Scamming and the Reputation of Drug Dealers on Darknet Markets

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July 2019

Forthcoming in the International Journal of Industrial Organization

Abstract

In this paper I investigate the role of e-reputation mechanisms on illegal platforms that specialize in drug sales. I ask whether online reputation systems can limit the risk of scamming (i.e. fraud) by dishonest sellers, and thus prevent Akerlof-like market destruction. I do so by analyzing all published offers on the second-largest platform operating on March 18th 2017 (Hansa). Three types of drugs show relatively low scamming risks, with the average probability that a random seller effectively send the ordered good of over 83%. The recent shutdowns of the two leading platforms are likely to increase this probability by 2.7 to 9.7%. Endogeneity may either lead us to overestimate the effect of e-reputation mechanisms (e.g., unobserved heterogeneity in sellers) or underestimate it (e.g., better-functioning markets may attract more scammers).

Keywords: Darknet markets, Hansa, e-reputation, scamming, drug price, honesty, trust.

JEL Codes: L14, L15, K42, K24.

1 Introduction

Economists consider online reputation mechanisms as virtuous tools that can protect markets from low-quality sellers. From this point of view, these mechanisms help reduce the negative externalities resulting from low-quality products and bad sellers (Akerlof (1970)). Honest sellers can thus signal their trustworthiness to imperfectly-informed buyers via their positive e-reputation, with dishonest sellers being punished by negative ratings (MacLeod (2007)). The core question at the heart of

*I am very grateful to Antoine B. for his precious help in establishing TOR-compatible web-scraping methods and Ewen Gallic for his advice on parallel estimations in R. I also thank Andrew Clark, Thierry Pénard, Thomas Le Texier, Joeffrey Drouard, Claudine Desrieux, Noé Ciet, Marie Obidzinski, Sophie Bienenstock, Benjamin Monnery and two anonymous reviewers for their helpful comments. I would like to express my gratitude to participants at the following workshops and seminars: the French Law and Economics Association (AFED, 2017), the French Economic Association (AFSE, 2018), Public Economic Theory (PET, 2018), Western Economic Association International (WEIA, 2019) and the CREM (Caen, 2018) and IAAEU (Trier, 2019) seminars.

this work is the sustainability of unregulated markets in the presence of asymmetric information. In other words: Does e-reputation on its own suffice to discipline the market and sustain high levels of trust and transactions between sellers and buyers? Most research on online platforms (e.g., eBay) confirms this intuition, showing that the overwhelming majority of buyers evaluate their past transactions positively. However, almost all work on the role of e-reputation has considered online legal marketplaces where legal enforcement can also be applied to restrain dishonest sellers. This research is therefore unable to disentangle the disciplinary effect of reputation from the threat of consumer-protection Law. In this paper, I instead investigate the effectiveness of reputation in disciplining the market when legal enforcement is not available by analyzing illicit drug transactions on Darknet Markets.

Illicit online marketplaces, also called Darknet Markets (DNMs), are illegal platforms mainly specialized in drug-selling that are only accessible through secured protocols (TOR, PGP). Transactions on these platforms are fully anonymized via the use of pseudonyms and crypto-currencies (e.g. Bitcoin) and do not benefit from legal protection. To offset the relatively high risks of scamming[1] (i.e. fraud), DNMs have made extensive use of technological developments (e.g. the use of multi-signatures for Bitcoin transactions), but have mostly relied on e-reputation mechanisms. As in clearnet marketplaces such as eBay, Amazon and Airbnb, Darknet Markets have reputation mechanisms that allow customers to supply feedback after the completion of their transactions. The very broad use of reputation mechanisms may be the key to the development and longevity of DNMs despite their associated substantial opportunities for scamming and their recurrent shutdowns by public authorities.

I here propose to investigate the role of e-reputation on DNMs and infer the quality of transactions, i.e. the risk of scamming. I do so by analyzing data that I collected on the second-largest platform for drug-dealing operating in March 2017 (the *Hansa* market). I first estimate the relationship between seller reputation and pricing, using about 6,000 unique offers for four types of drugs (*Weed, Hash, Ecstasy* and *LSD*). Second, I derive a model of reputation-building and pricing on Darknet Markets that I estimate for the four types of drugs considered. Finally, I discuss the short- and medium-run impact of the recent shutdown of the Hansa market on future transactions.

My results show that DNM sellers make extensive use of online reputation systems. As in legal marketplaces, I observe a distribution of reputations that is extremely favorable to sellers (a great deal of positive feedback and only little negative feedback). I then show that sellers with more positive reputation profiles charge significantly higher prices for at least three types of drugs (*Weed, Hash* and *Ecstasy*). This confirms Shapiro's well-established prediction of a reputation premium for high-quality products (Shapiro (1983)). Third, eliciting transaction quality from pricing strategies and reputation profiles, I find that sellers provide a surprisingly high quality of service on the *Hansa* Market: the probability that a random seller effectively send the order lies between 83% and 88%. Fourth, I show that consumers welfare varies greatly by drug type: customers retain about 25% of

[1]In this paper, I refer to 'scamming' as the behavior of some dishonest sellers consisting in accepting a transaction and taking the money, but then not shipping the ordered good (no shipment at all, or the shipment of below-strength or fake drugs). This terminology is widely-used on DNMs and forums.

their surplus for Weed and Ecstasy transactions, but only 1.4% for Hash. Fifth, the recent shutdown of the two leading platforms, the *Alphabay* and *Hansa* markets, is likely to have reduced the short-run risk of scamming but will also have reduced sellers' profits. While the Ecstasy market is likely the least affected by the shutdown, with an average price fall of 2.9% to 5%, Weed and Hash sellers are expected to suffer significantly from these shutdowns (with average price falls of 4.4% to 8.9% and 11.3% to 14.2% respectively).

This research contributes to the existing literature in several innovative ways. First, although numerous contributions have considered clearnet platforms, this is one of the first to discuss reputational effects on darknet markets. In this respect, I analyze the effect of reputation when it is the most needed, namely when customers have no legal protection. Second, the vast majority of work on clearnet markets has considered auction-based models to structurally estimate the role of reputation. I here propose a new perspective on e-reputation that takes into account the particularities of darknet markets. Third, this is the first attempt to estimate the risk of scamming on darknet markets. Understanding this risk helps us to better understand the efficiency of environments outside of the Law. The discussion proposes some elements to help predict the effects of the shutdown of illegal platforms; this is central for public authorities who seek to reduce drug addiction and fight against organized crime.

The remainder of the paper is organized as follows. Section 2 reviews the literature on Darknet Markets and previous work on e-reputation mechanisms, and Section 3 discusses the *Hansa* market. Section 4 presents the data collected on the *Hansa* market and Section 5 the use of reputation mechanisms on this platform. Section 6 is devoted to the estimation of a model of reputation-building and pricing for the four drug types. In Section 7, I then discuss the impact of the recent shutdowns of the two leading platforms. Last, Section 8 concludes.

2 Darknet Markets and Reputation Mechanisms

Academic research has devoted increasing attention to Darknet Markets over the past few years. The first work on this issue was mainly on the first worldwide drug-dealing platform, *Silk Road* (e.g. Hardy and Norgaard (2016)). Martin (2014) analyzes the emergence of *Silk Road* in 2011 and describes it as "*a website which facilitates the sale of illicit drugs and operates on the TOR network, an encrypted part of the internet otherwise known as the dark net*". In his view, canonical DNMs share the following features: access must be guaranteed by the TOR network, users use cryptonyms to conceal their identity, goods are delivered by post, administration and hosting is carried out by a third-party, transactions rely on decentralized exchange networks and are effected via an encrypted electronic currency (e.g. Bitcoin).

Following the initial research on the role played by the historical DNM *Silk Road*, growing attention has been focused on the challenges raised by the emergence of online drug selling (e.g. Barratt et al. (2013); Aldridge and Décary-Hétu (2016); Ladegaard (2018b)). Barratt et al. (2016) provide information about the profile of Darknet marketplace users. Their survey shows that users are relatively young (22 years old), mostly male (82.3%) and white (91.5%). The majority of users are employed (55%) but a significant share are still students (35%). A relatively high proportion are educated, with 82.4% having completed secondary school, and 38% holding a university degree. Most users declare that they buy drugs for their own consumption (58%) or for somebody else (55.6%). Ecstasy (54.6%), Cannabis (42.9%) and LSD (34.8%) are reported s the most popular drugs among consumers. More importantly, some work has compared the use and composition of online markets to standard face-to-face supply. For instance, Barratt et al. (2016) show that consumers are less likely to experience threats or violence using cryptomarkets than in standard drug-dealing channels. They conclude that DNMs are associated with easier product access, higher quality and a lower scamming risk.

These results may at first sight appear surprising, considering that standard drug dealing is a repeated game with fixed identities, while sales on DNMs are anonymous transactions where sellers can easily scam consumers. In this context, Tzanetakis et al. (2016) investigate the role of trust and dispute resolution in conventional and online drug markets. Using survey data, they underline the central role of trust in drug markets, where law enforcement and drug quality are two major concerns for both sellers and consumers. While trust is typically achieved by the disclosure of identities in conventional drug markets, DNMs seek to establish trust via trust-building procedures on the platform: these include conflict resolution by third parties (the platform manager) and the use of customer-feedback systems (reputation systems).

Customer feedback is of course not limited to Darknet Markets, and can be found in numerous clearnet markets. In particular, all leading online marketplaces now have a consumer-feedback system (e.g. Airbnb, Amazon, Facebook and Alibaba). A considerable body of research has considered the determinants and impact of the reputation obtained on these platforms (e.g., Anderson and Magruder (2012); Melnik and Alm (2002)). As Houser and Wooders (2006) explain, reputation mechanisms on online platforms serve as "*a means by which honest sellers can (eventually) be distinguished from dishonest ones*" (p. 354). As in a growing literature,[2] the authors attempt to estimate the benefits associated with a positive eBay reputation. Their results suggest that positive reputation was responsible for $55 million of the $1.6 billion in sales in the fourth quarter of 2000; on the contrary, negative reputation reduced sales by $15 million over the same period. Bajari and Hortaçsu (2004) underline that reputation mechanisms are the most useful when there are limited possibilities for repeated interactions, goods are expensive, and there is a considerable information asymmetry regarding product quality. Dellarocas et al. (2004) consider the three main reasons for which users leave feedback on these platforms (self-interest, reciprocity, and altruism) and analyze rare-coin auctions on eBay. They find that users who leave comments are mostly self-interested, but a significant proportion display reciprocity norms (i.e. they give feedback if they have received feedback). On the contrary, they conclude that altruism is not a significant driver of feedback. Some work has also revealed the limits of online-reputation systems, which are characterized by a disproportionately high percentage of positive feedback (Dellarocas and Wood (2008)).

[2] For instance: Ba and Pavlou (2002); Melnik and Alm (2002); Cabral and Hortacsu (2010).

Overall, the DNM literature has underlined the central role of trust in drug dealing. Work on clearnet markets has shown that reputation mechanisms successfully generate trust between buyers and sellers, and affect transactions by providing reputation premia to well-rated sellers. However, transactions on clearnet markets are always backed up by consumer protection that can be enforced by Courts. We therefore expect reputation mechanisms to matter more in DNMs, which are characterized by greater information asymmetry, anonymity, health concerns over product quality, and the absence of law enforcement. My contribution to this literature is therefore to explore whether reputation on the DNM can drive out dishonest sellers (i.e. scammers) and ensure good-quality drug sales. Unlike Hardy and Norgaard (2016), I here consider a second-generation DNM that developed after the shutdown of the first-generation DNM *Silkroad*, and evaluate reputation effects for four types of drugs. One of the main contributions of this paper is to propose a completely new theoretical model of online reputation that captures the particularities of DNMs.

3 The *Hansa* Marketplace

Overview. The *Hansa* market was closed in July 2017 after three years of operation. It was one of the largest platforms created after the shutdown of the reknowned *Silk Road* darknet market in 2014. In early 2017, *Hansa* was the second-largest platform for the sale of drugs.[3] Unlike other darknet markets, *Hansa* mostly focused on drug sales and banned transactions related to weapons or child pornography. It had a very good reputation among online platforms, offering its members double escrowing and relatively low transaction fees.[4] When the police took over the website, the platform had more than 1,000 daily orders, 40,000 advertisements (i.e. unique offers) and 1,765 sellers. The police seized more than 1,000 bitcoins (about $2,778,830).[5]

On June 20th 2017, German authorities arrested the two platform managers, and kept their arrest secret. The Dutch police discovered that the platform's servers were located in Lithuania. Experts in online security then created a copy of the website, and started running the *Hansa* Market as if nothing had happened. For one month, the Dutch authorities collected personal information on negligent buyers and sellers (those who did not encrypt their data with PGP and/or provided their real identity or postal address). At the same time, the American authorities shut the largest platform for drug sales, *AlphaBay*, on July 4th 2017. The *AlphaBay* platform had around 100,000 items on sale when the police arrested the platform's alleged manager. The shutdown of *AlphaBay* led numerous buyers and sellers to switch to *Hansa* Market, which was already secretly under the control of Dutch authorities. The Dutch police were therefore able to collect a large amount of information on market participants. New registrations to the *Hansa* Market rose from under

[3] The Chief Prosecutor of Frankfurt declared after the shutdown: "*We estimate that this platform had a customer base in the five-digits. It was therefore the second largest Darknet market place in the world*". See: `http://www.dw.com/en/details-emerge-of-the-german-administrators-of-hansa-market-on-the-darknet/a-39804272`.

[4] The website DarkNetNews wrote about Hansa Market: "*Hansa Market is the Dark Web market which boasts of its really extreme safety measures; it even goes so far as to claim that there is no possibility of anyone running away with customers' bitcoins – neither vendors nor the site itself; so it's basically immune to exit-scam, which is really nice to know*". See `https://darkwebnews.com/darkwebmarkets/hansa-market/`.

[5] One bitcoin was worth $2778.83 on June 20th 2017.

1,000 to over 8,000 per day after the *AlphaBay* shutdown. After one month of running *Hansa*, the Dutch police shut the website down permanently and transferred about 10,000 postal addresses to Europol.[6]

Transactions and Conflict Resolution. *Hansa* required marketplace participants to set up a wallet on the platform, i.e. to place some bitcoins on the website. It also proposed buyers and sellers escrow mechanisms,[7] whereby payments made by buyers were not immediately transferred to the sellers, but only after the buyer reported receiving the good. *Hansa* used *Multi-sig* protocols, which require more than one signature to unlock funds. The 2-of-3 multi-sig system was the most recommended of these, where the transaction funds could be unlocked with at least two of the three signatures associated with the transaction. *Hansa* managers were responsible for one signature, and each of the two parties to the transaction were responsible for his/her own signature. This ensured that no party was able to *exit scam*, i.e. take the money and leave the market without fulfilling their obligations. DarkWebNews, a website specialized in the darknet, declared that *Hansa* was considered as one of the safest platforms, with no 'Finalize Early' option (i.e. no possibility to pay just after the order was passed).[8]

Transactions on the *Hansa* market could be terminated in two ways. In the first case, buyers reported that they had received their order. Once the platform received the consumer's confirmation, either platform managers or the customers themselves used their signature to complete the transaction and wire the money to the seller (who had already entered his/her signature to finalize the transaction). In the second case, buyers declared that they had not received the good and contested the transaction. By doing so, they suspended the transaction, and a moderator was assigned to discuss with both parties. If no mutual agreement was found, the moderator was in charge of litigating the conflict. He/she either finalized the transaction (unlocking the payment in favor of the seller) or wired the money back to the buyer (using the moderator's and buyer's signatures). When litigating the case, platform managers were said to favor mediation, and, in the case of failure, to litigate based on the elements available to them. Seller's reputation played a substantial role in this process by indicating the number of conflicts the seller had previously experienced. Sellers with good reputation profiles were likely to have actually sent the order, which turned out to have been unfortunately seized by Customs. On the contrary, sellers with relatively bad reputations were more likely not to have sent the good and have taken the possibility of Customs seizure as an excuse for the good's non-delivery.

Reputation Effects. Buyers could provide feedback on the seller in the *Hansa* market. After the completion of the transaction, a screen was displayed to buyers where they could assign either a positive, negative or neutral review to the transaction. The feedback system was not however

[6] All of these numbers can be found on the specialized website for darknet services DeepDotWeb. `https://www.deepdotweb.com/2017/07/20/globally-coordinated-operation-just-took-alphabay-hansa/`.

[7] Figure A1 in the Appendix shows the characterization of Hansa Market by DeepDotWeb.

[8] See: `https://darkwebnews.com/darkwebmarkets/hansa-market/`.

mandatory, and participants could decide not to evaluate the transaction. All reviews were available on the seller's profile page. The seller's reputation was also displayed (in bold) on both the seller's page and each offer page he/she published, which made it very salient for customers. Only positive and negative feedback was displayed on the listing menu and the offer page (see Figure A2 in the Appendix). As Tzanetakis et al. (2016) note for similar markets, customers consider several dimensions of the quality of the service when rating the sellers (quality and quantity of drug, shipping time, concealment techniques, and seller responsiveness).

Sellers were very careful about their reputation, and used a number of strategies to improve it (e.g., Ladegaard (2018a)). A standard practice, as Tzanetakis et al. (2016) report, was to include more drugs in the package than were actually ordered. Figures A3 and A4 in the Appendix show two screenshots of vendors' sales conditions that were written below their offers. The sellers obviously mimic the standard practices observed in clearnet marketplaces. For instance, sellers emphasize the speed of their service (Figure A3: "*99% of orders arrive in 3-10 days in Europa*"; Figure A4: "*All orders placed during the day (before 6pm) will be shipped on next morning and all questions will be answered within 24H*"). They also underline the quality of their stealth/shipping methods (Figure A3: "*vacuum sealed, mylar bags, anti-dog spray etc.*'; Figure A4: "*2 times sealed, anonymous envelopes and mylar bags*").

Reputation was thought to be a key determinant of success on this market. As is standard in clearnet marketplaces, sellers with a bad reputation profile were able to close their account and open a new one. A well-known strategy in darknet markets is to build a good reputation and, at some point, stop sending the products and start scamming new consumers. After these *exit scams*,[9] sellers either definitively leave the market or come back to the market under a new identity (new PGP, new Bitcoin wallet). These strategies can yield high benefits in the short-run, but come at some cost (the time and effort to create a new identity, the risk of being chased by platform managers or deceived consumers). Sellers who consider that the benefits outweigh the costs are thus likely to engage in such exit scams with anonymous re-entry on the market, such that consumers might not be able to distinguish honest new sellers from former scammers when facing a blank reputation profile.

Impact of the shutdown. The shutdown of two of the largest online drug platforms was the largest shock to the illegal industry since the closure of the Silk Road in 2014. By taking control of *Hansa* and running it for one month, European authorities aimed to dismantle the network of criminals who can easily migrate from one platform to another. Although this is likely more effective than just closing the targeted platform, it possibly only had a limited impact on the industry in the medium run. First, the police collected unprotected data, i.e. data from users who did not use PGP encryption or displayed real-life information about themselves. These buyers or sellers are more often amateurs who are not familiar with the standard protection techniques necessary for the use of DNMs. As such, professional buyers or sellers were probably not caught, and only occasional

[9] For an example of an exit scam, see `https://motherboard.vice.com/en_us/article/xyw7xn/darknet-slang-watch-exit-scam`.

consumers and sellers arrested. Second, the takeover by law enforcement authorities likely stimulated the market. While *AlphaBay* and *Hansa* were able to benefit from a well-established reputation, their shutdown prevented the emergence of reputation effects that would lead to the concentration of the market in the hands of a few marketplaces (such as Amazon in clearnet markets). Smaller platforms then benefit from renewed interest, and the entry costs for new entrants will fall. As has been the case in the past, the shutdown of the two market leaders stimulated innovation to increase data protection for all parties (consumers, sellers and platform managers).

Future generations of DNMs are therefore expected to be concentrated in the hands of professionals (in the short-run) and to offer greater transaction anonymity. The overall impact on online product quality is *a priori* ambiguous. On the one hand, the exclusion of non-professional sellers is likely to positively affect drug quality in the short-run. On the other hand, greater anonymity will reduce potential control over sellers and increase the risk of opportunistic behaviors (i.e. sellers who register, carry out a few transactions and then leave the market without fulfilling their contracts) and reduce entry costs for dishonest sellers.

4 Data

To investigate the effects of *Hansa*'s reputation mechanisms, I collected data on the offers that were listed on the website for a series of particular drugs. This collection was carried out via a web-scraping script I developed that used a TOR server to access *Hansa*. The script screened all offers available on March 18th 2017 in four drug categories.

4.1 Drug types

The data from *Hansa* covered four drug categories (Weed, Hash, Ecstasy and LSD). These differ in two dimensions: their effects (stimulants, sedatives or hallucinogens) and their mode of consumption (ingested or smoked).[10] Cannabis is one of the most popular drugs and can be sold either as dried leaves (Weed, also called Marijuana) or as a resin (Hash). Cannabis has two main effects, as a calming drug that also alters perceptions. It can be either smoked (with or without tobacco), or can be eaten as part of a food product (e.g., space cakes). Its consumption can distort sensory perception and change users' mood, thoughts and consciousness. Hash is typically stronger than Weed due to its higher concentration of tetrahydrocannabinol (THC). Cannabis is mostly consumed for recreational or pharmaceutical reasons, as it also serves as a pain-killer. Ecstasy is a psychedelic stimulant drug that is mostly sold as candy-like pills. It contains MDMA molecules, that increase wakefulness and general brain activity. It is frequently consumed in night clubs as it can make individuals feel more alert, affectionate and chatty, and music and colors seem more intense. Finally, Lysigeric-acid-diethylamide (LSD) is also sold as small tablets to be consumed; this psychedelic drug makes users

[10]See: `https://www.nhs.uk/Livewell/drugs/Pages/Drugsoverview.aspx`
, `http://www.rcmp-grc.gc.ca/drugs-drogues/poster-affiche/index-eng.htm`
, and `https://www.nhs.uk/Livewell/drugs/Pages/Dodrugsdamagebrain.aspx`.

see, hear and experience the world differently. It is popular among those who seek hallucinations, hilarity and restlessness.

4.2 Offers

I collected all unique offers on March 18th 2017 using web-scraping techniques for the four drug types described above.[11] For each category of drugs, I accessed the listing of offers that presented offers in decreasing order of popularity. The most important elements of each offer were displayed on the listing page (see Figure A2), and consumers were able to click on the offer to access a dedicated webpage on which they could order. Regarding reputation, the platform displayed for each offer the numbers of positive and negative evaluations of the seller proposing the offer. Positive evaluations were displayed in bold green, while negative evaluations were displayed in bold red. Both numbers were positive integers.[12]

For each offer, I have information on the list number, the title of the offer, the seller's name, the number of positive and negative evaluations of the seller, the number of shipping options and the price in US Dollars and Bitcoin. As a first step, I used an algorithm to identify, for each offer, the quantity of the product proposed. I then checked the algorithm's outcome for each offer by hand. This process sufficed to describe offers for Weed and Hash. For products which are consumed as pills (Ecstasy and LSD), I coded separately the strength and the number of pills. I dropped duplicate offers and extreme prices.[13] The final sample consists of 5,951 unique offers.

Table 1 shows the descriptive statistics for these remaining offers. Weed and Hash are relatively similarly priced (\$9.145 vs. \$8.962 per gram), consistent with these two products being relatively good substitutes for each other (similar use and effects); Ecstasy and LSD are more expensive. This is unsurprising given that a 'joint' of Weed uses about 0.32 grams[14] (\$2.93 per use), while in our dataset, Ecstasy and LSD pills contain on average 0.213 grams (\$3.24 per pill) and 0.146 grams (\$4.86) respectively. The price difference also reflects differences in the duration of the effect (longer for Ecstasy and LSD than for Weed and Hash) and intensity (LSD is stronger than Ecstasy). Second, the number of shipping options is similar for the different drugs. LSD does however have a more international coverage, with 90.7% of offers proposing worldwide shipment options. On the contrary, Weed is the least likely to be offered worldwide (34.5%), while Hash and Ecstasy have similar figures (73.3% and 66.2%). There is considerable heterogeneity in the number of grams contained in offers, both between and within drug types: the standard deviations for the number of grams range from 2.4 (Ecstasy) to 6.4 (LSD) times the means. Last, Ecstasy pills are more concentrated than LSD, which, again, reflects that LSD has a stronger effect.

[11] A *Hansa* offer on was similar to those on Amazon, containing a description of the product (mostly in the offer's title) and price and shipment options. A buyer's acceptance of the offer was non-exclusive, in that purchase was possible as long as the offer was online.

[12] Note from Figure A2 that sellers were also associated with "Levels" that reflected their number of transactions. I was not able to retrieve information on these levels, which might have an additional effect on reputation.

[13] I dropped observations where the price per gram was above the 98th percentile to remove outliers that produced a significant gap between the mean and median of the distribution, and were unlikely to be purchased.

[14] See Ridgeway and Kilmer (2016).

Table 1: Descriptive Statistics.

Drug	Weed	Hash	Ecstasy	LSD
Price per gram in $	9.15	8.96	15.21	33.26
	(3.61)	(4.26)	(8.81)	(12.84)
No. of shipping options	1.90	2.21	2.11	2.35
	(1.25)	(1.30)	(1.29)	(1.54)
Worldwide shipping	0.35	0.73	0.66	0.91
	(0.48)	(0.44)	(0.47)	(0.29)
Number of grams	109.4	125.0	195.2	83.9
	(537.0)	(633.0)	(464.1)	(537.6)
Dosage per pill (mg)			213.4	145.9
			(41.6)	(47.8)
Number of unique offers	2506	1140	1451	854

Note: The figures here are the means, with standard deviations in parentheses.

4.3 Sellers

Table 2 shows the summary statistics for seller reputation. There are fare more positive than negative evaluations (almost 100 times more positive than negative for existing sellers' profiles). This is in line with the stylized facts on clearnet markets. For instance, Cabral and Hortacsu (2010) show that only 0.9% of all comments are negative on eBay, and that the median seller has 1 negative and 819 positive comments.[15] There are few negative evaluations: the median sellers in all four drug markets have no negative evaluations. Sellers with negative feedback also have very many positive evaluations, and the seller who had the most negative feedback in each market also had 1609, 1567, 1508 and 1504 positive evaluations (in the Ecstasy, LSD, Hash and Weed markets respectively). This is consistent with negative feedback being very costly for sellers, so that only those with good reputation can overcome the burden of negative feedback. On the contrary, sellers with only few evaluations are expected to create a new profile when the burden of negative feedback weighs too heavily on their limited positive evaluations.

5 The Relationship between Price and Reputation on *Hansa*

This section proposes the econometric estimation of the relationship between price and reputation. I follow previous work on e-reputation and pricing (e.g., Houser and Wooders (2006); Cabral and Hortacsu (2010)) and consider a log-log specification to capture the elasticity between feedback and prices. In detail, I estimate a multilevel model in which prices are explained by offer-level factors and seller individual effects. These latter include information on the seller's reputation profile (positive

[15]Houser and Wooders (2006) find similar patterns for eBay auctions of Processor III 500: on average, sellers had 0.65 negative comments but 38.74 positive comments.

Table 2: Distribution of sellers' reputation by type of drug

Feedback	Drug	Mean	Standard Dev.	Median	Min	Max
Positive	Weed	176.18	364.65	33	0	2075
	Hash	213.10	433.07	43.5	0	2077
	Ecstasy	154.24	349.66	19	0	2076
	LSD	153.42	402.69	18	0	2078
Negative	Weed	1.07	3.53	0	0	34
	Hash	1.98	5.16	0	0	34
	Ecstasy	2.12	9.58	0	0	94
	LSD	1.14	3.33	0	0	18

The associated number of sellers is 209 for Weed, 106 for Hash, 109 for Ecstasy and 59 for LSD.

and negative feedback), as in Equation (1) below. Formally, I estimate the following model:

$$\begin{aligned} \log(\text{price}_i) &= \beta_0 + \beta X_i + \alpha_{j(i)} + u_i \\ \alpha_j &= \gamma_0 + \gamma_1 \log(1{+}\text{positiveFB}_j) + \gamma_2 \log(1{+}\text{negativeFB}_j) + \rho Z_j + \epsilon_j \end{aligned} \tag{1}$$

where $\alpha_{j(i)}$ is the individual effect of seller j who posted offer i, X_i the vector of offer-level variables, Z_j the vector of seller-level variables, and u_i an idiosyncratic error term that is assumed to be normally distributed. The vector X_i contains information on the (log) number of grams, the number of shipment options, the (log) dosage per pill for Ecstasy and LSD, a dummy variable for the offer being shipped worldwide, the offer's order of appearance when scrolling the website for the given category, and the link number.[16] The vector Z_j includes the number of different offers that seller j has for the same type of drug, and a series of dummy variables for whether the seller also sells the other three drug types (i.e., multi-drug sellers). In this model, the individual effect of seller j is decomposed into the effects of the observed variables Z_j and the unobserved characteristics ϵ_j that are random effects, assumed to be normally-distributed with variance σ^2_ϵ (see Chapters 11 and 12 in Gelman and Hill (2006) for multilevel models).

This is a two-tier multilevel model, where the first level is the offer and the second the seller. I use two estimation methods. The first is a naive OLS specification that does not include seller individual effects. Second, I use Stata's mixed effect model estimation procedure (function *mixed*) to fit the two-tier model in Equation (1). I do not cluster observations at the seller level, since heterogeneity at this level is captured by the individual effects and there is no reason for the offers to be correlated beyond these individual effects (see the robustness checks below).

Tables 3 (OLS) and 4 (Multilevel) present the estimated coefficients in Equation (1) for each

[16]The link number is the offer's unique identifier that is used in the URL to access the offer. It is defined at the date of creation as one plus the link number of the previously-registered offer. Higher link numbers are thus more recent, and controlling for the link number reveals whether there is a trend in prices over time.

Table 3: Regression of log price per gram, OLS.

Variable	Weed	Hash	Ecstasy	LSD
Positive Evaluations (log)	0.00970**	0.0385***	0.0319***	-0.0161**
	(0.00466)	(0.00851)	(0.00686)	(0.00821)
Negative Evaluations (log)	-0.0299***	-0.0630***	-0.0614***	0.0313
	(0.00843)	(0.0161)	(0.0138)	(0.0240)
Number of observations	2,506	1,140	1,451	854
R^2	0.496	0.448	0.574	0.587

Ordinary Least Squares estimation.
Standard errors in parentheses.
Significance levels: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.
The control variables include the (log) number of grams, number of shipment options, (log) dosage per pill in mg for LSD and Ecstasy, a dummy variable for worldwide shipment, the order number, the link number, the number of offers the seller has for this type of drug, a dummy variable for each of the other types of drug the seller proposes, and a constant.

drug type. Table 4 further shows a number of statistics associated with the estimation: the variances of the individual random effects (σ_ϵ^2) and the idiosyncratic error terms (σ_u^2), and the p-value of the likelihood-ratio test that compares the mixed model to an ordinary regression.

The results in Tables 3 and 4 show that sellers with more positive feedback price significantly higher for three types of drugs (Weed, Hash and Ecstasy);[17] the reverse holds for negative feedback, which is associated with lower prices. The estimates for the Hash market lose significance in the multilevel model (which better captures seller heterogeneity), although they retain the same sign. The effects in the LSD market are opposite, but are insignificant in the multilevel model and with only one significant estimate in the OLS model.[18]

These results are overall in line with those on clearnet markets (Dellarocas et al. (2004)), where prices rise with reputation. For instance, Houser and Wooders (2006) find that 10% higher positive feedback is associated with a 0.17% higher prices, but 10% higher negative feedback with 0.33% lower prices. The size of the reputation effect is similar here: 10% higher positive feedback for Weed sellers is associated with 0.32% higher prices (with analogosus figures of 0.35% for Hash and 0.61% for Ecstasy); similarly, a Weed seller with 10% more negative feedback has prices 0.84% lower (with this figure being 1.1% for Ecstasy).

Last, the regression diagnostics indicate that the multilevel model performs significantly better than the standard regression model (that without individual seller effects). We further observe

[17]The full regression tables appear in Appendix Tables B1 and B2.

[18]The negative coefficient for positive evaluations for LSD is not consistent with the results in the clearnet-market literature. This should be interpreted with caution as it is not significant in the multilevel model, and since this drug type has the fewest sellers. The negative estimated relationship might reflect a non-competitive market, in which sellers with a low reputation profile might try to overprice their products. Alternatively, we can not rule out the possibility that highly-ranked sellers may operate on the quantitative margin, and try to charge low prices to increase their sales.

Table 4: Regression of log price per gram, multilevel model.

Variable	Weed	Hash	Ecstasy	LSD
Positive Evaluations (log)	0.0327***	0.0353*	0.0612***	-0.0281
	(0.0104)	(0.0209)	(0.0216)	(0.0351)
Negative Evaluations (log)	-0.0839**	-0.0253	-0.111**	0.0231
	(0.0327)	(0.0501)	(0.0549)	(0.111)
Number of observations	2,506	1,140	1,451	854
Number of sellers	209	106	109	59
σ^2_ϵ	0.0696	0.1297	0.1456	0.1733
	(0.0082)	(0.0198)	(0.0212)	(0.0346)
σ^2_u	0.0565	0.0524	0.0357	0.0338
	(0.0017)	(0.0023)	(0.0014)	(0.0017)
LR-test (p-value)	<0.1%	<0.1%	<0.1%	<0.1%

Multilevel random effect model.
Standard errors in parentheses.
Significance levels: *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.
The control variables include the (log) number of grams, number of shipment options, (log) dosage per pill in mg for LSD and Ecstasy, a dummy variable for worldwide shipment, the order number, the link number, the number of offers the seller has for this type of drug, a dummy variable for each of the other types of drug the seller proposes, and a constant.

that most of the unexplained heterogeneity in prices comes from seller characteristics. The ratio $\frac{\sigma^2_\epsilon}{\sigma^2_\epsilon+\sigma^2_u}$ shows the proportion of the unexplained heterogeneity due to the seller (vs. the individual-offer level). This is 55.2% for Weed, 71.2% for Hash, 80.3% for Ecstasy and 83.7% for LSD. In other words, the unexplained heterogeneity in price strategies is in the majority (55.2% to 83.7%) explained by seller heterogeneity.

Robustness Checks. I evaluate the robustness of the above results in a number of other specifications. First, it is possible that some of the offers scraped on *Hansa* were actually not accepted by consumers: sellers with no reputation may then affect the regression analysis but be outliers on the market, as their offers are never purchased. I thus re-run the above multilevel model for the four drug types excluding sellers with no reputation profile: the results in Appendix Table B3 remain unchanged. Second, I consider that sellers may have multi-offer strategies and not set prices independently across their offers. A seller may for example price more for lower quantities to encourage consumers to purchase higher quantities. I account for this interdependence between offers from the same seller by clustering standard errors at the seller level. The results in Appendix Table B4 again confirm the above baseline findings. Last, I account for the relatively large share of sellers without negative feedback by replacing the (log) number of negative evaluations by a dummy for seller having at least one negative evaluation. The results in Appendix Table B5 show that the impact of positive feedback is not changed in this new specification. The coefficients on negative feedback do not change sign, retain their significance for Weed, and lose significance for Ecstasy but do come close to rejecting the null hypothesis ($p = .106$).

6 Structural Analysis of the Price-reputation Relationship on DNM

This section proposes a model of price-setting on Darknet Markets that I estimate using *Hansa* data. The objective is to first estimate the risk of scamming on the market, which is the expected probability that a random seller effectively send the ordered good (fulfilling the order without understrength or fake drugs), and second consumer surplus after the transaction. The model relies on the reputation given by the seller's number of positive and negative evaluations displayed on the offer page. Feedback provides market-specific information about the seller's type, which may affect his/her pricing. The quality of this information will however depend on market characteristics, which can vary across drug type.

6.1 Model

The following model is based on the perspective of a buyer who faces numerous offers on the platform for a given type of drug. I first discuss the information that a buyer can infer from the seller's reputation based on the market characteristics, and then consider how market competition is assumed to work on these markets, and how conflicts between buyers and sellers are resolved.

Seller's reputation. In this model of reputation-building by sellers we need to understand how positive and negative feedback is generated. I make a number of assumptions regarding feedback behavior. First, I assume that consumers can have two types of experience: positive if they receive the product (i.e. if it was effectively sent by the seller, was not fake or understrength, and was not seized by customs) or negative if they do not receive the product as promised in the offer. I denote the probability of customs seizure by γ and the probability that seller j effectively send the order as promised by ϕ_j. Buyers can either remain silent or report their experience via feedback (positive or negative): buyers report their experience with probability χ and remain silent with probability $1 - \chi$.[19]

[19] One of the underlying assumptions here is that the probability of giving feedback is the same for positive and negative experiences. To my knowledge, Dellarocas and Wood (2008) is the only paper that tries to address this issue in the economic literature. They find that individuals have an 80% probability of reporting a positive experience, but only a 40% probability of reporting a negative experience. These results should however be interpreted with caution in the context of DNMs, as the environments are very different. Dellarocas and Wood (2008) considers the case of eBay, where buyers must compete to win the auctions. On this platform, sellers can exclude buyers who have a negative feedback score (see: `https://www.ebay.com/help/selling/listings/creating-managing-listings/setting-buyer-requirements?id=4152`). Reciprocity has been shown to help determine feedback-giving, which makes it risky for consumers to report negative experiences. In the case of *Hansa*, buyers could not be excluded from offers, which reduces the risk from giving negative feedback. Second, buyers could more easily close their profile and open a new one on *Hansa*. This is not the case for eBay, where users are closely-monitored to prevent the creation of new accounts (`https://www.thebalancesmb.com/dont-reregister-after-getting-suspended-1140315`). Third, eBay users act both as sellers and buyers with the same profile. In this case, leaving a negative comment as a buyer creates the possibility of receiving, by reciprocity, negative feedback that will then affect sales. As *Hansa*

Reputation building. Let r_t be the number of positive evaluations of a seller after t evaluations. The probability that the seller receive a new positive evaluation from the next transaction is the probability of a good experience ($\phi_j(1-\gamma)$) times the probability of reporting this experience (χ); that of a negative evaluation is the probability of not receiving the order as expected ($1-\phi_j(1-\gamma)$) times the probability of reporting this experience (χ). Conditional on receiving feedback, the probability that the next feedback be positive for the seller is $\phi_j(1-\gamma)$[20] and $1-\phi_j(1-\gamma)$ for negative feedback.

The evolution of a seller's stock of positive feedback is given by the following relationship:

$$r_{t+1} = \begin{cases} r_t + 1 & \text{with probability } q_j = \phi_j(1-\gamma) \\ r_t & \text{with probability } 1 - q_j \end{cases} \tag{2}$$

Honest and dishonest sellers. In the following, I assume that the market is made up of two kinds of sellers: honest sellers, who always fulfill orders ($\phi_H = 1$), and dishonest sellers, who send the goods as described in the offer with probability ϕ_D ($\phi_D = \phi$). Denote by $\theta \in (0,1)$ the proportion of honest sellers on the market. From the above stochastic reputation-building process, I am able to retrieve the probability that, given their reputation profile, a seller be honest ($Pr[\phi = \phi_H | r, t]$). These calculations appear in Appendix C.

Buyer's utility. I assume a risk-neutral rational representative buyer who chooses among all the offers available on the platform. The utility from seller j's offer is denoted by u_j. A customer who receives his order j obtains utility u_j and pays price p_j. A customer who does not receive the order, either because it was understrength, fake, not sent or seized, ends up in one of two situations: with probability α_j the platform manager will agree with seller j, and the buyer will have to pay p_j without receiving his order;[21] with probability $1-\alpha_j$ the platform manager will agree with the buyer and the buyer will not pay p_j (and not receive any utility).

The utility of the buyer facing offer j is then:

specialized mainly in one type of product (drugs), buyers and sellers are far more distinct than on eBay (where people can produce in one sector and sell in another. Overall, I believe that the probability of reporting a negative experience on *Hansa* was significantly higher than that estimated for eBay by Dellarocas and Wood (2008). I therefore assume that the probabilities of reporting each type of experience are equal.

[20]This corresponds to $\frac{\Pr[\text{positive FB}]}{\Pr[\text{positive FB}]+\Pr[\text{negative FB}]} = \frac{\chi\phi_j(1-\gamma)}{\chi\phi_j(1-\gamma)+\chi(1-\phi_j(1-\gamma))} = \phi_j(1-\gamma)$.

[21]This is possible via the use of the multisig system, which requires at least two of the three parties to agree to finalize the transaction and unlock the payment. If the platform manager agrees with the seller, the latter receives payment; if the platform manager agrees with the buyer, the payment is wired back to the buyer. Although the exact decision rules for managers were not explicitly set out on *Hansa*, they indicated that they considered the seller's reputation when making their decision.

$$
\begin{aligned}
u_j &= \phi_j(1-\gamma)(u-p_j) - (1-\phi_j)\alpha_j p_j - \phi_j\gamma\alpha_j p_j \\
&= -p_j[(1-\phi_j)\alpha_j + \phi_j\gamma\alpha_j + \phi_j(1-\gamma)] + \phi_j(1-\gamma)u \\
&= -p_j[\alpha_j(1-\phi_j+\phi_j\gamma) + \phi_j(1-\gamma)] + \phi_j(1-\gamma)u \\
&= -p_j[\alpha_j(1-(1-\gamma)\phi_j) + \phi_j(1-\gamma)] + \phi_j(1-\gamma)u
\end{aligned} \tag{3}
$$

Given that the seller's reputation is public, the buyer considers this reputation (r, t) when forming expectations about the utility associated with the offer:

$$
\mathbb{E}(u_j|r,t) = -p_j[\alpha_j(1-(1-\gamma)\mathbb{E}(\phi_j|r,t)) + \mathbb{E}(\phi_j|r,t))(1-\gamma)] + \mathbb{E}(\phi_j|r,t)(1-\gamma)u \tag{4}
$$

with $\mathbb{E}(\phi_j|r,t) = Pr[\phi = \phi_H|r,t] + \phi(1 - Pr[\phi = \phi_H|r,t])$.

Market competition. Given that all offers are easily accessible on the platform, the (sufficiently) large number of sellers and the absence of entry costs (except reputation), I assume perfect competition. In particular, I assume that all offers yield the same expected utility for buyers: if sellers were to see that, given their reputation, they could increase their profit by increasing their prices they would do so.

Given that customers take sellers' reputation into consideration when they decide which good to buy, perfect competition yields the following condition:

$$
\forall j, \mathbb{E}(u_j|r,t) = \mu \tag{5}
$$

Prices in equilibrium are therefore defined by the following equation:

$$
p_j^* = \frac{\mathbb{E}(\phi_j|r_j,t_j)(1-\gamma)u - \mu}{\alpha(r_j,t_j)[1-(1-\gamma)\mathbb{E}(\phi_j|r_j,t_j)] + \mathbb{E}(\phi_j|r_j,t_j)(1-\gamma)} \tag{6}
$$

Conflict resolution. A particular feature of Hansa is the role of the platform manager in the case of conflict (when the buyer did not receive their order). I assume that conflicts arise either because sellers did not send the good or the good was seized by Customs.[22] In case of conflict, it is well known that the platform manager considers the reputation of the seller in order to decide

[22] I do not consider cases where buyers misreport receiving the good. This would require information on buyers as well, which I do not have in the dataset. If some buyers are dishonest, the following results underestimate the trustworthiness of sellers on the market. Negative feedback can be both honest and dishonest, implying that there is less scamming than the negative feedback indicates.

whether he/she is of good faith, and whether he/she deserves the payment. I therefore assume that the platform manager pays the seller with probability $\alpha(r_j, t_j) = \frac{Pr[\phi=\phi_H|r_j,t_j]^\tau}{\beta}$.[23]

6.2 Parameter Estimation

To estimate market characteristics, I assume that the observed prices correspond to equilibrium prices subject to random normal shocks:

$$p_j = p_j^* + \epsilon_j \tag{7}$$

where ϵ_j is a normally-distributed random term with mean 0 and variance σ^2.

The log-likelihood function is:

$$LL(p; p^*, \sigma^2) = -\frac{N}{2}ln(2\pi) - \frac{N}{2}ln(\sigma^2) - \frac{1}{2\sigma^2}\sum_{j=1}^{N}(p_j - p_j^*)^2 \tag{8}$$

where p is the vector of observed prices[24] and p_* the associated vector of prices predicted by the model.

I estimate the above model parameters via exact maximum likelihood. To improve the estimation, I set out intervals of possible values for the parameters of interest. First, γ, ϕ and θ are probabilities and proportions and so are assumed to take on values between 0 and 1 (excluded). Second, u, the utility a buyer derives from a good cannot be below the price he/she is ready to pay for it. I therefore take the lowest price observed as a lower bound for buyer utility ($u > \min(p_j)$). Third, the expected utility of a given offer must be positive, and cannot exceed the utility of the good itself ($0 < \mu < u$). Finally, I impose an upper bound on u to have a closed set. I assume that the utility obtained from the good does not exceed twice the maximum price observed on the market ($u < 2\max(p_j)$). [25]

I make two further estimation assumptions. First, whenever a seller has more than 100 evaluations, he/she is an honest seller (i.e. $Pr[\phi_k = \phi_H|t \geq 100] = 1$). This assumption helps to

[23]The two parameters τ and β allow us to capture the shape of the decision function of the platform manager. Based on Hansa policy, I assume that the platform manager is more likely to decide in favor of the seller in case of conflict the higher is the seller's reputation. In other words, $\alpha(.)$ is expected to rise with the probability that the seller be honest. The parameter β captures the overall burden on the seller: when the seller is honest with probability 1, the probability that the platform manager decide in his favor in case of conflict is $1/\beta$. The higher is β, the less the seller will win even when he has a good reputation. The parameter τ captures the curvature of the function. When τ is equal to 1, the decision function is a linear function of the probability that the seller be honest. As long as τ is greater than zero, the function is increasing. Low positive values of τ are associated with higher probabilities of winning, whatever the reputation of the seller. In the extreme case, when $\tau = 0$, the probability of winning becomes $1/\beta$ for all sellers.

[24]I consider here the average offer price per gram per seller corrected for the log of the number of grams, the number of shipment options, the unique identifier, the link number and the existence of an option for worldwide shipment.

[25]I do not estimate the parameter δ presented in Appendix C, which is instead endogenously determined as the solution to Equation (26).

reduce the number of matrix products required to calculate $Pr[\phi|t]$ (without it, calculating $Pr[\phi|t]$ for sellers would require 2075! matrix products per type of seller and for each iteration). Second, I assume that the threshold w is given by the lowest proportion of positive evaluations observed on each drug market.

I estimate the associated likelihood in three steps. I first decompose each parameter space into 15 equidistant points, excluding the two boundaries. The proportions therefore take the values $\frac{1}{16}, \frac{2}{16}, ..., \frac{14}{16}, \frac{15}{16}$. For each combination, I compute the exact ML. Second, I use the set of parameters leading to the highest likelihood as starting values for optimization, which is carried out using the *optim* package in R, with a user-defined log-likelihood function. All estimations converged. I estimate the 95% confidence interval for each parameter via likelihood-profile confidence intervals.[26]

Table 5: The estimation of market parameters

	Weed	Hash	Ecstasy
Proportion of honest sellers ($\widehat{\theta}$)	47.94%	68.29%	48.53%
	[46.44%, 50.54%]	[65.79%, 72.79%]	[42.03%,57.03%]
Probability that a dishonest seller send the order ($\widehat{\phi}$)	68.13%	58.89%	76.32%
	[65.63%, 71.63%]	[40.39%, 78.39%]	[71.82%,81.82%]
Probability of seizure ($\widehat{\gamma}$)	15.77%	58.58%	25.13%
	[14.27%, 17.27%]	[56.1%, 61.2%]	[22.63%,27.63%]
Utility of consuming the good ($\widehat{u}$)	23.03	27.97	106.70
	[22.71, 23.34]	[26.28,29.66]	[104.88, 108.54]
Expected utility of an offer ($\widehat{\mu}$)	5.78	0.404	26.75
	[5.57, 5.98]	[0,0.959]	[25.58, 27.90]
Parameter of the conflict resolution function $\widehat{\tau}$	0.511	0.167	0.539
	[0.33, 0.946]	[0.122,0.212]	[0.364, 0.974]
Parameter of the conflict resolution function $\widehat{\beta}$	1.00	1.00	1.77
	[1.00, 1.12]	[1.00,1.22]	[1.43, 2.29]
Probability that a random seller send the order ($\widehat{\theta}+(1-\widehat{\theta})\widehat{\phi}$)	83.41%	86.96%	87.81%
	[81.89%, 85.21%]	[80.96%,94.77%]	[81.01%,96.85%]
Proportion of the utility left to the consumer ($\widehat{\mu}/\widehat{u}$)	25.1%	1.4%	25.1%
	[21.9%,27.9%]	[0%,7.5%]	[18.9%,29.4%]

Note: The 95% profile-likelihood confidence intervals appear in brackets.

Table 5 shows the estimated parameters for the three drug types for which reputation had a statistically-significant impact in the previous section (Weed, Hash and Ecstasy). First, dishonest sellers send on average at least half of their orders ($\widehat{\phi} > 50\%$ in all markets), suggesting a relatively

[26] I rely on likelihood-profile confidence intervals rather than standard errors derived from the Cramer-Rao bound as the set of parameters is constrained and the numerical estimation of the Hessian matrix requires going beyond these boundaries. The profile likelihood 95% CI is constructed by moving to the right and left of each estimated value and retaining all values that are not rejected by a likelihood-ratio test with $\alpha = 5\%$. The Appendix sets out the details of the procedure used to determine the profile likelihood 95% CI of parameter combinations.

low degree of scamming: even dishonest sellers default under half of the time, which is relatively low given the lack of legal redress. This mixed strategy is the least detrimental in the Ecstasy market where 76.32% of the orders are expected to be actually sent. This proportion drops to 68.13% for Weed and 58.89% for Hash. Second, to compare the overall quality of services over the three types of drugs, we need to take into account both the proportion of (dis)honest sellers, and the probability that dishonest sellers effectively send the goods. On average, 5 to 7 out of 10 sellers are expected to be 'honest' in these three marketplaces ($\widehat{\theta}_{\text{Weed}} = 47.94\%$, $\widehat{\theta}_{\text{Hash}} = 68.29\%$ and $\widehat{\theta}_{\text{Ecstasy}} = 48.53\%$). To illustrate the quality of services associated with each type of drug, I calculate the probability that a buyer ordering from a randomly-selected seller will actually have their order shipped ($\theta+(1-\theta)\phi$). This probability lies between 83% (Weed) and 87% (Ecstasy). This high probability of sending the ordered goods reflects the good operation of the *Hansa* market.

In addition to the probability of having the order sent, consumer utility depends further on two elements: the probability of Customs seizure and the surplus that is left after payment. Seizure probabilities vary greatly by drug type. Weed has the lowest seizure rate ($\widehat{\gamma}_{\text{Weed}} = 15.77\%$), probably because it is now legal in a growing number of places and its relatively low rate of international shipment (34.5% in Table 1). About one-quarter of Ecstasy orders are seized ($\widehat{\gamma}_{\text{Ecstasy}} = 26.75\%$), with this figure rising sharply to about one half for Hash ($\widehat{\gamma}_{\text{Hash}} = 58.58\%$), which has one of the highest international-shipment rates (73% in Table 1). We furthermore observe two market types regarding the surplus left to the consumer. I calculate the ratio $\frac{\mu}{u}$, which reflects the percentage of consumer utility from the consumption of the good that remains once the offer is accepted. Consumer final utility is about one-quarter of the total utility they derive from consuming the good for Weed (25.1%) and Ecstasy (25.1%). However, this proportion is much lower for Hash, where all the surplus is extracted from the consumers ($\frac{\widehat{\mu}_{\text{Hash}}}{\widehat{u}_{\text{Hash}}} = 1.4\%$). We can see in Table 5 that this smaller ratio mainly results from a lower expected utility of the offers ($\hat{\mu} = 0.404$), which, in turn, comes from a higher probability of seizure (as discussed above). Given that drug packages are more likely to be detected when they cross country borders, Hash offers are less likely to be delivered to customers, which reduces the expected utility of the offers.

Results. The Weed, Hash and Ecstasy marketplaces are characterized by a good level of service, with the probability that a random seller effectively send the good as promised being above 80%. Weed and Ecstasy sellers extract about 75% of consumer surplus, while the analogous figure for Hash is almost 100%.

Quality of the estimation. In order to assess the quality of the model estimation, I propose to discuss how well it does in explaining out-of-sample observations. To do so, I rely on a bootstrap process of 400 iterations, in which I estimate the above model 400 times for each type of drug by excluding one observation at each iteration and calculating the predicted price for the excluded observation. The results of this bootstrap process appear in the Appendix (see Table B6). First, we see that the average error is close to zero, suggesting that the model has no systematic bias. This is confirmed by the t-test that fails to reject the null hypothesis that the model has no systematic bias. However, when looking at the range of prices, it appears that a significant share of the price heterogeneity remains unexplained. For Weed, the lowest (respectively highest) price predicted by the model is 10.99 (resp. 13.68), while the lowest observed price is 7.83 (resp. 20.34). We face similar concerns for Hash and Ecstasy.

Robustness Check. The above specification assumes that buyers have equal probabilities of reporting positive and negative experiences. In the online Appendix, we explore the robustness of these results by considering a higher probability of reporting a negative than a positive experience. The associated results presented in the online Appendix are very similar to those presented above.

7 Discussion

The shutdown of the two leading Darknet Markets (*Alphabay* and *Hansa*) by Western authorities likely had short- and medium-run effects on online drug-dealing. In the short-run, the former sellers and buyers from *AlphaBay* and *Hansa* likely migrated to competing platforms to conduct their online activities. However, Law enforcement probably affected these activities in two ways. First, the Dutch police claim to have collected over 10,000 postal addresses that they transferred to Europol. The wave of arrests following this revelation is likely to have affected market composition. Second, the shutdown of the two leading platforms will have fed through to the existing platforms. Rising concerns over privacy for sellers and buyers together with the market share left by the two leading platforms is expected to have stimulates competition across platforms. New platforms may then emerge with technological changes (as was the case for previous shutdowns), on which sellers will start with blank reputation profiles. In the following, I discuss the short-run impact of the shutdown on online drug-dealing. I first discuss the short-run impact of the shutdown should all surviving sellers migrate to a new platform, and second when they migrate to an existing platform.

7.1 Migration to a New Platform

Composition Effect. First, the shutdown of the two leading platforms will affect the composition of the sellers who operate on online drug markets. Considering the market characteristics from Section 6, let ρ denote the proportion of honest sellers who will continue their activities after the shutdown of the two platforms (e.g., those who are not are caught by the police). Assuming that honest sellers are more likely to be professionals than dishonest sellers, I postulate that honest sellers are more likely to continue their activities after the shutdown (as they are less likely to have disclosed private information and, therefore, to be arrested).[27] I denote by $\rho\nu$ the proportion of

[27] Honest sellers are expected to ship the ordered good every time a transaction is made. To do so, they must undertake considerable investments, and are therefore more likely to be professional dealers. On the contrary, anyone can act as a dishonest seller. The mixed strategy required to be a profitable dishonest seller on the market demands that opportunistic sellers fulfill only some of their transactions: individuals can buy some drugs from professional sellers and resell them with a probability of effectively sending the order of less than one. I do not rule out the possibility that some dishonest sellers are professionals, but I assume that being an honest seller requires more professionalism than being a dishonest seller.

dishonest sellers who continue operating after the shutdown (with $0 < \nu < 1$).

The composition effect of the shutdown of the two DNMs can be captured by the change in the probability that a random seller effectively send the good on the market. Before the shutdown, this probability was given by:

$$\begin{aligned} M_1 &= \theta\phi_H + (1-\theta)\phi_D \\ &= \theta + (1-\theta)\phi \end{aligned} \tag{9}$$

After the shutdown, this probability becomes:

$$\begin{aligned} M_2 &= \widetilde{\theta}\phi_H + (1-\widetilde{\theta})\phi_D \\ &= \widetilde{\theta} + (1-\widetilde{\theta})\phi \end{aligned} \tag{10}$$

where $\widetilde{\theta}$ is the new proportion of honest sellers. We have: $\widetilde{\theta} = \frac{\theta\rho}{\theta\rho+(1-\theta)\rho\nu} = \frac{\theta}{\theta+(1-\theta)\nu}$ (by Bayes' rule).

The change in the probability of shipping the good is given by:

$$\begin{aligned} \Delta M &= \frac{M_2 - M_1}{M_1} \\ &= \frac{\widetilde{\theta} + (1-\widetilde{\theta})\phi - \theta - (1-\theta)\phi}{\theta + (1-\theta)\phi} \\ &= \frac{(\widetilde{\theta} - \theta)(1-\phi)}{\theta + (1-\theta)\phi} \end{aligned} \tag{11}$$

Given our estimates of θ and ϕ, we can calculate the composition effect of the shutdown of the *Hansa* market for given values of ν. Table 6 shows the estimated effects for each drug type under three scenarios: honest sellers are 50% more likely to continue their activities after the shutdown than dishonest sellers ($\nu = \frac{1}{1.5}$), twice as likely ($\nu = \frac{1}{2}$) or three times as likely ($\nu = \frac{1}{3}$).

The estimates in Table 6 show that the effects in the three markets are similar. If honest sellers are 50% more likely to continue after the shutdown than dishonest sellers, we predict an increase in service quality ranging from 2.71% (Ecstasy) to 3.85% (Weed). This effect is larger the more likely honest sellers are to survive relative to dishonest sellers. In the most extreme scenario, when honest sellers are three times as likely to continue their activity, we observe an increase in good shipment of up to 9.74% for Weed, 8.65% for Hash and 6.84% for Ecstasy. The somewhat lower Ecstasy figure mainly reflects that dishonest sellers already send the offers quite regularly for this drug type (76%), leaving less room for improvement.

Table 6: The estimated effects of the shutdown of the Hansa Market.

Effect	Scenario	Weed	Hash	Ecstasy
Composition effect (ΔM)	$\nu = \frac{1}{1.5}$	+3.85 %	+3.82%	+2.71%
		[+3.42%,+4.25%]	[+1.50%,+5.98%]	[+0.91%,+3.50%]
	$\nu = \frac{1}{2}$	+6.45 %	+6.08%	+4.54%
		[+6.37%,+7.12%]	[+2.35%,+9.52%]	[+1.42%,+6.3%]
	$\nu = \frac{1}{3}$	+9.74 %	+8.65%	+6.84%
		[+8.59%,+10.78%]	[+3.30%,+13.55%]	[+1.98%,+9.57%]
Pooling effect (Δp)		-15.78%	-9.96%	-7.74%
		[-17.71%,-13.61%]	[-22.72%,-4.74%]	[-15.83%,-2.18%]
Total effect (Δp)	$\nu = \frac{1}{1.5}$	-13.37%	-7.53%	-6.57%
		[-14.97%,-11.53%]	[-17.24%,-3.60%]	[-14.47%,-1.69%]
	$\nu = \frac{1}{2}$	-11.53%	-6.04%	-5.67%
		[-12.91%,-9.95%]	[-13.91%,-2.89%]	[-13.17%,-1.36%]
	$\nu = \frac{1}{3}$	-9.02%	-4.33%	-4.42%
		[-10.08%,-7.76%]	[-10.03%,-2.07%]	[-11.03%,-0.98%]

Composition effect: the estimated change in quality (the probability that a random seller effectively ship his/her order).
Pooling and total effects: the estimated change in price for an average seller.
Note: The 95% profile-likelihood confidence intervals appear in brackets.

Pooling Effect. The shutdown of the *Hansa* Market will force existing sellers and buyers to migrate to emerging or existing platforms. Both honest and dishonest *Hansa* sellers will open new profiles on these platforms with blank reputation profiles. Buyers then face a pooled market in which they cannot differentiate between new honest and dishonest sellers. In the long-run, the surviving honest sellers will be able to reconstruct their reputations. However, in the short-run honest sellers will suffer in this pooling market that erases their (positive) reputation profile.

Consider the case where all surviving sellers migrate to a new platform and start from scratch. Sellers used to make a profit of $p_j^*(r_j, t_j, \theta) - c_j$ per sale in the Hansa Market (where c_j is the cost associated with the delivery of their service ϕ_j). To determine the pooling effect, I assume that the average service quality remains unchanged after the shutdown. Assuming that sellers do not change strategies (i.e., they keep the same probability of shipping the offers), the per sale profit or loss is:

$$\Delta p = \frac{q(\theta) - p_j^*(r_j, t_j, \theta)}{p_j^*(r_j, t_j, \theta)} \tag{12}$$

where $q(\theta)$ is the unique price on the new market on which all sellers have a blank reputation, and the proportion of the two seller types is unchanged. As the reputation system disappears the price equation simplifies to:

$$q(\theta) = \frac{\mathbb{E}(\phi)(1-\gamma)u - \mu}{\alpha[1-(1-\gamma)\mathbb{E}(\phi)] + \mathbb{E}(\phi)(1-\gamma)} \tag{13}$$

with $E(\phi) = Pr[\phi = \phi_H] + (1 - Pr[\phi = \phi_H])\phi$, $Pr[\phi = \phi_H] = \theta$, and $\alpha = \frac{\theta\tau}{\beta}$.

The estimated values of Δp for the three drug types appear in Table 6. There is a sharp drop in the average seller price on the three markets, which is largest for Weed where the average seller reduces price by about one sixth (-15.78%). The impact is smallest for Ecstasy (-7.74%), since the probability that dishonest sellers send their offers is relatively high: being pooled with dishonest sellers in this case is less costly than being pooled with dishonest sellers who ship their offer more rarely.

Total Effect. I now look at the total effect of the shutdown of the two leading platforms. The total effect is the sum of the two above phenomena, namely the increase in quality and the absence of reputation. Sellers will sell at a lower price to compensate for the absence of reputation, but can also price higher due to the relatively sharper drop in dishonest sellers.

$$\Delta p = \frac{q(\tilde{\theta}) - p_j^*(r_j, t_j, \theta)}{p_j^*(r_j, t_j, \theta)} \tag{14}$$

The total-effect estimations are shown in the last three rows of Table 6. The pooling effect dominates: all prices are expected to fall following the shutdown. The effect is of course mitigated by the change in quality: the more dishonest sellers stop trading, the smaller the drop in price for average sellers. In all scenarios, the Weed market is the most heavily affected (a price change of -9.0% to -13.4%). This mainly reflects the strong pooling effect depicted above. The Weed market is sensitive to the proportion of dishonest sellers who stop their activity. The average price effect ranges from -4.3% to -7.5%. Finally, Ecstasy offers are the least affected by the shutdown of the two leading platforms (a price change of - 4.4% to -6.6%). This is mainly driven by the lower heterogeneity between dishonest and honest sellers on the Ecstasy market ($\phi_H = 100\%$ and $\widehat{\phi}_D = 76.3\%$).

7.2 Migration to an Existing Platform

The above discussion provides some qualitative insights about the impact of the Hansa shutdown on surviving sellers. It considers however the extreme case where the surviving sellers would migrate to an empty marketplace. While it is possible in the medium-run that new platforms emerge, I propose now to consider the intermediate case where surviving sellers migrate to an existing Platform (that I will refer to as *Platform B*) with pre-existing sellers who have already constructed a reputation profile.

First, let us denote by s_H the number of Hansa migrant sellers and s_B the number of historical sellers on Platform B. Denote by $s = \frac{s_H}{s_H + s_B}$ the relative size of the Hansa migrants compared to the historical Platform-B sellers. Whenever $s > 0.5$, there are more migrant sellers from Hansa than historical Platform-B sellers. On the contrary, $s < 0.5$ indicates that there are more historical Platform-B sellers than Hansa migrants.

Second, let M_H, M_B and M_{HB} be market quality in the pre-shutdown Hansa market, the pre-migration Platform B, and the post-migration Platform B respectively. We also denote by $M_{H'}$ market quality for surviving Hansa sellers. I postulate that the pre-migration market quality in Platform B can be expressed as a function of the quality of Hansa: $M_B = \kappa M_H$. If $\kappa = 1$, both markets were of the same quality before the shutdown. If $\kappa = 0.9$, the quality of Platform B before the shutdown was 10% lower than that of Hansa.

In this case, the quality of the combined market (i.e., post migration) is given by:

$$M_{HB} = sM_{H'} + (1 - s)M_B \tag{15}$$

The composition effect is now defined as the change in quality that Platform B experiences, namely:

$$\Delta M = \frac{M_{HB} - M_B}{M_B} \tag{16}$$

The total effect for a surviving seller of Hansa is now defined as:

$$\Delta p_H = \frac{p_j^*(0, 0, \theta_{HB}) - p_j^*(r_j, t_j, \theta_H)}{p_j^*(r_j, t_j, \theta_H)} \tag{17}$$

The impact of Hansa's shutdown on Platform B therefore depends on three parameters: the likelihood that honest sellers be caught by the police relative to dishonest sellers (the parameter ν discussed in the previous subsection), the relative quality of offers on Platform B compared to those on Hansa before the shutdown (κ) and the weight of Hansa migrants on Platform B after the migration (s). First, Hansa was the second-largest platform on the darknet and was known to be more secure than other platforms, so that the quality of the Hansa market was very likely higher than that on the remaining platforms. I thus assume three values of κ: Platform-B quality was the same as that in Hansa pre-shutdown ($\kappa = 1$), 10% lower ($\kappa = 0.9$) or 20% lower ($\kappa = 0.8$). Second, Alphabay and Hansa were the two largest platforms operating at the time the data were scraped, so that Hansa was larger than any of the other surviving platforms. The main question is whether the *surviving* Hansa sellers were more numerous than the existing Platform-B sellers. I explore three scenarios: there were as many surviving Hansa sellers as historical Platform-B sellers

($s = 0.5$), 50% more ($s = 0.6$) or one third fewer ($s = 0.4$). Third, as we have already discussed the impact of ν in the previous subsection, I consider a fixed parameter ν that is equal to the median value explored above, i.e. $\nu = \frac{1}{2}$. This corresponds to the case where dishonest sellers are twice as likely to be arrested as honest sellers.

I present the results of these new simulations in Table 7. First consider the change in quality on Platform B following the migration of Hansa's surviving sellers. From the assumption that Hansa was of better quality, overall Platform-B quality will rise. The estimates ranges from +2.58% to +19.83% for Weed, from +2.43% to +19.56% for Hash, and from +1.81% to +18.40% for Ecstasy. The estimates are similar for all types of drugs, which is unsurprising given that estimated quality was similar across drug type. As expected, Platform B benefits from the largest rise in quality the lower its original quality (i.e. ΔM is increasing in κ). We also see that the rise in quality is higher the more Hansa sellers migrate to Platform B (i.e. ΔM is increasing in s).

Second, there are three conflicting effects on the total impact. First, surviving Hansa sellers lose their reputation, which is behind their market power to charge higher prices. Second, the higher was the quality on Hansa compared to Platform B, the more low-reputation individuals are likely to be of good quality (as a share share of blank-reputation sellers come from Hansa). We can see that this is indeed the case: for instance, as κ falls from 1 to 0.9 for Weed (and $s = 0.4$), the change in prices for the average Hansa seller changes from -5.49% to -4.89%. Third, as the relative size of the surviving Hansa sellers rises, we become increasingly close to the discussion above where surviving Hansa sellers start on a new platform. This reduces the prices that the median seller can charge. We do indeed see prices that fall with the relative share of surviving Hansa sellers, from -5.49% to -7.35% for Weed ($\kappa = 1$); we find similar effects for Hash and Ecstasy.

Table 7: Simulations of the impact of migration to Platform B

Weed	$\kappa = 1$	$\kappa = 0.9$	$\kappa = 0.8$
s=0.4	$\Delta M = +2.58\%$	$\Delta M = +7.31\%$	$\Delta M = +13.22\%$
	[2.28%,2.85%]	[6.98%,7.61%]	[12.85%,13.56%]
	$\Delta p_H = -5.49\%$	$\Delta p_H = -5.03\%$	$\Delta p_H = -4.89\%$
	[-8.25%,-2.88%]	[-7.92%,-2.20%]	[-7.83%,-1.96%]
s=0.5	$\Delta M = +3.22\%$	$\Delta M = +9.14\%$	$\Delta M = +16.53\%$
	[2.85%,3.56%]	[8.73%,9.51%]	[16.07%,16.95%]
	$\Delta p_H = -6.26\%$	$\Delta p_H = -5.31\%$	$\Delta p_H = -5.02\%$
	[-8.89%,-3.81%]	[-8.11%,-2.63%]	[-7.91%,-2.17%]
s=0.6	$\Delta M = +3.87\%$	$\Delta M = +10.96\%$	$\Delta M = +19.83\%$
	[3.42%,4.27%]	[10.47%,11.42%]	[19.28%,20.34%]
	$\Delta p_H = -7.35\%$	$\Delta p_H = -6.13\%$	$\Delta p_H = -5.37\%$
	[-9.85%,-5.03%]	[-8.78%,-3.65%]	[-8.15%,-2.71%]

Hash	$\kappa = 1$	$\kappa = 0.9$	$\kappa = 0.8$
s=0.4	$\Delta M = +2.43\%$	$\Delta M = +7.15\%$	$\Delta M = 13.04\%$
	[0.09%,3.81%]	[5.49%,8.68%]	[11.12%,14.76%]
	$\Delta p_H = -8.13\%$	$\Delta p_H = +3.73\%$	$\Delta p_H = +22.99\%$
	[-17.65%,1.23%]	[-6.89%,13.11%]	[2.72%,42.82%]
s=0.5	$\Delta M = +3.04\%$	$\Delta M = +8.93\%$	$\Delta M = +16.30\%$
	[1.18%,4.76%]	[6.86%,10.84%]	[13.97%,18.45%]
	$\Delta p_H = -10.88\%$	$\Delta p_H = -2.67\%$	$\Delta p_H = +9.47\%$
	[-20.9%,-0.29%]	[-11.46%,4.8%]	[-2.67%,21.07%]
s=0.6	$\Delta M = +3.65\%$	$\Delta M = +10.72\%$	$\Delta M = +19.56\%$
	[1.41%,5.71%]	[8.24%,13.01%]	[16.77%,22.14%]
	$\Delta p_H = -13.28\%$	$\Delta p_H = -7.77\%$	$\Delta p_H = -0.37\%$
	[-24.31%,-1.42%]	[-16.65%,1.28%]	[-8.97%,6.29%]

Ecstasy	$\kappa = 1$	$\kappa = 0.9$	$\kappa = 0.8$
s=0.4	$\Delta M = +1.81\%$	$\Delta M = +6.46\%$	$\Delta M = +12.27\%$
	[0.57%,2.41%]	[5.08%,7.13%]	[10.71%,13.02%]
	$\Delta p_H = -1.08\%$	$\Delta p_H = -0.26\%$	$\Delta p_H = -0.11\%$
	[-7.81%,-0.42%]	[-6.6%,0.67%]	[-5.81%,1.83%]
s=0.5	$\Delta M = +2.27\%$	$\Delta M = +8.08\%$	$\Delta M = +15.33\%$
	[0.71%,3.02%]	[6/34%,8.91%]	[13.39%,16.27%]
	$\Delta p_H = -1.83\%$	$\Delta p_H = -0.81\%$	$\Delta p_H = -0.22\%$
	[-0.90%,-%]	[-7.47%,-0.10%]	[-6.49%,0.81%]
s=0.6	$\Delta M = +2.72\%$	$\Delta M = +9.69\%$	$\Delta M = +18.40\%$
	[0.85%,3.62%]	[7.61%,10.69%]	[16.07%,19.53%]
	$\Delta p_H = -2.69\%$	$\Delta p_H = -1.71\%$	$\Delta p_H = -0.89\%$
	[-9.25%,-1.21%]	[-8.4%,-0.73%]	[-7.55%,-0.12%]

Note: The 95% profile-likelihood confidence intervals appear in brackets.

8 Conclusion

The negative externalities from dishonest sellers on markets have been widely recognized in the economic literature. The emergence of online reputation mechanisms has been seen as a way of reducing the asymmetry of information by better signaling the quality of services provided by sellers. Previous work on clearnet platforms has underlined the importance of reputation for pricing. In this paper, I have analyzed the role of e-reputation when legal enforcement is not possible, i.e. in online illicit drug-dealing.

The price premia associated with reputation that I find are similar to those in clearnet markets: a 10% increase in sellers' positive evaluations corresponds to 0.32%, 0.35% and 0.61% higher prices for Weed, Hash and Ecstasy respectively. On the contrary, 10% more negative feedback reduces Weed prices by 0.84% and Ecstasy prices by 1.1%. Building a model of e-reputation for darknet markets, I conclude that the *Hansa* market had a relatively low scamming risk: the probability that a random seller effectively ship his offer is over 83% for three drug types (Weed, Hash and Ecstasy). Regarding consumer welfare, I show that Weed and Ecstasy leave consumers with about one quarter of their total utility, while Hash offers seem to extract all the consumer's surplus. Finally, I discuss the short-term impact of the shutdown of the two leading platforms in 2017 under two scenarios. First, assuming that surviving sellers migrate to a new platform, I show that service quality is expected to rise in the short-run by 2.7% to 9.7%, while prices for average sellers fall by 4.4% to 13.4% if sellers stick to their pre-shutdown business strategies. Second, there are similar effects if surviving sellers migrate to a pre-existing platform. The impact on prices for surviving Hansa sellers can however be largely compensated by the difference in quality with the pre-existing platform: the lower was the quality in the latter, the smaller the drop in profits for surviving sellers.

This paper is one of the first contributions to the economic literature on darknet markets, and opens the way for further research. It first does not address the volume of transactions, which could help us to better understand the attractiveness of offers. Second, the non-structural econometric investigation only measures the correlation between prices and reputation profiles: further work could attempt to capture causal effects, as for clearnet markets. Third, I did not consider here any potential under- or mis-reporting by buyers. Were data on buyers to be collected in the future, this would help capture transaction quality and in addition evaluate buyer honesty. Third, one of the main risks associated with the above analysis is the possibility that sellers artificially improve their reputation by creating fake accounts. While the platform managers were very careful to maintain the quality of the feedback system, this may have occurred on the *Hansa* marketplace. The extent to which this happened is an empirical question that is impossible to address on darknet markets given the great concerns for anonymity and the associated difficulty in tracking sellers. The non-negligible proportion of sellers who have zero positive feedback on the market makes us think that this strategy was somewhat limited. Note also that these strategies are both time-consuming and costly for sellers: they would need to create new virtual identities to generate fake accounts (new PGP, new Bitcoin wallets) and pay the 4% commission fee to the platform for the fake transactions necessary for feedback. Last, the dataset here is cross-sectional. Panel data would help improve estimation quality by better capturing unobserved seller heterogeneity via fixed effects, discussing the (endogenous) number of sellers or the volume of transactions as pointed out above. Fixed effects could for instance help disentangle the effect of reputation from factors that drive actual reputation, such as the way sellers display their offers on the marketplace. Analyzing the number of sellers could also inform us about the quality of competition on the market. For example, higher-quality marketplaces may attract more dishonest sellers who wish to benefit from overall marketplace reputation to scam naive customers. The analysis of panel data would help to mitigate such endogeneity issues.

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Appendix A: Figures

Figure A1: Screen shot of DeepDotWeb for its categorization of Hansa Market (Access: November 13th, 2017).

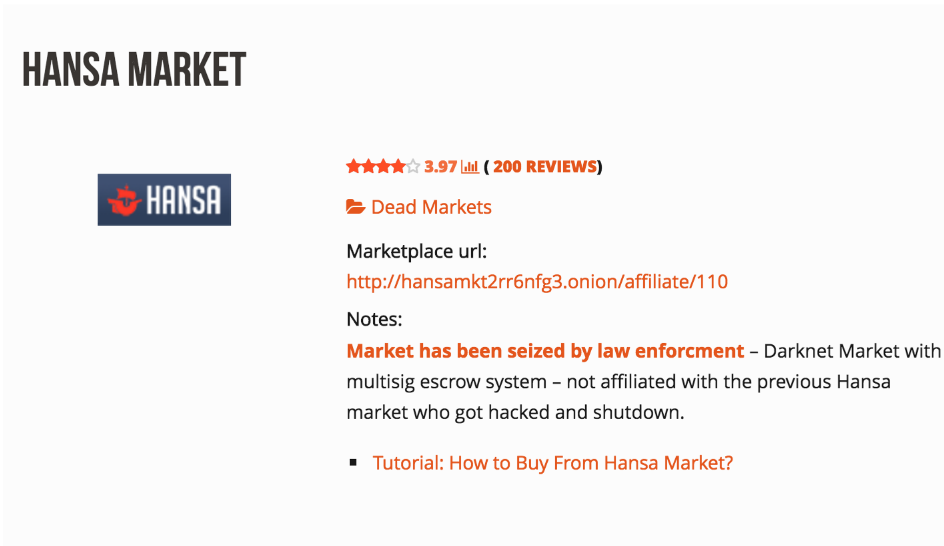

Figure A2: Example of the listing menu for drugs (all categories).

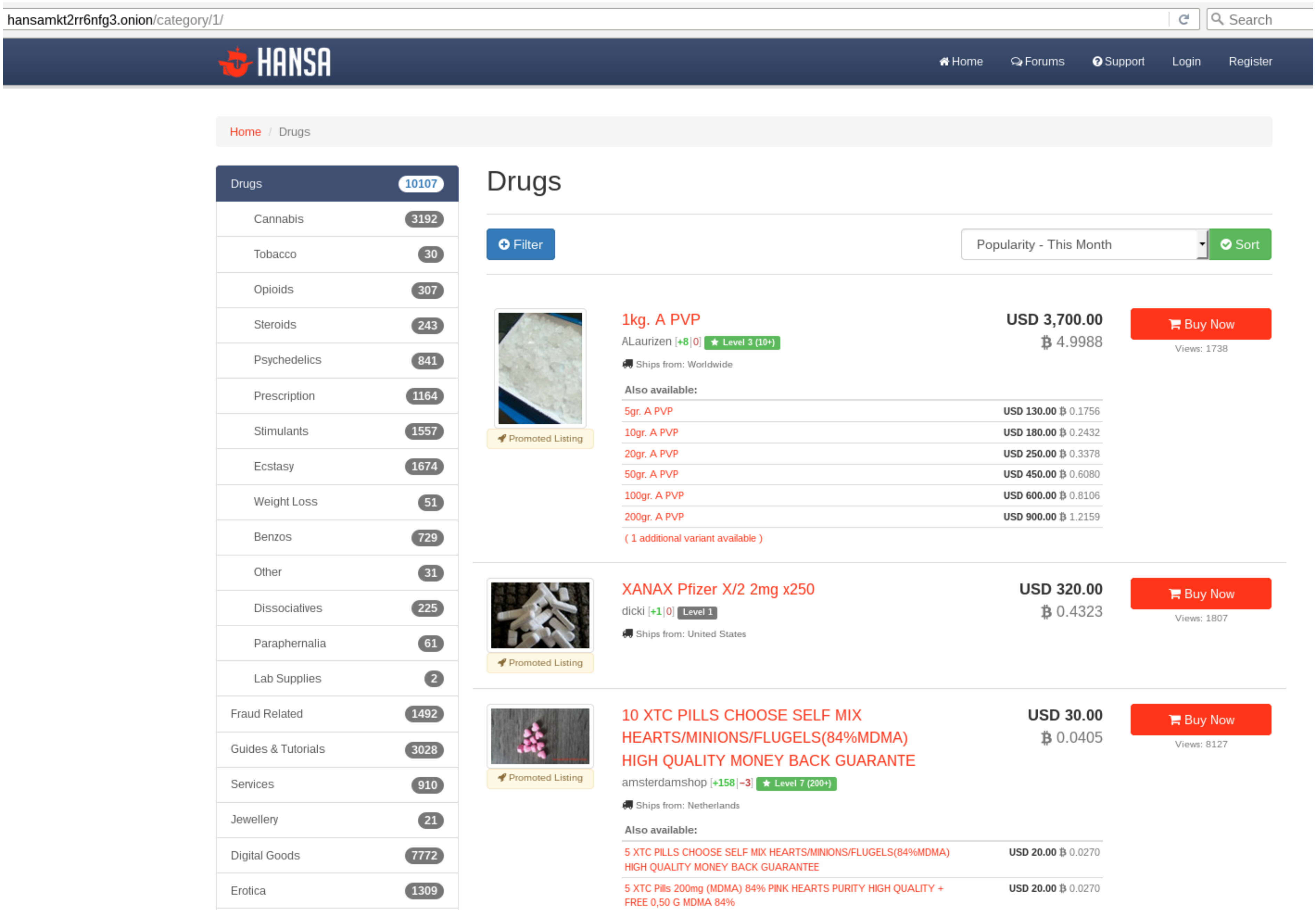

Figure A3: Seller's description of his/her service (first example).

Over 2 years experience mailing illicit goods
- Same day shipping
- 99% of orders arrive in 3-10 days in Europa
- Rest of the world: 5-15 business days

*** SHIPPING & STEALTH ***

- Vacuum sealed
- Mylar bags
- Anti dog spray
- Anti smell spray
- Stealth Package
- Return address.
- We only use regular post (without tracking).

All orders will be processed and shipped within 24 hours. When your package is ready for shipment you will be informed.

Estimated shipping times (in working days (monday till friday)
Benelux: 2-4 days
EU: 3-10 days

You can use the clearnetlink for the correct

Example adress:
Name: (first name and last name)
Street name and number:
Zip/Postal code:
City:
Country:

*** CONTACT ***
Send us a PM. We will reply in 12 - 24 hours (usually faster).

REFUND POLICY
In case of non-arrival we offer a reship of 50% to the same or new address.
We have a very high success rate, but in the rare case of non-arrival, please send us a PM.
We will always help you out and try to find a solution.

When you dont trust, we advice you to start with smaller amounts.

Figure A4: Seller's description of his/her service (second example).

Welcome to our shop, we are a french team, we are coming to the darknet after a long time in real life business.
We are coming to Hansa, Dream et Alpha !
Our goal is to provide you safely with grams and grams of plenty of our products !

All orders placed during the day (before 6pm) will be shipped on next morning and all questions will be answered within 24H.

Our priority and our commitment to our customers are :

- Quality ; All products are HQ drugs ! Uncut by our hands. We provide the best that can currently be found on market (net and IRL)

- Security : When placing an order to our shop you ensure yourself a communication encrypted with PGP, All your info will be deleted right after the shipping. we ship in a safe and stealth way that keeps packages anonymous on every level. We ship from a neutral country (for LE, not like NL, Belgium and Spain)

- Customer service : As you will soon realize our goal is to satisfy our customers. If you don't find any answer on our profile feel free to send us a pm !

Products :

- Cannabis :
Weed : Amnesia Haze, a classic that requires no introduction ! Coffee Shop quality !
Hash : " M " A very strong polm, for daily smokers, tastes and smells like weed, bends and crumbles.
"L" a black hash, it's very sticky, strong stone here ! Taste is amazing !

- Mdma / Xtc
- Mdma rocks or powder (depends on quantity) 84% pure (labtest energy) ! Be careful very strong products !
- Xtc ; Red defcon 240mg. Once again be aware that these are strong, start with 1/2
(this is not to show off, this is for your safety, and we like you :))

Others drugs will come to our shop very soon (soft and hard drugs), all suggestions are appreciated !

Stealth / Shipping

Your safety is our priority, we prepare every order like professionals.
2X sealed, anonymous envelopes and mylar bags.
More than that your order is shipped from a neutral country (for customs and LE) which minimize a lot the chance of your order getting seized.

Each order is sent with tracking, in case non arrival (tracking don't activate / seized) we will find a suitable solution But 99% of the cases your order will be in your mailbox shortly.

Shipping to UE with tracking : 8€

If you have any questions left feel free to message us !
We are looking forward for your orders !

Appendix B: Tables

Table B1: Regression of log price per gram, OLS.

Variable	Weed	Hash	Ecstasy	LSD
Positive Evaluations (log)	0.00970**	0.0385***	0.0319***	-0.0161**
	(0.00466)	(0.00851)	(0.00686)	(0.00821)
Negative Evaluations (log)	-0.0299***	-0.0630***	-0.0614***	0.0313
	(0.00843)	(0.0161)	(0.0138)	(0.0240)
No. of grams (log)	-0.181***	-0.154***	-0.125***	-0.145***
	(0.00399)	(0.00604)	(0.00485)	(0.00541)
No. of Shipment options	0.0168***	-0.0141	0.0520***	0.0391***
	(0.00591)	(0.00884)	(0.00774)	(0.00699)
Dosage per pill (log)			-0.385***	-0.117***
			(0.0510)	(0.0334)
Worldwide shipment	-0.106***	-0.109***	-0.178***	-0.128***
	(0.0178)	(0.0289)	(0.0237)	(0.0362)
Order	6.01e-05***	0.000187***	4.13e-05	0.000294***
	(8.88e-06)	(3.81e-05)	(2.84e-05)	(4.48e-05)
Link number	-4.45e-07	4.99e-07	-3.82e-06***	-4.78e-06***
	(3.16e-07)	(6.76e-07)	(5.97e-07)	(6.01e-07)
Number of offers	0.00181***	0.00444***	-0.00435***	0.000584***
	(0.000285)	(0.000683)	(0.000312)	(0.000221)
Sells Weed		-0.129***	-0.106***	-0.0406
		(0.0251)	(0.0246)	(0.0342)
Sells Hash	0.119***		-0.0468*	0.0787**
	(0.0163)		(0.0250)	(0.0306)
Sells Ecstasy	0.101***	-0.134***		-0.166***
	(0.0303)	(0.0363)		(0.0322)
Sells LSD	-0.0879**	0.133***	0.0538**	
	(0.0371)	(0.0429)	(0.0240)	
Constant	2.471***	2.325***	5.318***	4.409***
	(0.0352)	(0.0724)	(0.277)	(0.163)
Number of observations	2,506	1,140	1,451	854
R^2	0.496	0.448	0.574	0.587

Ordinary Least Squares estimation.
Standard errors in parentheses.
Significance levels: ***, ** and * = significant at the 10%, 5% and 1% levels.

Table B2: Regression of log price per gram, Multilevel Model.

Variable	Weed	Hash	Ecstasy	LSD
Positive Evaluations (log)	0.0327***	0.0353*	0.0612***	-0.0281
	(0.0104)	(0.0209)	(0.0216)	(0.0351)
Negative Evaluations (log)	-0.0839**	-0.0253	-0.111**	0.0231
	(0.0327)	(0.0501)	(0.0549)	(0.111)
No. of grams (log)	-0.148***	-0.137***	-0.131***	-0.125***
	(0.00385)	(0.00443)	(0.00329)	(0.00484)
No. of Shipment options	-0.0381***	0.0199	0.0236***	0.0368***
	(0.0117)	(0.0137)	(0.00876)	(0.00621)
Dosage per pill (log)			-0.394***	-0.105***
			(0.0435)	(0.0294)
Worldwide shipment	0.0931***	-0.0916**	-0.0956*	-0.178***
	(0.0298)	(0.0441)	(0.0523)	(0.0662)
Order	7.10e-05***	0.000133***	0.000100***	0.000199***
	(9.04e-06)	(3.75e-05)	(2.62e-05)	(4.45e-05)
Link number	-3.66e-07	3.36e-06***	6.85e-07	-5.37e-06***
	(4.44e-07)	(7.19e-07)	(7.26e-07)	(8.03e-07)
Number of offers	0.000667	-0.000687	-0.00406**	0.00120
	(0.00131)	(0.00299)	(0.00188)	(0.00191)
Sells Weed		-0.0451	-0.0742	-0.0366
		(0.0747)	(0.0943)	(0.145)
Sells Hash	0.0969**		-0.126	0.136
	(0.0460)		(0.0916)	(0.151)
Sells Ecstasy	0.130*	-0.193**		-0.105
	(0.0749)	(0.0945)		(0.131)
Sells LSD	-0.167*	0.198	0.00562	
	(0.0971)	(0.122)	(0.0819)	
Constant	2.369***	2.136***	5.049***	4.382***
	(0.0566)	(0.110)	(0.247)	(0.201)
Number of observations	2,506	1,140	1,451	854
Number of sellers	209	106	109	59
σ_ϵ^2	0.0696	0.1297	0.1456	0.1733
	(0.0082)	(0.0198)	(0.0212)	(0.0346)
σ_u^2	0.0565	0.0524	0.0357	0.0338
	(0.0017)	(0.0023)	(0.0014)	(0.0017)
LR-test (p-value)	<0.1%	<0.1%	<0.1%	<0.1%

Multilevel random-effect model.
Standard errors in parentheses.
Significance levels: ***, ** and * = significant at the 10%, 5% and 1% levels.

Table B3: Regression of log price per gram, Multilevel Model, Excluding blank-reputation sellers.

Variable	Weed	Hash	Ecstasy	LSD
Positive Evaluations (log)	0.0346**	0.0804***	0.113***	-0.0551
	(0.0136)	(0.0262)	(0.0282)	(0.0417)
Negative Evaluations (log)	-0.0840**	-0.0579	-0.159***	0.0765
	(0.0328)	(0.0480)	(0.0566)	(0.113)
No. of grams (log)	-0.151***	-0.136***	-0.125***	-0.135***
	(0.00401)	(0.00454)	(0.00363)	(0.00630)
No. of Shipment options	-0.0464***	0.0179	0.0220**	0.0415***
	(0.0122)	(0.0138)	(0.00923)	(0.00710)
Dosage per pill (log)			-0.331***	-0.0916**
			(0.0517)	(0.0373)
Worldwide shipment	0.0999***	-0.0850*	-0.00739	-0.247**
	(0.0315)	(0.0441)	(0.0655)	(0.107)
Order	7.27e-05***	0.000150***	0.000104***	0.000237***
	(9.10e-06)	(3.76e-05)	(2.75e-05)	(5.09e-05)
Link number	-2.56e-07	3.25e-06***	3.63e-07	-5.36e-06***
	(4.51e-07)	(7.22e-07)	(7.60e-07)	(8.76e-07)
Number of offers	0.000536	0.000943	-0.00479**	0.00103
	(0.00131)	(0.00283)	(0.00199)	(0.00247)
Sells Weed		-0.0833	-0.0762	-0.0447
		(0.0768)	(0.100)	(0.154)
Sells Hash	0.122**		-0.192**	0.185
	(0.0508)		(0.0964)	(0.159)
Sells Ecstasy	0.0874	-0.194**		-0.205
	(0.0768)	(0.0911)		(0.140)
Sells LSD	-0.173*	0.125	-0.0232	
	(0.101)	(0.120)	(0.0904)	
Constant	2.373***	1.950***	4.509***	4.493***
	(0.0692)	(0.125)	(0.299)	(0.249)
Number of observations	2,305	1,076	1,208	602
Number of sellers	174	92	90	51
σ^2_ϵ	.0643	.1050	.1326	.1572
	(.0083)	(.0173)	(.0220)	(.0344)
σ^2_u	.0566	.0527	.0364	.0404
	(.0017)	(.0024)	(.0015)	(.0024)
LR-test (p-value)	<0.1%	<0.1%	<0.1%	<0.1%

Multilevel random-effect model, excluding sellers with blank reputation profiles.
Standard errors in parentheses.
Significance levels: ***, ** and * = significant at the 10%, 5% and 1% levels.

Table B4: Regression of log price per gram, Multilevel Model, Excluding blank-reputation sellers, Clustered standard errors by sellers

Variable	Weed	Hash	Ecstasy	LSD
Positive Evaluations (log)	0.0346***	0.0804***	0.113***	-0.0551
	(0.0132)	(0.0297)	(0.0330)	(0.0384)
Negative Evaluations (log)	-0.0840**	-0.0579	-0.159***	0.0765
	(0.0351)	(0.0449)	(0.0531)	(0.0716)
No. of grams (log)	-0.151***	-0.136***	-0.125***	-0.135***
	(0.0153)	(0.00816)	(0.0141)	(0.0129)
No. of Shipment options	-0.0464	0.0179	0.0220	0.0415***
	(0.0306)	(0.0181)	(0.0192)	(0.00507)
Dosage per pill (log)			-0.331***	-0.0916
			(0.112)	(0.0672)
Worldwide shipment	0.0999	-0.0850	-0.00739	-0.247
	(0.0981)	(0.0826)	(0.123)	(0.155)
Order	7.27e-05***	0.000150**	0.000104	0.000237***
	(1.32e-05)	(7.49e-05)	(0.000126)	(7.36e-05)
Link number	-2.56e-07	3.25e-06***	3.63e-07	-5.36e-06***
	(8.09e-07)	(1.10e-06)	(7.52e-07)	(1.75e-06)
Number of offers	0.000536	0.000943	-0.00479***	0.00103
	(0.00113)	(0.00230)	(0.00166)	(0.000740)
Sells Weed		-0.0833	-0.0762	-0.0447
		(0.0817)	(0.102)	(0.0968)
Sells Hash	0.122*		-0.192**	0.185
	(0.0646)		(0.0883)	(0.120)
Sells Ecstasy	0.0874	-0.194***		-0.205
	(0.0675)	(0.0750)		(0.130)
Sells LSD	-0.173*	0.125	-0.0232	
	(0.101)	(0.100)	(0.0804)	
Constant	2.373***	1.950***	4.509***	4.493***
	(0.0844)	(0.163)	(0.628)	(0.272)
Number of observations	2,305	1,076	1,208	602
Number of sellers	174	92	90	51
σ^2_ϵ	.0643	.1050	.1326	.1572
	(.0114)	(.0178)	(.0246)	(.1073)
σ^2_u	.0566	.0527	.0364	.0403
	(.0090)	(.0068)	(.0134)	(.0065)
LR-test (p-value)	<0.1%	<0.1%	<0.1%	<0.1%

Multilevel random-effect model, excluding sellers with blank reputation profiles and with clustered standard errors by sellers
Standard errors in parentheses.
Significance levels: ***, ** and * = significant at the 10%, 5% and 1% levels.

Table B5: Regression of log price per gram, Multilevel Model, Excluding blank-reputation sellers, Clustered standard errors by sellers, Dummy variable for negative feedback.

Variable	Weed	Hash	Ecstasy	LSD
Positive Evaluations (log)	0.0348**	0.0822***	0.0867***	-0.0458
	(0.0143)	(0.0282)	(0.0283)	(0.0351)
Dummy Neg. Feedback	-0.123**	-0.154	-0.156	0.0480
	(0.0627)	(0.0966)	(0.0964)	(0.113)
No. of grams (log)	-0.151***	-0.136***	-0.125***	-0.135***
	(0.0153)	(0.00816)	(0.0141)	(0.0129)
No. of Shipment options	-0.0468	0.0172	0.0226	0.0414***
	(0.0304)	(0.0179)	(0.0195)	(0.00506)
Dosage per pill (log)			-0.332***	-0.0922
			(0.112)	(0.0674)
Worldwide shipment	0.101	-0.0802	-0.0182	-0.244
	(0.0981)	(0.0821)	(0.129)	(0.163)
Order	7.20e-05***	0.000151**	0.000102	0.000238***
	(1.32e-05)	(7.47e-05)	(0.000127)	(7.36e-05)
Link number	-2.47e-07	3.27e-06***	4.37e-07	-5.38e-06***
	(8.13e-07)	(1.09e-06)	(7.66e-07)	(1.75e-06)
Number of offers	0.000123	0.000906	-0.00521***	0.00166*
	(0.00112)	(0.00230)	(0.00167)	(0.000921)
Sells Weed		-0.0716	-0.0635	-0.0365
		(0.0791)	(0.110)	(0.0971)
Sells Hash	0.107		-0.196**	0.186
	(0.0661)		(0.0901)	(0.123)
Sells Ecstasy	0.0858	-0.206***		-0.190
	(0.0674)	(0.0739)		(0.125)
Sells LSD	-0.160	0.148	-0.0231	
	(0.103)	(0.0974)	(0.0849)	
Constant	2.386***	1.954***	4.599***	4.460***
	(0.0841)	(0.157)	(0.624)	(0.278)
Number of observations	2,305	1,076	1,208	602
Number of sellers	174	92	90	51
σ^2_ϵ	0.0643	0.1031	0.1397	0.1584
	(0.0083)	(0.0170)	(0.0276)	(0.1081)
σ^2_u	0.0567	0.0527	0.0364	0.0404
	(0.0017)	(0.0024)	(0.0135)	(0.0065)
LR-test (p-value)	<0.1%	<0.1%	<0.1%	<0.1%

Multilevel random-effect model, excluding sellers with blank reputation profiles, with clustered standard errors by sellers and with a dummy variable for negative comments.
Standard errors in parentheses.
Significance levels: ***, ** and * = significant at the 10%, 5% and 1% levels.

Table B6: Quality of the Maximum Likelihood Estimations.

	Weed	Hash	Ecstasy
Mean of the Error (μ_ϵ)	-0.039	0.070	-0.269
Standard Error of the Error	0.106	0.188	0.472
$H_0 : \mu_\epsilon = 0$	Don't reject ($p = 0.712$)	Don't reject ($p = 0.710$)	Don't reject ($p = 0.568$)
Mean of Real Prices	13.21	10.78	58.60
Min & Max of Real Prices	[7.83,20.34]	[3.73,25.30]	[47.77,88.83]
Mean of Predicted Prices	13.18	10.85	58.33
Min & Max of Predicted Prices	[10.99,13.68]	[8.39,12.21]	[53.21,59.90]
Number of iterations	400	400	400

Appendix C: Calculation of the probability of being a honest seller

I derive below the probability of being a honest seller for a given reputation profile.

Survival probabilities. Let $S_t(\phi_k)$ denote the survival function associated with sellers of type k, i.e. the probability that a seller of type k survive t feedbacks.

In the reputation-building process, sellers start with a blank account ($t = 0$) and then receive feedback. At each new evaluation the seller decides whether to retain his/her account or close it and start a new one. We assume that there is a threshold w such that if the seller's reputation (the proportion of positive evaluations) falls below w the seller closes the account. Formally, I assume that seller j maintains his/her profile after t evaluations if and only if

$$\frac{r_j}{t_j} \geq w \tag{18}$$

If we observe a seller with a history of t evaluations, reputation r_t after t evaluations must have been sufficient to retain the profile. Moreover, the seller was only able to receive the t^{th} evaluation as he/she had survived until then (i.e. he/she survived $t-1$ evaluations). We thus have:

$$S(t|\ \phi_k) = S(t-1|\phi_k)Pr[\text{survive the t}^{\text{th}}\text{ evaluation}|\text{survived } t-1 \text{ evaluations}] \tag{19}$$

This recursive process reflects that a seller will only have a profile after t evaluations if it was worth keeping this profile open after 1, 2, 3, ... $t-1$, t evaluations.

Let λ_t^* be the minimum number of positive evaluations necessary for sellers to maintain their profile after t evaluations. This is defined by:

$$\begin{aligned} \frac{\lambda_t^*}{t} &= w \\ \lambda_t^* &= tw \end{aligned} \tag{20}$$

Let λ_t equal λ_t^* rounded up to the next whole number. A seller therefore decides to maintain their profile after t evaluations only after receiving at least λ_t positive comments ($r_t \geq \lambda_t$). Furthermore, we know that a seller who survived t evaluations will always keep their profile open after $t+1$ evaluations if the $t+1^{\text{th}}$ evaluation was positive: $r_t \geq \lambda_t$ implies $r_t + 1 \geq \lambda_t + 1 \geq \lambda_{t+1}$, since $\lambda_{t+1} \in \{\lambda_t, \lambda_t + 1\}$. Only sellers who receive negative feedback may close their account. If $\lambda_{t+1} = \lambda_t$, sellers who receive negative feedback at the $t+1^{\text{th}}$ evaluation will retain their profile. Whether these sellers close their account when $\lambda_{t+1} = \lambda_t + 1$ depends on their reputation r_t.

We know that, for a given number of evaluations t, the reputation of the existing sellers takes values in the set: $\{\lambda_t, \lambda_t + 1, \lambda_t + 2, ..., t\}$. When $\lambda_{t+1} = \lambda_t$, existing sellers after $t+1$ evaluations will have a number of positive evaluations of $\{\lambda_t, \lambda_t+1, ..., t, t+1\}$; when $\lambda_{t+1} = \lambda_t + 1$, their reputation will be in the set $\{\lambda_t+1, \lambda_t+2, ..., t, t+1\}$.

Denote by P_t the transition matrix of sellers from $t-1$ to t evaluations. This matrix shows, for each seller who still exists after $t-1$ evaluations, the probability of being in each possible state after t evaluations (conditional on having survived the t$^{\text{th}}$ evaluation).

When $\lambda_{t+1} = \lambda_t$, we have:

$$P_t(\phi_k) = \begin{array}{c} \\ t-1 \\ t-2 \\ ... \\ \lambda_{t-1}+1 \\ \lambda_{t-1} \end{array} \begin{array}{c} \begin{array}{ccccccc} t & t-1 & t-2 & ... & \lambda_{t-1}+2 & \lambda_{t-1}+1 & \lambda_{t-1} \end{array} \\ \begin{pmatrix} q_j & 1-q_j & 0 & ... & 0 & 0 & 0 \\ 0 & q_j & 1-q_j & ... & 0 & 0 & 0 \\ ... & ... & ... & & & & \\ 0 & 0 & 0 & ... & q_j & 1-q_j & 0 \\ 0 & 0 & 0 & ... & 0 & q_j & 1-q_j \end{pmatrix} \end{array}$$

The first row lists the probabilities that a seller with $t-1$ positive evaluations after $t-1$ evaluations end up with a given number of positive evaluations after the t^{th} evaluation. The seller obtains positive feedback with probability q_j for a total reputation of t positive evaluations, and negative feedback with probability $1-q_j$ for an unchanged reputation of $t-1$.

When $\lambda_{t+1} = \lambda_t + 1$, we drop the last column so that:

$$P_t(\phi_k) = \begin{array}{c} \\ t-1 \\ t-2 \\ ... \\ \lambda_{t-1}+1 \\ \lambda_{t-1} \end{array} \begin{array}{c} \begin{array}{cccccc} t & t-1 & t-2 & ... & \lambda_{t-1}+2 & \lambda_{t-1}+1 \end{array} \\ \begin{pmatrix} q_j & 1-q_j & 0 & ... & 0 & 0 \\ 0 & q_j & 1-q_j & ... & 0 & 0 \\ ... & ... & ... & & & \\ 0 & 0 & 0 & ... & q_j & 1-q_j \\ 0 & 0 & 0 & ... & 0 & q_j \end{pmatrix} \end{array}$$

The number of columns in the matrix P_t is equal to the number of rows in P_{t+1}. Let Q_t be the vector defining the probability associated with all possible reputation profiles on the market after t evaluations. This is defined by:

$$Q_t(\phi_k) = \prod_{s=1}^{s=t} P_s(\phi_k) \tag{21}$$

Q_t is a vector[28] of size $t - \lambda_t + 1$ (the number of columns of P_t).

The probability that a seller of type k survive t evaluations corresponds to the sum of probabil-

[28] Q_t is a vector since P_1 has one row (at $t=0$ all sellers have no positive feedback). It can come about that P_1 (and some subsequent P_t) are scalars, but there will be a sufficiently large t^* for which for P_{t^*} is a vector and so the subsequent P_s are matrices ($s > t^*$).

ities of all possible states in which he/she can survive this feedback. Then:

$$S_t(\phi_k) = \sum_{i=1}^{i=t-\lambda_t+1} Q_t(\phi_k)_i \tag{22}$$

The function $S_t(\phi_k)$ describes the probability that a type-k seller survive t evaluations. I assume that when sellers are forced to close their profile, they open a new profile (or they are replaced by a seller of the same type with a new profile).

The probability of observing a seller with reputation r given that he/she is of type k and survived t evaluations is:

$$Pr[r|\phi_k, t] = \frac{Q_t(\phi_k)_{t-r+1}}{S_t(\phi_k)} \tag{23}$$

where $Q_t(\phi_k)_{t-r+1}$ is the $t - r + 1^{\text{th}}$ element of the vector $Q_t(\phi_k)$.

Probability of a good type. I then assume that the market is made up of two kinds of sellers: honest sellers, who always fulfil orders ($\phi_H = 1$), and dishonest sellers, who send goods as described in the offer with probability ϕ_D ($\phi_D = \phi$). Denote by $\theta \in (0, 1)$ the proportion of honest sellers on the market. The probability that a seller be honest given their reputation is given by the following expression (Bayes' rule):

$$\begin{aligned}
Pr[\phi = \phi_H|r, t] &= \frac{Pr[r|\phi_H, t]Pr[\phi_H|t]}{Pr[r|\phi_H, t]Pr[\phi_H|t] + Pr[r|\phi_D, t]Pr[\phi_D|t]} \\
&= \frac{1}{1 + \frac{Pr[r|\phi_D,t]}{Pr[r|\phi_H,t]}\frac{Pr[\phi_D|t]}{Pr[\phi_H|t]}} \\
&= \frac{1}{1 + f(r, t)}
\end{aligned} \tag{24}$$

The ratio of probabilities of being type ϕ_k given that the seller survived t evaluations is (Bayes' rule):

$$\begin{aligned}
\frac{Pr[\phi_D|t]}{Pr[\phi_H|t]} &= \delta \frac{\frac{Pr[\text{survived t}|\phi_D]Pr[\phi_D]}{Pr[\text{survived t}|\phi_D]Pr[\phi_D]+Pr[\text{survived t}|\phi_H]Pr[\phi_H]}}{\frac{Pr[\text{survived t}|\phi_H]Pr[\phi_H]}{Pr[\text{survived t}|\phi_D]Pr[\phi_D]+Pr[\text{survived t}|\phi_H]Pr[\phi_H]}} \\
&= \delta \frac{Pr[\text{survived t}|\phi_D]Pr[\phi_D]}{Pr[\text{survived t}|\phi_H]Pr[\phi_H]} \\
&= \delta \frac{S_t(\phi_D)}{S_t(\phi_H)} \frac{(1-\theta)}{\theta}
\end{aligned}$$

The parameter δ represents the overrepresentation of dishonest sellers (D) at the lower end of the distribution, i.e. among sellers with few evaluations. At $t = 0$, both survival ratios are 1, which leads to $\frac{Pr[\phi_D|t=0]}{Pr[\phi_H|t=0]} = \delta\frac{1-\theta}{\theta}$. If $\delta = 1$, the probability that a seller with no reputation be honest (dishonest) is given by the average proportion of honest (dishonest) sellers on the market). The parameter $\delta > 1$ reflects that dishonest sellers are more likely to have a blank reputation profile than honest sellers.

We thus have:

$$\begin{aligned} \frac{Pr[r|\phi_D, t]}{Pr[r|\phi_H, t]}\frac{Pr[\phi_D|t]}{Pr[\phi_H|t]} &= \frac{Q_t(\phi_D)_{t-r+1}}{Q_t(\phi_H)_{t-r+1}}\frac{S_t(\phi_H)}{S_t(\phi_D)}\delta\frac{S_t(\phi_D)}{S_t(\phi_H)}\frac{(1-\theta)}{\theta} \\ &= \delta\frac{Q_t(\phi_D)_{t-r+1}}{Q_t(\phi_H)_{t-r+1}}\left(\frac{1}{\theta} - 1\right) \end{aligned} \tag{25}$$

The ratio $\frac{Q_t(\phi_D)_{t-r+1}}{Q_t(\phi_H)_{t-r+1}}$ corresponds to the likelihood of facing a seller of type D rather than type H when the seller has survived t evaluations with reputation r.

I moreover assume that buyers have consistent beliefs, so that the expected number of honest sellers must equal the effective number of honest sellers (equilibrium beliefs):

$$\sum_i Pr[\phi = \phi_H|t_i, r_i] = N\theta \tag{26}$$

where N is the number of sellers on the market.

Altogether, these conditions allow us to derive for each seller in the MLE the probability that he/she is honest.

Appendix D: Calculation of likelihood-profile confidence intervals for a combination of parameters

Consider a likelihood function $L(.)$ that we seek to maximize given a dataset x. The Maximum Likelihood Estimators θ_{ML} are given by:

$$\hat{\theta}_{ML} \in \text{argmax}_{\theta}\ L(\theta|x)$$

The likelihood-profile confidence intervals are estimated using likelihood-ratio tests. To do so, we compare the likelihood of the data given our estimated parameters $\hat{\theta}_{ML}$ with the likelihood obtained using deviations from our estimated parameters $\theta_{\epsilon} = \hat{\theta}_{ML} + / - \epsilon$. We start the iteration process with ϵ close to zero and increase it up to the point where we reject the likelihood ratio test at 5%.

More formally, the boundaries of the confidence interval $[\underline{\theta}, \overline{\theta}]$ are defined such that:

$$\begin{aligned}
\text{If } \theta \in [\underline{\theta}, \overline{\theta}] &: -2(ln(L(\theta) - ln(L(\hat{\theta}_{ML}))) < 3.84 \\
\text{If } \theta = \underline{\theta} - \epsilon &: -2(ln(L(\hat{\theta}_{ML}) - ln(L(\theta))) > 3.84 \\
\text{If } \theta = \overline{\theta} + \epsilon &: -2(ln(L(\hat{\theta}_{ML}) - ln(L(\theta))) > 3.84
\end{aligned}$$

Online Appendix 1: Robustness checks for the probability of reporting negative feedback

In the above analysis, I assumed equal probabilities of reporting positive and negative experiences (χ). I explore here the possibility that the probability of reporting a negative experience (χ_n) exceed the probability of reporting a positive experience (χ_p). The probability of giving positive feedback conditional on giving feedback is now:

$$\frac{\chi_p \phi_j (1-\gamma)}{\chi_p \phi_j (1-\gamma) + \chi_n (1-\phi_j(1-\gamma))} \tag{27}$$

If we assume that individuals are more likely to report a negative than a positive experience by a factor of x, we can write: $(1+x)\chi_p = \chi_n$, with $x > 0$. The above equation simplifies to:

$$\frac{\phi_j (1-\gamma)}{\phi_j (1-\gamma) + (1+x)(1-\phi_j(1-\gamma))} \tag{28}$$

To investigate the impact of underreporting positive experiences, I explore three situations: negative experiences are 10% more likely to be reported than positive experiences, then 20% and 30%. I then re-estimate by MLE the set of parameters, and take as starting values the parameters obtained in the baseline scenario (i.e. when $x = 0\%$). The results for Weed, Hash, and Ecstasy are presented in Tables OA1, OA2 and OA3 respectively.

As can be seen, the results are relatively robust to these changes. Regarding Weed, the estimated probability that a random seller send the order is 83.41% in the baseline model. This figure varies from 83.93% to 84.67% depending on the specification. We observe similar results for Hash (from 87.07% to 87.24%) and Ecstasy (from 88.14% to 88.99%). Second, there is also stability regarding the share of utility left to consumers. For Weed, the original ratio was equal to 25.1%, and varies between 25.5% and 26.2% in the alternative specifications. The same applies to Hash (from 1.4% to 1.5%) and Ecstasy (25.1% in all specifications).

Table OA1: Weed - Higher proportion of negative feedback

	Baseline	x=10%	x=20%	x=30%
Proportion of honest sellers ($\widehat{\theta}$)	47.94%	47.89%	47.85%	47.82%
	[46.44%, 50.54%]	[46.39%, 50.39%]	[46.35%,49.35%]	[46.32%,49.32%]
Probability that a dishonest seller send the order ($\widehat{\phi}$)	68.13%	69.16%	69.88%	70.62%
	[65.63%, 71.63%]]	[66.66%,72.67%]	[67.38%,73.38%]	[68.12%,74.12%]
Probability of seizure ($\widehat{\gamma}$)	15.77%	15.07%	14.65%	14.2%
	[14.27%, 17.27%]	[13.57%, 16.57%]	[13.15%,16.15%]	[12.70%,15.70%]
Utility of consuming the good ($\widehat{u}$)	23.03	22.93	22.90	22.86
	[22.71, 23.34]	[22.61,23.24]	[22.58,23.21]	[22.54%,23.17%]
Expected utility of an offer ($\widehat{\mu}$)	5.78	5.85	5.93	6.00
	[5.57, 5.98]	[5.65,6.06]	[5.71,6.14]	[5.78,6.21]
Parameter of the conflict resolution function $\widehat{\tau}$	0.511	0.484	0.459	0.438
	[0.33, 0.946]	[0.309,0.919]	[0.294,0.894]	[0.273,0.873]
Parameter of the conflict resolution function $\widehat{\beta}$	1.00	1.00	1.00	1.00
	[1.00, 1.12]	[1.00,1.23]	[1.00,1.24]	[1.00,1.25]
Probability that a random seller send the order ($\widehat{\theta}+(1-\widehat{\theta})\widehat{\phi}$)	83.41%	83.93%	84.29%	84.67%
Proportion of utility left to the consumer ($\widehat{\mu}/\widehat{u}$)	25.1%	25.5%	25.9%	26.2%

Note: The 95% profile-likelihood confidence intervals appear in brackets.

Table OA2: Hash - Higher proportion of negative feedback

	Baseline	x=10%	x=20%	x=30%
Proportion of honest sellers ($\widehat{\theta}$)	68.29%	68.24%	68.21%	68.17%
	[65.79%,72.79%]	[65.74%,72.74%]	[65.71%,72.71%]	[65.67%,72.67%]
Probability that a dishonest seller send the order ($\widehat{\phi}$)	58.89%	59.28%	59.61%	59.91%
	[40.39%,78.39%]	[40.78%,78.78%]	[41.1%,79.12%]	[41.41%79.41%,]
Probability of seizure ($\widehat{\gamma}$)	58.58%	58.58%	58.57%	58.54%
	[56.1%,61.2%]	[56.1%,61.1%]	[56.07%,61.07%]	[56.04%,61.04%]
Utility of consuming the good ($\widehat{u}$)	27.97	27.97	27.97	27.96
	[26.28,29.66]	[26.28,29.66]	[26.28,29.66]	[26.28,29.66]
Expected utility of an offer ($\widehat{\mu}$)	0.404	0.405	0.409	0.418
	[0,0.959]	[0,0.970]	[0.004,0.974]	[0.003,0.983]
Parameter of the conflict resolution function $\widehat{\tau}$	0.167	0.162	0.158	0.155
	[0.122,0.212]	[0.117,0.207]	[0.113,0.203]	[0.110,0.200]
Parameter of the conflict resolution function $\widehat{\beta}$	1.00	1.00	1.00	1.00
	[1.00,1.22]	[1.00,1.12]	[1.00,1.12]	[1.00, 1.12]
Probability that a random seller send the order ($\widehat{\theta}+(1-\widehat{\theta})\widehat{\phi}$)	86.96%	87.07%	87.16%	87.24%
Proportion of utility left to the consumer ($\widehat{\mu}/\widehat{u}$)	1.4%	1.4%	1.5%	1.5%

Note: The 95% profile-likelihood confidence intervals appear in brackets.

Table OA3: Ecstasy - Higher proportion of negative feedback

	Baseline	x=10%	x=20%	x=30%
Proportion of honest sellers ($\widehat{\theta}$)	48.53%	48.38%	48.27%	48.16%
	[42.03%,57.03%]	[41.88%,56.88%]	[41.77%,56.77%]	[42.66%,55.66%]
Probability that a dishonest seller send the order ($\widehat{\phi}$)	76.32	77.03%	78.03%	78.77%
	[71.82%,81.82%]	[72.53%,82.53%]	[73.53%,83.53%]	[74.27%,84.27%]
Probability of seizure ($\widehat{\gamma}$)	25.13%	25.61%	26.11%	26.49%
	[22.63%,27.63%]	[23.11%,28.11%]	[23.61%,28.61%]	[23.99%,28.99%]
Utility of consuming the good ($\widehat{u}$)	106.70	106.70	106.69	106.69
	[104.88,108.54]	[104.86,108.53]	[104.85,108.52]	[104.86,108.52]
Expected utility of an offer ($\widehat{\mu}$)	26.75	26.76	26.78	26.77
	[25.58,27.90]	[25.60,27.91]	[25.61,27.93]	[25.61,27.94]
Parameter of the conflict resolution function $\widehat{\tau}$	0.539	0.502	0.459	0.423
	[0.364,0.974]	[0.337,0.917]	[0.304,0.834]	[0.278,0.758]
Parameter of the conflict resolution function $\widehat{\beta}$	1.77	1.86	1.96	2.03
	[1.43,2.29]	[1.50,2.42]	[1.56,2.55]	[1.626,2.656]
Probability that a random seller send the order ($\widehat{\theta}+(1-\widehat{\theta})\widehat{\phi}$)	87.81%	88.14%	88.63%	88.99%
Proportion of utility left to the consumer ($\widehat{\mu}/\widehat{u}$)	25.1%	25.1%	25.1%	25.1%

Note: The 95% profile-likelihood confidence intervals appear in brackets.