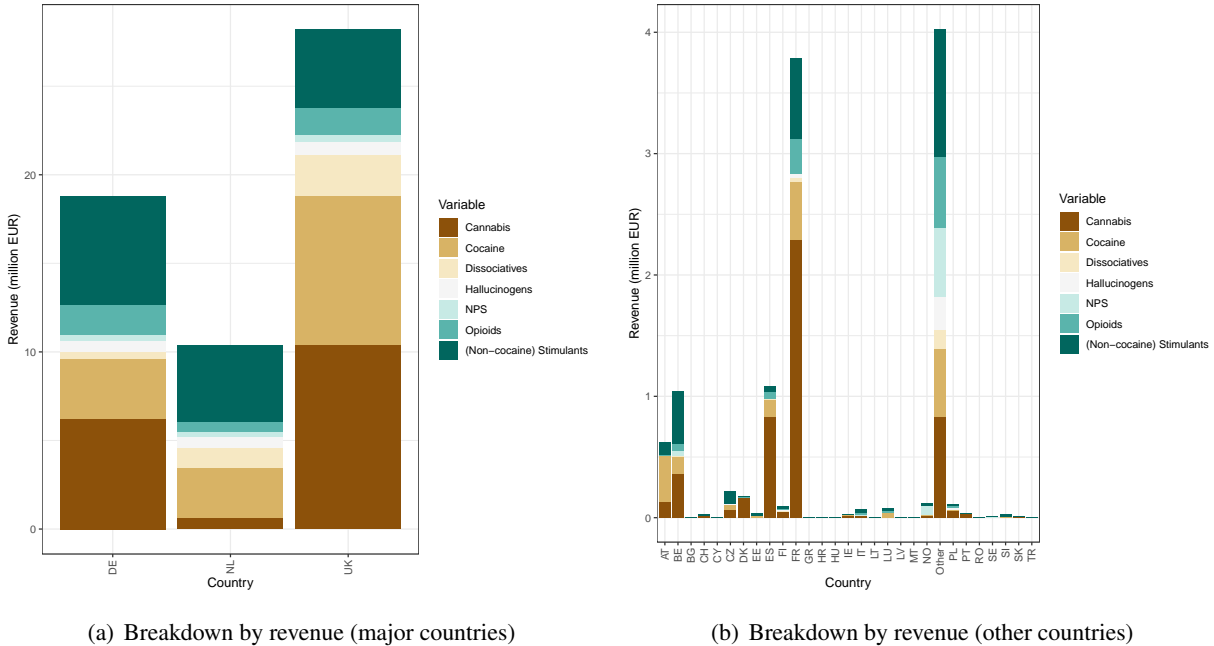


Figure 5: **Breakdown of sales revenue originating from the EU (plus Norway and Turkey) by country.** For clarity, the three major countries are represented on a different scale (5(a)).

the white area represents the transactions for which we could not identify a category, due to an orphaned piece of feedback.⁽⁵⁾ Figures 4(b) and 4(d) show a familiar picture: as in our previous reports (Christin, 2016, 2017; Soska and Christin, 2015), cannabis, stimulants (MDMA/ecstasy), and cocaine represent over two-thirds of all trade. It is remarkable that this figure has essentially remained near-constant since the dawn of the online anonymous marketplace ecosystem. The share of benzodiazepines and opioids seems to have continued growing compared with 2011-15, as have, to a smaller extent, prescription drugs. However, the most remarkable aspect of the plots is their eerie similarity to past data (Christin, 2016, 2017; Soska and Christin, 2015). Simply stated, marketplaces come and go, but customer demand appears – in relative terms – to be quite stable over time.

4.3 Sales from EU sellers

We next focus solely on the drugs originating from the EU. For the seven categories of drugs of primary interest (see Section 3.2), Figures 5 and 6 present a breakdown of sales originating from the EU (plus Norway and Turkey) by country. Both plots are stacked plots. NPS are aggregated in a single category. Figure 5 represents the aggregate amount of transactions over our entire data collection interval (10 March 2017 to 19 August 2018).

⁽⁵⁾ We could have attempted to classify these transactions based on the listing title, but would have probably run into inconsistencies with the item-description-based classification we perform for all items.

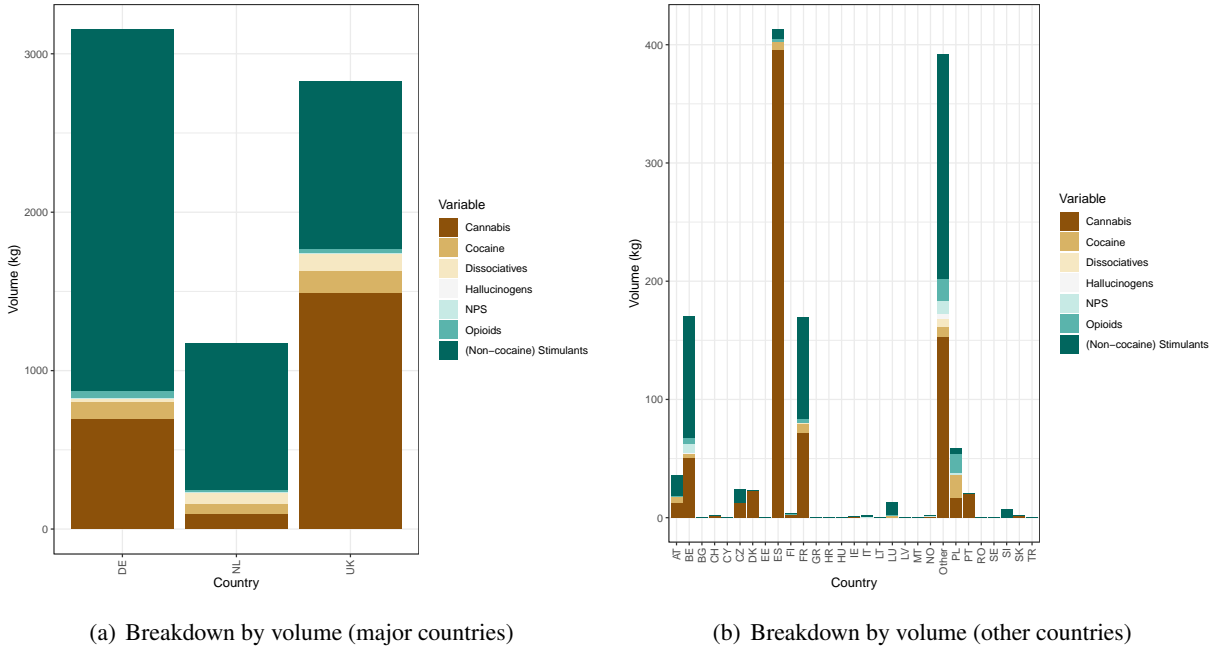


Figure 6: **Breakdown of sales volumes originating from the EU (plus Norway and Turkey) by country.** For clarity, the three major countries are represented on a different scale (6(a)).

Revenue analysis As we can see in Figure 5, as was the case for the marketplace ecosystem as a whole between 2011 and 2015 (Christin, 2016), and for AlphaBay until 2017 (Christin, 2017), the vast majority of sales originating from the EU comes from (the same) three countries: the United Kingdom, with approximately EUR 28.2 million total sales for the seven drug categories of interest – compared with the EUR 20.3 million that were sold between 2011-15 on other marketplaces (Christin, 2016) and the 19.7 million sold on AlphaBay (Christin, 2017); Germany, with EUR 18.8 million sales compared with EUR 26.6 million for 2011-15 (Christin, 2016) and 12.1 million on AlphaBay (Christin, 2017); and the Netherlands, with slightly more than EUR 10.3 million sales (compared with EUR 17.9 million in the 2011-15 study (Christin, 2016) and 10.6 million in the AlphaBay study (Christin, 2017)). ‘Second-tier’ countries remain relatively consistent compared with previous studies: France (EUR 3.8M), Spain (EUR 1.1M), and Belgium (EUR 1.0M) are the only countries with a gross revenue higher than EUR 1M. This list of countries is somewhat similar to that observed in previous studies (AlphaBay (Christin, 2017): France (EUR 2.0M), Spain (EUR 533K), Czech Republic (EUR 424K), and Belgium (EUR 375K); the 2011-2015 study (Christin, 2016) showed Belgium (EUR 4.7M), Croatia (EUR 2.3M), Sweden (EUR 1.3M), Spain (EUR 1.2M) and ‘Others’, leading the pack.) An interesting change is that ‘Others’, that is vendors purporting to ship from multiple possible locations, is back to being a significant player (EUR 4.0M).

We had discovered in our previous study that the top three countries were primarily selling stimulants other than cocaine, that is, MDMA, ecstasy and related products (Christin, 2016). The situation then appears to have changed a bit on AlphaBay (Christin, 2017), with revenues that now appear more evenly distributed between cannabis, cocaine and other stimulants, with a second tier (opioids, hallucinogens, and

Table 2: **Comparison of drug versus other sales in the EU, and the rest of the world.** Volumetric breakdowns are not given for total sales, given that volumes make no sense for certain items (e.g., digital goods).

April–November 2017 and April–August 2018 sales combined	Drug sales⁽⁶⁾		Total sales
	Volume (g)	Revenue (EUR)	Revenue (EUR)
EU (plus Norway, Turkey)	8 493 212	68 923 757	78 014 459
Rest of the world	14 168 300	88 598 698	119 065 112
Total	22 661 512	157 571 582	197 079 571

dissociatives) also roughly evenly distributed. Our new results confirm this trend. They also confirm that the Netherlands appears to sell significantly less cannabis than other countries, and, proportionally, more cocaine and stimulants. Sales of NPS overall remain quite small, but, again, it is quite possible that a lot of NPS opiates are instead classified as opioids.

Volume analysis Figure 6 shows a breakdown by volume. Results are generally consistent with those of Figure 5: Germany (3 153 kg overall), the Netherlands (1 174 kg overall), and the United Kingdom (2 825 kg overall) dominate the ecosystem; these are the only countries where products shipped exceed, in aggregate, a metric tonne. Interestingly, the United Kingdom generates more revenue with less volume. The results seem to hint that United Kingdom sales overall feature slightly higher prices per unit of product – consistent with what had been observed for AlphaBay (Christin, 2017).

Comparison with non-EU sales Table 2 compares sales originating from the EU (plus Norway and Turkey) with those originating from other countries, both for the drugs in the seven categories of interest, and for all products. First, we notice that drug sales are, as previously reported (Christin, 2017), an overwhelming majority (>88%) of all EU sales. This is less so the case for the rest of the world ($\approx 74\%$), which makes sense: any item whose origin cannot be established with certainty will be marked as ‘unknown’, i.e. outside the EU. This includes, in particular, a large number of digital goods (e.g., e-books, credit card numbers, stolen credentials) whose origin is listed as unknown, even if a number of these sales probably originate from Europe. This finding is consistent with our two previous reports (Christin, 2016, 2017), and in particular extremely close to what we observed on AlphaBay in 2015–2017 (Christin, 2017).

We had noted, in the 2011-15 report, that EU countries represented roughly 46% of all revenue, but only 34% of all volumes, for 2011-15 (Christin, 2016). In the discussion of AlphaBay (Christin, 2017), it had been shown that the percentages had become markedly smaller: 28.4% of all revenue, and 24.4% of all volumes. The numbers we gathered in 2017-18 seem very close to measurements from the 2011-15 period: we indeed observed that, here, EU-sales account for 44% of revenue and 37% of volume.

⁽⁶⁾ In the seven categories of interest.

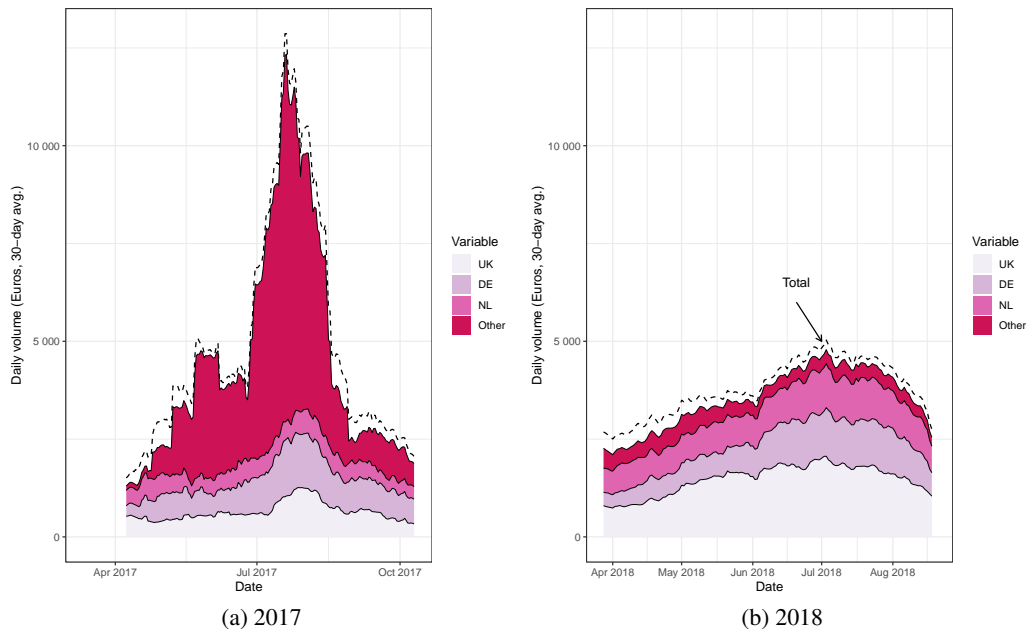


Figure 7: **Breakdown of NPS sales originating from the EU (plus Norway and Turkey)**. Data points are averaged over 30 days. The dip at the end of the plot is more pronounced due to the lack of future data in the computation of the moving average.

4.4 New Psychoactive Substances

In an effort to compare data from AlphaBay with that from older marketplaces, we next focus on NPS. Previous measurements (Christin, 2016, 2017) showed that NPS accounted for a very small fraction of all narcotics traffic on online anonymous marketplaces – in the order of EUR 2 500-3 000/day at most. With reports of ‘opioid epidemics’, it stands to reason that the amount of NPS being sold online would also increase.

Figure 7 provides a more detailed view of the sales of NPS on online anonymous marketplaces, over time, as a stacked plot. The high-level result is that these sales remain modest, but overall higher than what was previously observed in the 2011-17 period (Christin, 2016, 2017). In 2018, NPS originate primarily from the United Kingdom and Germany, with the Netherlands a distant third, and all other EU Member States accounting for negligible volumes. Different from previous reports, ‘Other’, usually meaning vendors shipping from multiple countries, accounted for a non-negligible share of all sales, particularly in 2017. We emphasise again that many synthetic opioids (e.g., fentanyl variants) are actually labelled as opioids by our classifier – rather than NPS, which certainly causes this graph to be an underestimate. However, when it comes to ‘legal highs’, manual inspection confirms that online anonymous marketplaces are certainly not a hub of activity. Consistent with our previous reporting, most NPS sold and classified as such appear to be hallucinogens.

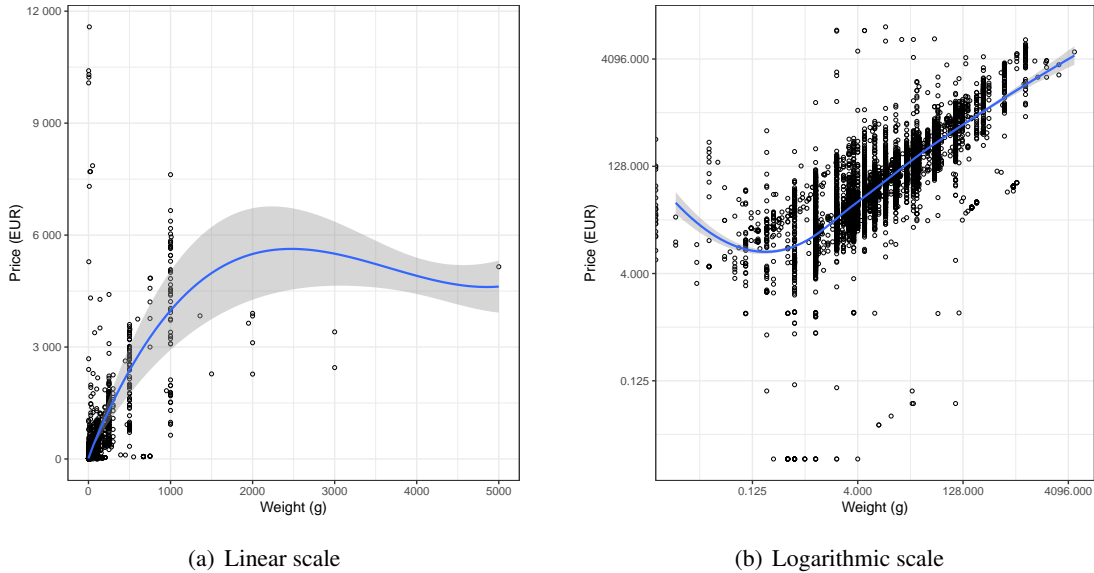


Figure 8: **Cannabis prices as a function of weight.** The curve is a local polynomial regression fitting; the grey shading corresponds to the 95% confidence interval.

4.5 Transaction amounts broken down by drug and level

We next turn to a discussion of the transaction amounts broken down by drug and by level, and compare our findings with those of previous reports (Christin, 2016, 2017).

Cannabis Figure 8 is a scatter plot, in which each point represents the weight (x coordinate) and price (y coordinate) of each cannabis item in our dataset for which (1) we could infer the weight and (2) we observed at least one transaction. Figure 8(a) shows this scatter plot on a linear scale. Because the vast majority of items correspond to small quantities, we find it useful to present the same data on a logarithmic-logarithmic scale (Figure 8(b)). The blue curve corresponds to a non-parametric regression (using a local polynomial regression fitting (Cleveland et al., 1992)), with 95% confidence interval represented by the grey shading. There appears to be a fairly strong volume discounting effect; however, we caution that the number of observations at high volumes are considerably smaller than at low volumes – and, thus, one single vendor selling relatively low quality products in large volumes could greatly influence the regression. In other words, regression fits are probably more questionable at high volumes. Very low volumes – below 1g – are also likely to be incorrect, and should probably be ignored. The results are roughly aligned with those of previous reports (Christin, 2016, 2017).

The most common units sold are 5 grams (1 261 items, median price EUR 50, standard deviation EUR 409), 1 gram (1 183 items, median price EUR 12, standard deviation EUR 35), and 10 grams (1 151 items, median price EUR 90, standard deviation EUR 402). We also observed a number of listings for 1 kg (52 listings, median price EUR 4 127, standard deviation EUR 1 807) and 500 grams (66 listings, median price EUR 2 078, standard deviation EUR 915).

All of these values are very much in line with what had been previously observed.⁽⁷⁾

As in the previous reports (Christin, 2016, 2017), the high standard deviations can be explained by the large dispersion due to a range of different products (oils, edibles, etc) being classified as cannabis; and, as before, we note the presence of a few items with very small volumes (close to zero grams). Some of these are sample offers, some (particularly those with high cost) are the few items for which our heuristics for extracting quantities have failed.

Cocaine and other stimulants Figure 9 shows similar scatter plots for cocaine products. Figure 9(a) uses a linear scale, and Figure 9(b) uses a logarithmic scale. We use again a local polynomial regression, which shows that the volume discounting effect is less pronounced here than it was in the case of cannabis products, and markedly less pronounced than what had been observed in previous reports (Christin, 2016, 2017).

For cocaine, the most common unit sold is 1 gram (728 items, median price EUR 63, standard deviation EUR 21). These numbers are nearly identical to those observed on AlphaBay ($\mu = \text{EUR } 68$, $\sigma = \text{EUR } 22$ (Christin, 2017))

Stimulants (other than cocaine), shown in Figure 9(c), exhibit a near-linear relationship for products labelled as MDMA (in red). Other products include various types of drugs (e.g. anything labelled ‘ecstasy’, ‘speed’, or ‘meth’ would end up in this category) of highly varying quality. The weight is defined the product of the unit weight by the number of units. For instance, somebody selling 1 000 200mg MDMA pills would be considered as selling 200 grams.

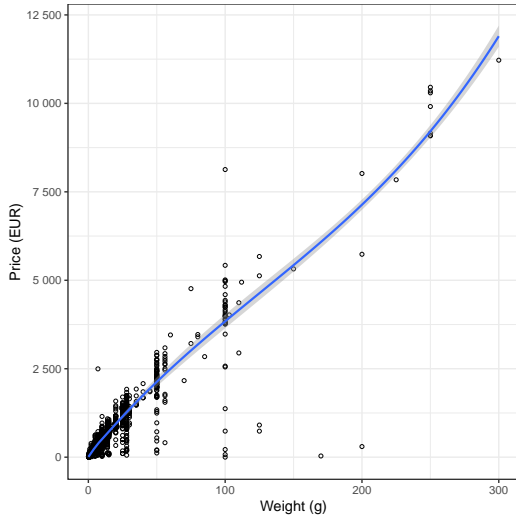
As in the report for 2011-2015, we see extreme dispersion at low volumes for stimulants other than cocaine and MDMA. We suspect that, as before, it is primarily due to bad labelling of a few egregiously wrong quantities.

Dissociatives We next turn to dissociatives. Figure 10 provides a similar scatter plot in log-log scale for ketamine. Consistent with previous reports (Christin, 2016, 2017), there is not much bulk discounting, apparently. Data for other products (GHB/GBL, and PCP and others) were too limited to provide meaningful regressions and are omitted from the plot.

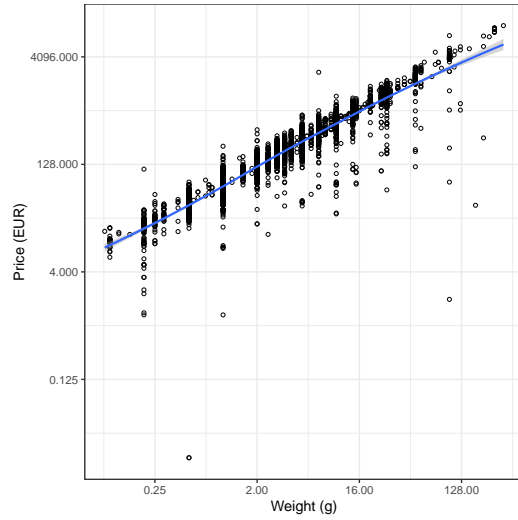
As in our AlphaBay study (Christin, 2017), the most common unit sold (for ketamine) is 1 gram (209 items, median price EUR 23, standard deviation EUR 9). This is slightly cheaper than what had been previously observed ($\mu = \text{EUR } 30$, $\sigma = \text{EUR } 13$ on AlphaBay (Christin, 2017)).

Other drugs: hallucinogens, NPS (hallucinogens), and opioids We next turn to the other three categories of drugs of interest, depicted in Figure 11, in which all scatter plots use a log-log scale. For hallucinogens, the results are strikingly similar to those in previous reports (Christin, 2016, 2017). Hallucinogens (i.e., primarily LSD), represented in Figure 11(a), show two clear clusters: there is a large price variance

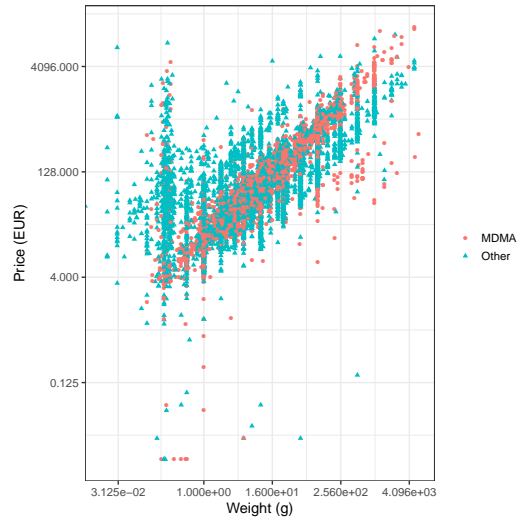
⁽⁷⁾ For comparison purposes, there were 1 610 1-gram listings ($\mu = \text{EUR } 17$, $\sigma = \text{EUR } 16$); 1 745 5-gram listings ($\mu = \text{EUR } 58$, $\sigma = \text{EUR } 39$); and 1 165 10-gram listings ($\mu = \text{EUR } 99$, $\sigma = \text{EUR } 55$) in the study of 2011-15 data (Christin, 2016); and 1 239 1-gram listing ($\mu = \text{EUR } 12$, $\sigma = \text{EUR } 20$), 976 5-gram listings ($\mu = \text{EUR } 49$, $\sigma = \text{EUR } 28$), 910 10-gram listings ($\mu = \text{EUR } 86$, $\sigma = \text{EUR } 204$) on AlphaBay (Christin, 2017)



(a) Cocaine (Linear scale)



(b) Cocaine (Logarithmic scale)



(c) Stimulants other than cocaine

Figure 9: **Cocaine and other stimulant prices as a function of weight.** The curve in parts (a) and (b) is a local polynomial regression fitting; the grey shading corresponds to the 95% confidence interval.

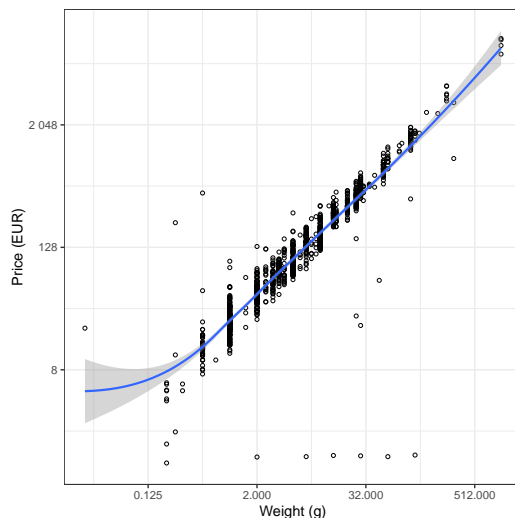


Figure 10: **Dissociative (ketamine) prices as a function of weight.** The blue curve is a local polynomial regression fitting; the grey shading corresponds to the 95% confidence interval. Note the different estimators depending on the type of dissociative sold. We removed the (separate) plots for GHB and other dissociatives (PCP), as there were too few datapoints.

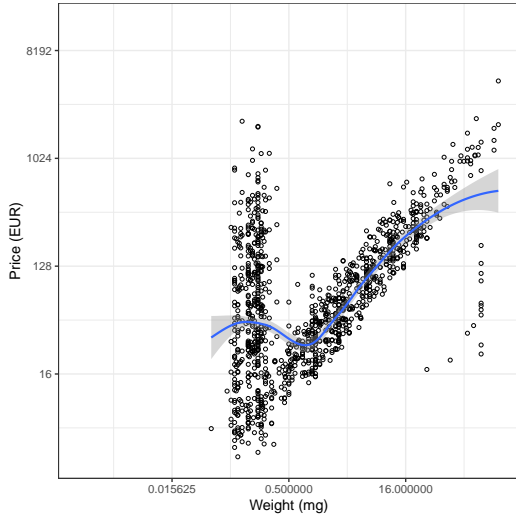
for low, single-use type of doses (250 micrograms and less). As in the previous report, this appears to be partially due to measurement errors at such low levels, and partially due to vendors offering samples for (nearly) free, or as part of lotteries. As the volume grows, the price also grows somewhat linearly. There appears to be mild volume discounting at high volumes, but this may be due to data scarcity.

In Figure 11(b), we show that NPS hallucinogens (NBOMe, dimethyltryptamine (DMT), etc.) demonstrate a similar behaviour, albeit with considerably larger weights (grams as opposed to milligrams) than for LSD, which is unsurprising. The higher quantities (and, to a certain extent, lower quantities as well) have high uncertainty due to limited data. Interestingly, these hallucinogens constitute the vast majority of the NPS sales in our database, as, apparently, during our measurement intervals, synthetic cannabinoids were not very well represented on underground marketplaces).

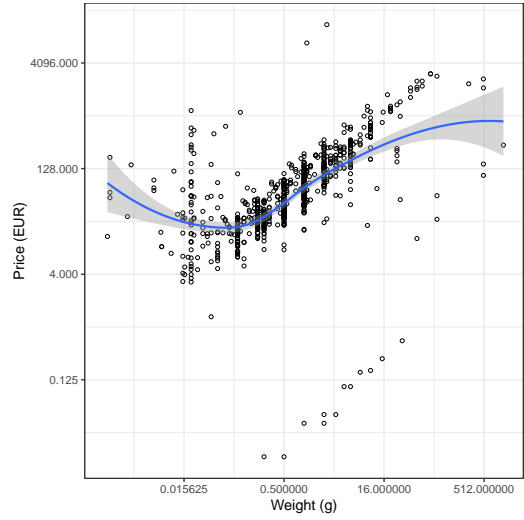
Opioids, presented in Figure 11(c), on the other hand, show far less price dispersion than had been observed in previous research. The regression, again using a local polynomial regression fitting, suggests two modes: below 2 grams, where prices increase modestly (dispersion due to quality heterogeneity seems to dominate), and above 1 gram, where we observe modest volume discounting; for high volumes (>16 grams), the scarcity of data makes the regression less precise.

4.6 Vendor diversification

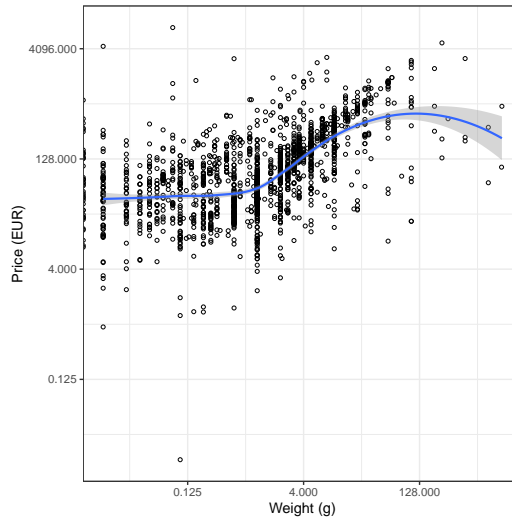
Following the same methodology as in our previous reports (Christin, 2016, 2017), we next examine the range of products and volumes that vendors offer. We start by looking at if, and how, vendors diversify in terms of the volumes they offer. That is, we try to determine whether vendors stay within their market



(a) Hallucinogens



(b) NPS (Hallucinogens)



(c) Opioids

Figure 11: **Prices as a function of weight for hallucinogens, NPS (hallucinogens), and opioids.** All plots are in log-log scale; the curves are local polynomial regression fitting; the grey shadings correspond to the 95% confidence interval.

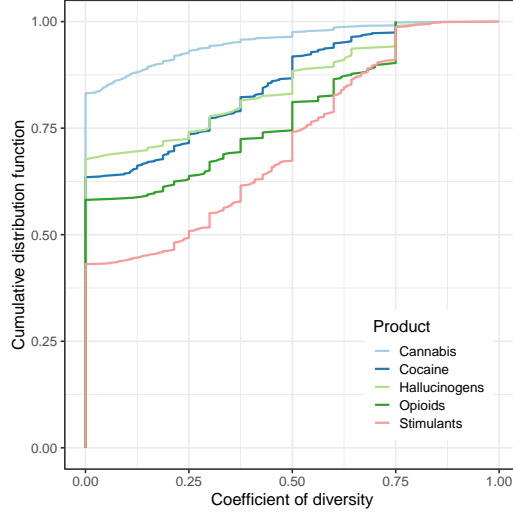


Figure 12: **Coefficient of diversity for vendors, by product, across volume tiers.**

area (e.g. always selling small quantities) or diversify their offerings, and, to what extent. We then discuss whether vendors who sell drugs *also* sell other types of goods.

As before, we use the coefficient of diversity defined by Soska and Christin (2015), whose definition we summarise here. We divide all items of interest in a set \mathcal{C} of groups. For instance, \mathcal{C} could denote a set of volume tiers, or a set of item categories. Let \mathcal{S} be the set of all sellers based in the EU (plus Norway and Turkey) across all marketplaces. We define $\mathcal{C}_i(s_j)$ as the normalised value of the i -th group for seller j , such that $\forall s_j \in \mathcal{S}, \sum_{i=1}^{|\mathcal{C}|} \mathcal{C}_i(s_j) = 1$. For instance, if vendor j 's revenue comes from 50% of items in group 1, 25% in group 2, and 25% in group 3, then $\mathcal{C}_1(s_j) = 0.5, \mathcal{C}_2(s_j) = 0.25, \mathcal{C}_3(s_j) = 0.25$. We can then define the coefficient of diversity for seller s_j as:

$$c_d(s_j) = \left(1 - \max_i (\mathcal{C}_i(s_j))\right) \frac{|\mathcal{C}|}{|\mathcal{C}| - 1}.$$

Intuitively, the coefficient of diversity measures how invested a seller is into their most popular group, normalised so that $c_d \in [0, 1]$. A vendor s_j with a coefficient of diversity of 0 sells only items from a specific group; a vendor s_j with a coefficient of diversity of 1 gets exactly the same amount of revenue from each group of items.

Diversification in terms of volumes offered We use the coefficient of diversity so defined to examine whether vendors who sell large quantities sell also small quantities. To do so, we define quantity tiers for each drug category in Table 3. We use a simple three-tier distinction between retail, middle-market, and bulk sales. We base our distinction between tiers on the EMCDDA's own classification (European Monitoring Centre for Drug and Drug Addition, 2016). For hallucinogens, the tiers are usually expressed in number of doses (50 doses or less, 50 to 1 000 doses, more than 1 000 doses); since we are using grams as a base unit, we convert this to volumetric tiers using a baseline of 160-microgram doses (which is close to the arithmetic mean of what we observed.) We exclude from this discussion NPS, as they are too heterogeneous

Table 3: **Quantity tiers for each drug of interest.**

	Cannabis	Cocaine	Hallucinogens	Opioids	Stimulants
Retail	<100 g	<10 g	<8 mg	<1 g	<10 g
Middle-market	100-999 g	10-999 g	8-159 mg	1-999 g	10-999 g
Bulk	$\geq 1\ 000$ g	$\geq 1\ 000$ g	≥ 160 mg	$\geq 1\ 000$ g	$\geq 1\ 000$ g

a set to provide meaningful comparisons, *and* the uncertainty over their legal status makes it hard to pick appropriate thresholds.

Here, we have $|\mathcal{C}| = 3$. Then, for each group of drugs listed in Table 3, we plot the cumulative distribution function of the coefficient of diversity of their vendors in Figure 12. Results are nearly identical to those observed in the 2011-15 and AlphaBay studies (Christin, 2016, 2017). That is, the figure shows that an overwhelming ($\approx 90\%$) majority of cannabis vendors stay within one volume tier (coefficient of diversity of 0). The rest are more spread out, without any noticeable jumps; almost no vendor has a coefficient of diversity greater than 0.75. In other words, most vendors stay within a single volume tier, but a minority sell across two tiers; almost no one has meaningful sales across three tiers. It is quite rare for a vendor to sell both bulk quantities and small volumes at the same time, but some vendors selling larger quantities sometimes offer ‘test samples’ to their customers. Likewise, hallucinogens present almost the same behaviour as in previous measurements.

As in previous studies (Christin, 2016, 2017), stimulants other than cocaine present the most diversity, with most vendors sticking to the retail tier, but some vendors selling across multiple tiers with a number of items in each tier. This can be explained by the ease of shipping fairly large quantities of pills stealthily.

We checked a few instances in our database that suggest that vendors selling in multiple categories tend to be ‘superstores’, that also carry more than one type of drug. They are also more likely to have higher sales volumes. Conversely, vendors who stick to one area (typically, the lowest one) tend to specialise in one item, and to have relatively low sales volumes. In other words, vendor behaviour, overall, has not changed much compared with previous measurements (Christin, 2016, 2017).

Diversification in terms of products offered In all, 2 050 vendors reportedly ship from the EU (which is comparable with the 1 956 EU-based vendors seen on AlphaBay (Christin, 2017)). We next look at the diversity across products being sold. We define \mathcal{C} here as the set of drugs of interest: cannabis, cocaine, dissociatives, hallucinogens, NPS, opioids, and stimulants. We plot, in Figure 13, the corresponding cumulative distribution function of the coefficient of diversity for all 2 050 vendors (including those who do not sell drugs). We see that approximately half (816) of all vendors specialize in exactly one category – this is frequently the case for vendors of cannabis (388 cases) and stimulants other than cocaine (199), which is not very surprising given that these are very frequently sold items. We find that 82 vendors specialise solely in cocaine; 83 specialise in opioids. On the other hand, only 19 vendors specialise purely in dissociatives. More generally, vendors selling dissociatives, hallucinogens or NPS rarely only sell from these categories.

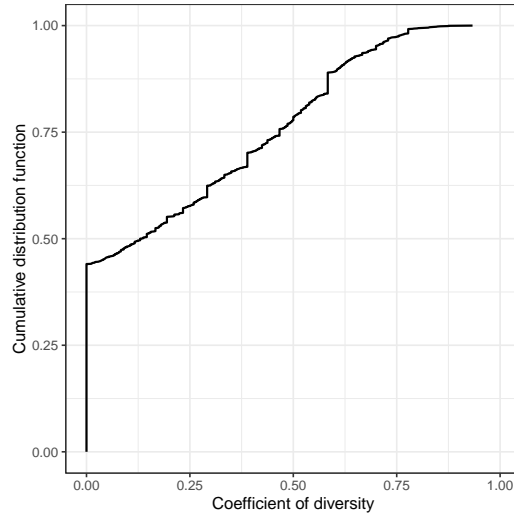


Figure 13: **Coefficient of diversity for vendors, across product categories.**

A very small number of vendors have a coefficient of diversity close to 1, denoting that they sell a little bit of everything (e.g., MDMA, ketamine, DMT and cannabis; LSD, cannabis, MDMA and mushrooms). Those vendors usually focus purely on individual or small doses.

Out of the 2 050 EU vendors, 1 229 sell drugs in at least one of the seven categories of interest. Of those 1 229 vendors, 217 (or 17.66%) also sell other types of drugs (e.g., prescription drugs). Furthermore, 604 (49.15%) also sell non-drug products: we found this diversity surprising in our initial study (Christin, 2016), but it has proven consistent since then – we observed similar results with AlphaBay (Christin, 2017).

We also discovered that 179 of those 604 vendors that sell non-drug products remain confined to one drug category (primarily cannabis, and stimulants other than cocaine). Among those 604 vendors, 168 vendors have on the other hand high diversity coefficients (>0.5). Many of these vendors sell cannabis, stimulants (sometimes including cocaine), and opioids.

These results are very consistent with what had been observed and reported for AlphaBay (Christin, 2017).

5 Conclusions

We have presented an analysis of four marketplaces (Dream Market, Valhalla, Berlusconi Market, and Traderoute), in 2017-18. Most of our reliable data are from the summers of 2017 and 2018. We attempted to reproduce the analysis done for the online anonymous marketplace ecosystem as a whole in 2011-15 (Christin, 2016; Soska and Christin, 2015) and for AlphaBay (Christin, 2017). We found that Dream Market appears to have become the overwhelmingly dominant player (to the extent that, other than Traderoute for a brief spell in 2017, the other marketplaces we studied have a negligible impact). We also found that the aggregate sales of the ecosystem have not slowed down since the AlphaBay and Hansa combined takedown of July 2017; if anything, aggregate volumes have continued to rise, albeit not as much as in the 2014-17

period. We emphasise that our data are not fully complete and are likely to produce (slight) underestimates of total revenues and volume; however they do not cause bias towards one specific item or category. We also emphasise that our study is not comprehensive, in the sense that we monitored only four marketplaces. Others, such as Wall Street Market, might be relatively important, although much smaller than what we observe on Dream Market.

Focusing on products reportedly shipping from the EU, we again found similarities between the marketplaces under investigation in our present report, and past data gleaned from AlphaBay (Christin, 2017), and the marketplaces we had previously considered (Christin, 2016): EU-originating drugs still primarily came from Germany, the Netherlands, and the United Kingdom. Many countries did not register any significant sales.

Likewise, while vendors on these marketplaces primarily operate in the retail space, with individual item weights and volumes frequently corresponding to personal amounts, there is evidence of much larger (bulk-like) sales. Regression-based analyses show that volume-based discounting tends to occur, albeit at relatively modest levels.

Furthermore, cannabis, cocaine and other stimulants (e.g. amphetamines, MDMA and ecstasy) together continued to represent the majority of all EU-based sales. Opioids and dissociatives formed a next tier; hallucinogens and NPS were more modest. As noted in previous studies (Christin, 2016, 2017), NPS volumes remained comparatively modest, with revenues below EUR 10 000 at market peak; this shows, however, a slight increase compared with previously reported measurements.

Similarly, the vendor ecosystem remains split in half: half of the vendors specialise in one type of drug, while the other half is far more diversified. Slightly less than half of the drug dealers tend to stick to a given weight category, while others present a more diverse set of offerings. These results were remarkably close to those of our previous study, indicating some overall stability.

The total share of EU-based supplier is back to the levels observed in 2011-15 – around 44 % for this study versus 45 % for the 2011-15 study. This is in contrast to AlphaBay, where European vendors accounted for approximately one-quarter of all revenue and one-quarter of all volumes.

In summary, the major finding is the overall stability of the ecosystem: revenues (and volumes, overall) increase steadily – we are far from the exponential increases of the Silk Road days – but perhaps more intriguing to us is the fact that so many results remain valid across the entire history of modern online anonymous marketplaces. Despite takedowns, scams, possible dents in user confidence, and general upheaval, the ecosystem seems to have settled to a very steady state overall, even though the markets we are looking at constantly change. In other words, *plus ça change, plus c'est la même chose...*

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