Dealing with Uncertainty: Seller Reputation in the Online Market for Illegal Drugs*

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This draft: October 24, 2018

Abstract

We analyse the reputational effects arising from information revealed in platform rating systems in the online market for illegal drugs. In this black market, no legal institutions exist to alleviate buyer uncertainty. We estimate the value of seller rating for unit prices charged by exploiting the sudden market exit of a major platform. We track sellers that were forced to migrate to the competing platform and make use of their ratings 'reset'. We find that on average an increase of one percentage point in rating results in a unit price increase of 20% of a standard deviation.

Keywords: Dark web, drugs, reputation, uncertainty, institutions

JEL-Classification: L15, L81, K42

*We are grateful to Berno Buechel, Stefan Buehler, Philemon Kraehenmann, Frank Pisch, Maximilian Conze, and seminar participants at EARIE 2018 (Athens), the University of Konstanz, and the University of St. Gallen for helpful discussions and comments. The usual disclaimer applies.

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1 Introduction

The rise of online commerce has given market participants the opportunity to move many transactions from the real world to the digital. Buyers benefit from the convenience of observing a large selection of goods and having them shipped to their doorstep, while sellers make use of online sales channels as an effective means to market and sell their goods. Often times online sales platforms are the central actor enabling this exchange. By offering a marketplace for buyers and sellers to interact, they allow trade to occur that might otherwise not happen.

However, some of the features of trade in the real world cannot simply be replicated on an online sales platform. In particular, buyers are unable to inspect the goods or verify a seller's identity due to trader anonymity, so that both the quality of a product and the reliability of the seller are unknown to buyers beforehand. The only assurance they have is provided by institutions that exist in the background, such as the law and its enforcement mechanisms. The platforms attempt to overcome this difficulty by providing a rating system of sellers and thereby creating a reputation mechanism, that is meant to ensure that honest trade is in the sellers interest. Their undeniable success across a wide range of different goods and services, such as used goods (e.g. eBay), hotel rooms (e.g. Booking), or car transport (e.g. Uber), seems to demonstrate the effectiveness of such rating systems.

In this paper, we study the reputational effects arising from information revealed in platform rating systems in a market that is characterized by both a complete lack of ordinarily available institutions and a powerful need for market participants to remain anonymous: the online market for illegal drugs. In the past decade, decentralized marketplaces for illegal goods and services have emerged and become increasingly popular.[1] These platforms are located on the Tor ('the onion router') network, ensuring anonymous communication and concealing user's locations, its market participants communicate amongst each other using encryption programs, and transactions are conducted exclusively in bitcoin. Since privacy networks such as Tor are commonly also referred to as the 'darknet', these marketplaces are often called 'darknet platforms'. It is only at the end of a purchase on such a site that individuals lose some of their anonymity and interact in the real world: when the product is shipped by mail to the customer.

[1]For example, the 2017 Global Drug Survey documents that in the UK in 2017, around a quarter of survey respondents report purchasing drugs online. The findings of the survey from 2017 can be found on the official website at `https://www.globaldrugsurvey.com/wp-content/themes/globaldrugsurvey/results/GDS2017_key-findings-report_final.pdf` or in Barratt et al. (2016). Soska and Christin (2015) in turn study the first of these platforms, which was called "Silk Road", and estimate that the website at its height in 2013 had an annual revenue of more than $100 million.

The nature of these marketplaces exacerbates the problem that reputational incentives are meant to overcome. In particular, the absence of any ability of buyers to enforce a contract suggests that moral hazard problems are severe. It is easy for a seller to simply ship an empty package to a customer or to not ship anything at all. To solve this problem, darknet markets offer escrow services. Instead of transferring payment directly to the seller, a buyer may pay the platform operator, who holds the money in an escrow account and only releases it to the seller when the product has been received by the buyer. However, this in turn provides the platform with the incentive to shut down and disappear with all money held in escrow at an opportune moment.[2]

We make use of webscrapes of individual offers on the two most popular platforms for illegal merchandise at the time covered in our data: "Agora" and "Evolution". We further add data provided by API requests of the darknet search engine "Grams". The resulting dataset provides a full overview of the supply of drugs on the two major platforms and covers the time period of June 2014 until July 2015. It contains information on the prices and quantities of each offer, the type of drug sold, whether the offer allows use of the escrow services, the country the good is shipped from, as well as the rating, size, name and public PGP key for encrypted communication of the seller.[3]

The Agora and Evolution platforms were known during their time of operation for high stability and professionalism, relative to other, small competitors. Evolution in particular had little to no issue with uptime and accessibility and became the largest platform by the end of 2014. However, in mid-March 2015, the administrators of Evolution executed an exit-scam and absconded with an estimated $34 million in bitcoins (at the time) stolen from their traders. Vendors selling exclusively on the Evolution platform were subsequently forced to migrate to a different platform (in all likelihood Agora) or exit the market altogether.

We exploit our knowledge of sellers' public PGP keys and names to link vendor accounts over time and across platforms. This allows us to track vendors that sold on Evolution prior to the exit and migrated to Agora following the exit. Sellers that 'switch' the marketplace reset their rating in the process. This exogenous shock to switchers' ratings provides us with an instrument to study the impact of a sellers' reputation, measured by

[2]This has happened numerous times, for example in 2013 alone, at least 7 darknet platforms ended in such exit scams. However, the majority of platforms are very shortlived and do not have a meaningful market share (see Bhaskar et al. (2017) for a detailed documentation of platform turnover and size). Exit-scams by dominant platforms are rare.

[3]We also observe the product titles, descriptions and individual reviews. Due to some incompleteness of the scrapes for the individual reviews, we choose not to make use of them and instead focus on the aggregate ratings measure.

the aggregate rating, on the prices of his/her products.

We estimate a statistically significant, positive and large causal effect of a sellers' aggregate rating on the unit price he/she charges. The effect varies slightly across the different types of drugs we consider. In our main results we find that the value of a one percentage-point improvement of the average rating causes up to a 45% of a standard deviation increase in the respective unit price (45% for Cannabis, 15% for Cocaine, 13% for MDMA and 7% for Amphetamine). We further provide evidence that as a switchers' rating recovers following the migration, the effect reduces in size and may even vanish. Finally, the impact of rating is significantly larger than the impact on prices due to increased competition or the use of the escrow system.

Our work in this paper makes two contributions to the literature. One, we study a unique black market that has received little attention so far in economics, in which legal institutions are replaced by centralized platform mechanisms to enable trade.[4] Traders make use of reputation to police themselves in order to overcome the institutional void and lack of legal recourse. Reputation has been suggested to play a crucial role in replacing governmental and legal institutions in various environments (e.g. in emerging markets (Gao et al., 2017), among medieval merchant guilds (Greif et al., 1994), in a private code of law for merchants in the middle ages (Milgrom et al., 1990), or in pirate organizations (Leeson, 2007)). Our results also document that reputation appears not to be transferable between different online marketplaces.

Two, we provide reduced-form estimates of reputation effects on online-sales platforms using a novel approach that exploits the reputational shock experienced by sellers following the Evolution exit. A sizable literature has developed that estimates the returns to reputation for high rated sellers in online markets (e.g. Resnick and Zeckhauser (2002); Cabral and Hortacsu (2010); Cai et al. (2014); Jolivet et al. (2016), see Tadelis (2016) for a recent survey). Much of the literature documents a relatively small, but positive and statistically significant effect of reputation on price. We document effects that are more pronounced than most of the reputational effects found in previous work on legal sales platforms, indicating that the value of reputation in the absence of enforcable contracts and legal certainty increases.

The remainder of this paper is structured as follows. Section 2 discusses the institutional setup of the market and its evolution. Section 3 explains how the data was collected and processed, and establishes important stylized facts about the nature of seller ratings

[4]We are aware of two recent papers studying the online market for illicit drugs: Bhaskar et al. (2017) and Janetos and Tilly (2017). However, there is also a literature in computer science and criminology on darknet marketplaces (e.g. Soska and Christin (2015); Aldridge and Decary-Hetu (2014); Barratt et al. (2016).)

and the determination of prices. Section 4 details the Evolution exit-scam and discusses the identification of the ratings effect. Section 5 documents and discusses the results. Finally, Section 6 concludes.

2 The darknet platforms

The origins of the online black market for illegal drugs lie with the first major darknet platform, Silk Road, launched in 2011. It grew to an unprecedented size, due to its focus on providing trader anonymity. It was shut down by law enforcement in 2013 and its founder later sentenced to life in prison. However, Silk Road combined a series of techological advances and inovations that have effectively been copied and developed further since then by every subsequent platform, including the two studied in this paper.

First, Silk Road was located on the Tor network. Tor ('the onion router') makes use of a private network that directs an internet users signal across different relays and encrypted nodes before reaching the intended destination, making it very difficult to track the site or its users. Second, it enabled and encouraged its users to communicate using PGP encryption. Sellers were expected to provide their public key alongside their descriptions and prices of their products. Third, transactions could only be conducted using the cryptocurrency Bitcoin. Each seller or buyer could deposit and withdraw bitcoins from a wallet attached to their account on the site in order to make payments. Fourth, a centralized feedback and rating system was implemented, in which buyers could leave feedback for sellers they had bought from. Fifth, Silk Road also provided an escrow system. Dealers could offer their buyers the use of the system in order to give them security that they will not be defrauded. Instead of making payment directly to the vendor's on-site wallet, the buyer would send his bitcoins to a wallet of the platform. Then, the vendor would send the merchandise and after the buyer confirmed its arrival, the platform would transfer payment to the seller.[5] Sellers could also choose to forego this system and require the buyers to finalize the payment early, meaning to send the funds directly to the seller prior to shipment of the merchandise. For the use of the platform, sellers would be charged a percentage-based fee for each transaction.

On the surface, Silk Road and its successors are structured in a way familiar to any user of eBay or Amazon (see Figure 1 for examples from the Agora platform). Sellers

[5] If the buyer did not signal the shipment to have concluded, the payment would be automatically released after a waiting period of a few weeks. In addition, platforms often offer mediation services in case of disputes (e.g. Agora). Such a system is not unique to illegal online markets. Airbnb for example holds a buyers payment until 24 hours after check-in "to make sure everything is as expected" (Airbnb, 2017). See Figure 6 in the Appendix for an overview of the escrow system on Silk Road.

can open accounts for a fixed refundable bond and create product listings. Each listing contains a description of the product on offer and a price set by the seller, as well as information on the shipping origin of the merchandise and the sellers rating and number of sales made. Buyers in turn can browse the listings by selecting the relevant category of products, or using the sites' search function. In addition, buyers are also able to observe the profile page of the seller, including his/her PGP key and history of reviews.

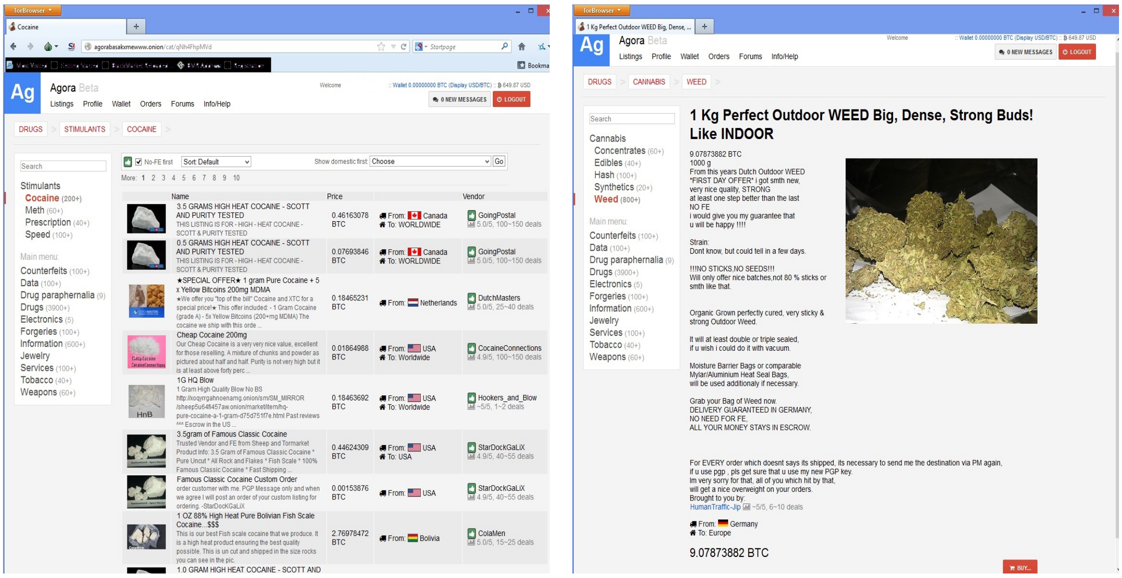


Figure 1: Screenshots from Agora

Notes: The figure shows two screenshots of the darknet platform Agora as it appears to potential buyers browsing.

In contrast to most legal markets, there is a great deal of darknet platform turnover. At any given point in time there are dozens of different marketplaces active on the darknet. However, trade is predominantly conducted on a few large platforms. Bhaskar et al. (2017) document the lifetime of 88 separate platforms from 2011-2015 and demonstrate that the vast majority of them were (very) small in terms of market size and had a very short lifespan. The few larger platforms (such as Silk Road, Agora, or Evolution) in turn dominate the market when active and operate for a significantly longer time period of at least a year. Platforms exit for multiple reasons, among others a shutdown by the authorities (e.g. Silk Road), an exit-scam (e.g. Evolution), or voluntarily due to for example security concerns (e.g. Agora). During the time frame studied in this paper, the Agora and Evolution platforms were the dominant players in the market. Following the Evolution exit-scam in March 2015, Agora continued to be the largest platform until its voluntary and pre-announced exit in August 2015.

3 Data and descriptives

We make use of daily webscrape data from the two darknet platforms Agora and Evolution, as well as of daily API requests of the darknet search engine Grams (see Figure 7 in the appendix for a screenshot of the website). Our data covers the time period of July 2014 to July 2015. The Grams data allows us to obtain information on the supply of goods on the two platforms. Illegal drugs account for the largest share of merchandise on offer.[6] For each item on offer we observe the title, price, product category, and shipping origin, as well as the vendors name and public PGP key. We add to this wealth of information the vendors rating, reviews, and total sales, as well as the item description from the platform scrapes. The resulting dataset provides a unique overview of the black market for illegal drugs over the course of a year.

Items advertised on the darknet platforms are placed in separate product categories, allowing us to distinguish different types of drugs. However, no further information on the product is directly provided. Instead, the title and description of an item contain important information for buyers such as the quantity of the drug that is sold. We focus on homogeneous goods within each drug type and extract from the item titles and descriptions information on the quantity being sold and the size of the batch. Figure 2 shows an example of an offer for MDMA. In this instance, we determine that the quantity sold in the offer is 1 gram.

Figure 2: Screenshot of Evolution item

Notes: The figure shows a screenshot of an example of an item being sold on the darknet platform Evolution.

We focus on eight product categories for illegal drugs, namely cannabis, MDMA, cocaine, amphetamine, methamphetamine, heroin, LSD, and ketamine, and observe a total of 37,057 unique offers of drugs made by 3,005 separate vendors. Since the accessability of the sites varies over time, our dataset sometimes contains gaps between observations of offers. These missing data patterns are unlikely to be systematic, as they relate to technical availability of the marketplaces and are common to us and buyers.

[6] Drugs and electronic goods (such as eBooks or credentials for hacked Netflix accounts) are by far the two largest categories, making up around 99% of the market.

Table 1 reports the summary statistics for all eight categories. It shows the average unit price (i.e. the price per consumption unit in USD), the number of vendors and offers, and the median quantity sold. Cannabis is the cheapest type of drug on offer (at around 11 dollars per gram), while meth and heroin are the most expensive (at over 150 dollars per gram). Cannabis is also the most popular drug type sold with the most unique offers. The median quantity advertised for the cheapest drugs cannabis (14g) and amphetamine (20g) is significantly larger than for the expensive drugs.[7]

Table 1: Summary statistics

Category	Mean unit price		# Dealers	# Offers	Median quantity
Cannabis	11.0	per 1g	1,415	18,331	14 g
MDMA	44.2	per 1g	779	5,067	10 g
Cocaine	112.8	per 1g	741	4,603	3.5 g
Amphetamine	15.7	per 1g	344	2,248	20 g
Meth	158.5	per 1g	319	1,889	3.5 g
Heroin	154.0	per 1g	271	1,841	1 g
LSD	48.0	per $10 \times 100 \mu g$	241	2,374	$100 \times 100 \mu g$
Ketamine	58.4	per 1g	137	698	5 g

Notes: The table reports summary statistics for the eight product categories considered. Prices are reported in $US. The Bitcoin exchange rate used corresponds to the day on which the item price was observed. Unit price refers to the price per consumption unit, defined as 1 gram for all categories except LSD, where it is 100 μg.

The average price however hides two important sources of price variation: country differences and quantity discounts. The price for the same type of drug, in the same quantity, often shows stark differences by the shipping origin of the product. To illustrate this, Table 8 in the Appendix documents the price variation for cocaine across the ten largest countries for the drug, measured by the total number of unique offers. The average price of one gram of cocaine ranges from $267.47 in Australia to $79.95 in the United States. A likely explanation is that because cocaine must be brought into the country first to be sold from there, differences in the ease of smuggling the merchandise through customs produce very large differences in the cost to obtain the drug.[8] Similarly, proximity between producer and consumer country may be an important factor in the cost as well. Furthermore, given the greater risk of detection when purchasing from abroad, buyers are likely to favour domestic offers. Table 8 also illustrates that the largest share of vendors

[7] Detailed information on the distribution of price and quantity can be found in the appendix in Figures 8 and 9.

[8] Australia operates a very strict customs regime to protect its unique ecosystem. In addition, cocaine is obtained from the coca plant which requires high moisture and low atmospheric pressure to grow. These conditions are difficult to find or reproduce outside of South America.

active ship their goods from the western world. Figure 10 in the appendix depicts the total number of items observed by the shipping origin country. The largest source of items is the United States at over 10,000 distinct offers, while other countries with a lot of activity in the market are for example the United Kingdom (around 4,600 items), or Germany (around 5,100 items).

Table 2: Quantity and finalize early discounts

	Price (single unit)		Discounts				
Category	All	Escrow	Finalize early	$\times$ 5	$\times$ 10	$\times$ 50	$\times$ 100
Cannabis	17.57	17.62	0.98	0.77	0.68	0.50	0.43
MDMA	65.47	64.42	1.09	0.62	0.49	0.33	0.27
Cocaine	130.19	132.23	0.94	0.71	0.62	0.56	0.50
Heroin	151.98	153.69	0.96	0.66	0.54	0.27	0.22
Amphetamine	43.16	37.25	1.84	0.35	0.24	0.14	0.10
Meth	177.56	174.94	1.07	0.58	0.42	0.23	0.17
LSD	54.13	55.22	0.91	0.78	0.73	0.57	0.51
Ketamine	78.89	80.07	0.94	0.58	0.54	0.43	0.37

Notes: The table reports the discount rates for the eight product categories by quantity and by finalizing early instead of using the escrow service. Prices are reported in $US. The Bitcoin exchange rate used corresponds to the day on which the item price was observed. Prices reported are the unit price, that is, the price per consumption unit, defined as 1 gram for all categories except LSD, where it is 100 μg.

The second source of large price variations are quantity and finalize early discounts. Dealers offer their potential customers significantly reduced prices for larger quantities in particular. Table 2 documents the extent of the discounts on offer. Across all categories, sellers continually demand a lower unit price as the quantity bought increases. In the most extreme case, buying 100 grams of amphetamine costs on average only 10% of the unit price of 1 gram of amphetamine. Table 2 also shows that the discount for sending the payment directly to the seller ('finalize early') instead of using the escrow system is much smaller than the documented quantity discounts. In some cases, the average price even increases. This appears to be driven by differences in offer composition. Reputable high quality or large volume sellers tend to offer only finalize early in order to minimize their risk exposure. We account for both aspects of country differences and quantity discounts in our estimations by including fixed effects for the shipping origin and for the quantity offered of a product. We also include use of the escrow service as an explanatory variable.

Figure 3 plots the number of unique vendor accounts on the two platforms over time. The size of the platforms increased over the latter half of 2014, stabilizing around October for Agora and in December for Evolution. Following the Evolution exit (indicated in grey), the number of vendors on Agora increased as sellers previously present on Evolution sought to continue their business on the only large platform left in the market. However, the limited size of the increase in vendor accounts indicates that in all likelihood not every Evolution seller switched the platform following the exit. As we will show in **??**, the vast majority of sellers in the market are single-platform sellers and of those on Evolution, around ten percent move their business onto the other platform. In addition, note that Agora had previously experienced technical difficulties and had more downtime and a reduced speed in accessing the site relative to Evolution. Due to the increased traffic on its site following the exit, the accessibility of the platform suffered further resulting in larger fluctuations of vendors observed in our scrapes. Figure 11 in the appendix documents the share uptime and speed in accessing the two sites in detail.

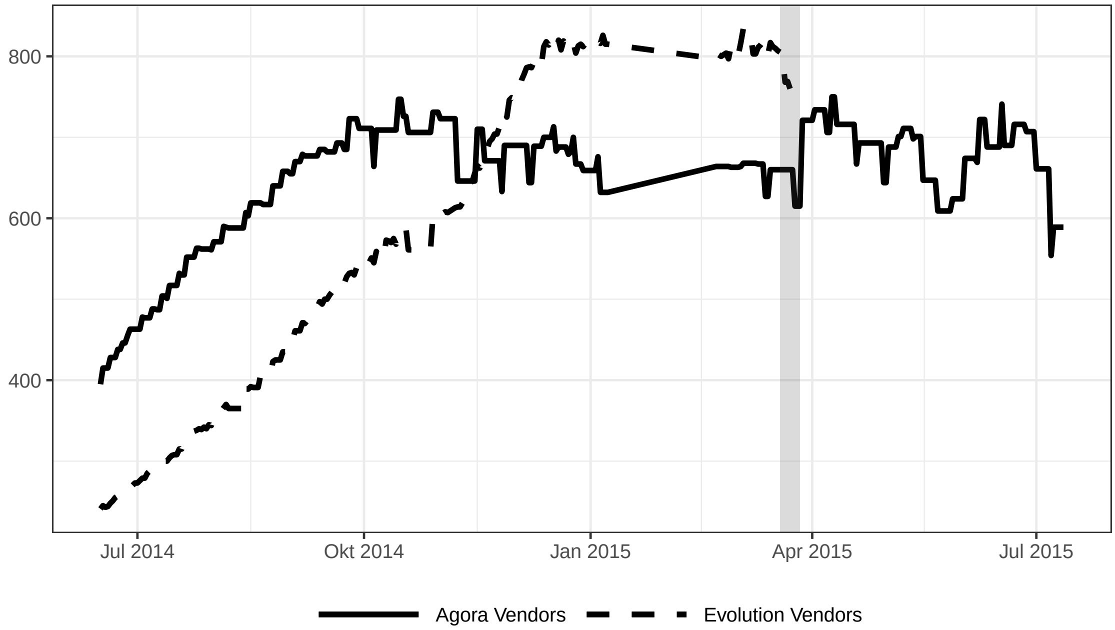


Figure 3: Platform size

Notes: The figure shows the number of unique vendor accounts active on the two platforms. The Evolution exit is indicated in grey. The flat lines in early 2015 are due to missing data. Accessability of the Agora platform deteriorated in particular after the exit (see Figure 11 in the appendix).

For our estimations in section 5 we restrict the analysis to the following five categories of cannabis, cocaine, MDMA, heroin, and amphetamine, since the remaining categories do not contain a sufficient number of sellers that switch. To focus on a set of homogeneous offers, we limit the sample to a time period around the Evolution exit date from late February to mid April, two weeks after the Evolution exit. Moreover, we only include product offers from countries where we observe switching vendors.

Finally, before proceeding to the analysis, we examine the rating of vendors in more detail. Previous work on the effects of reputation on legal sales platforms has documented that the average rating of a seller tends to be very high (for example in Cabral and Hortacsu, 2010).[9] Because conducting transactions in this market requires buyers to reveal their physical address to sellers, this may be further exacerbated due to fears of retaliation. Figure 12 in the appendix shows the distribution of rating across sellers. As expected, the distribution is extremely skewed towards the top on both platforms and exhibits the well-documented 'J-shape', indicating that the variation in seller rating between (relatively) highly-rated sellers and (relatively) lowly-rated sellers may be quite small in absolute numbers. It appears that when buyers leave a review, most of the time they will tend to leave a perfect or very good review, sometimes a very bad one, but rarely a mediocre one. This pattern is well documented for legal markets (Tadelis, 2016).

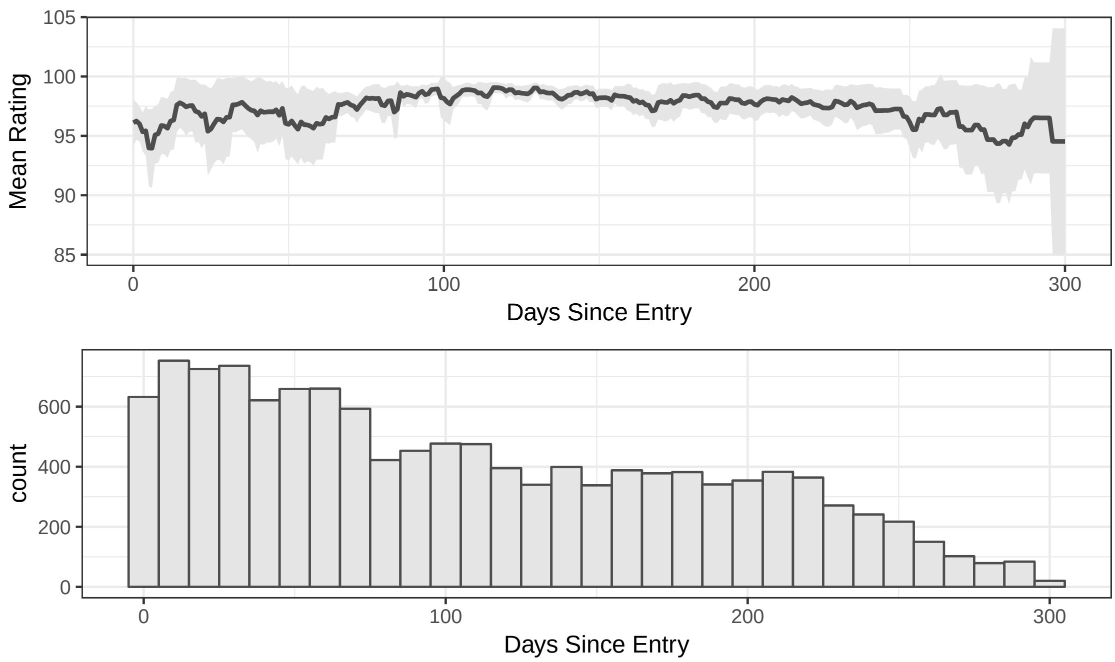


Figure 4: Vendor lifecycle

Notes: The figure shows the average rating in the top plot and the number of unique vendor accounts in the bottom plot observed by the number of days passed since the vendor entered the market. Rating is measured on a scale of 0 to 100 with higher numbers indicating better rating. Entry is defined as the first date of observation for the account. We exlude accounts of sellers that have already made sales before the first time they are observed. The 95% confidence band of the average rating is shown in grey.

Figure 4 plots the average rating of a vendor over his/her lifecycle. We track accounts that have been opened on one of the platforms from the day of entry over time. Entry

[9]Similar results have also been found for the darknet black market in Bhaskar et al. (2017).

is defined as the date on which the vendor is observed for the first time.[10] As vendors mature, the average rating improves and the variation in rating decreases significantly. The improvement in rating becomes increasingly less volatile over the first 80 days. Within 100 days of activity it appears that sellers on average have matured. The difference in the average rating between a new entrant and a mature vendor is very small in absolute numbers and around 3 (percentage) points. Figure 4 also indicates that as the average rating improves within the first 3 months, a sizable fraction of new entrants drop out of the market. The remaining share however continues to trade and its number is stable for a longer time. This suggests that 'good' sellers stay in the market long-term, while 'bad' types drop out early on (and may re-enter under a new pseudonym). Since our dataset covers a time period of one year, the number of observations starts to become small and the ratings information very volatile as we track the average entrant for more than 200 days.

4 Empirical approach

Our aim is to estimate the impact of a sellers rating on the prices charged for his/her products on offer. We define an individual item that is sold as the unique offer observed on one of the platforms, sold by one specific seller, belonging to one drug category, of a given quantity, and shipped from a specific country. We denote the individual items by the index i. We further define the product market that a given item i is associated with and competes in as the category of drug and the country of origin of item i, denoted by k and c respectively. We consider the following pricing equation:

$$Price_{t,i} = \beta_1 Rating_{t,j} + \beta_2 Nsellers_{t,k,c} + Escrow_i + \mu_i + Month_t + \varepsilon_{t,i}, \qquad (1)$$

where $Price_{t,i}$ denotes an item i's unit price at time t and $Rating_{t,j}$ denotes the seller j of item i's aggregate rating at time t. The variable μ_i represents the item-specific fixed effects of seller $\times$ category $\times$ quantity $\times$ country. We include a monthly time-fixed-effect denoted by $Month_t$. In addition, $Nsellers_{t,k,c}$ denotes the total number of sellers selling an item in the same product market, i.e. in the same category k from the same country c, as the item i at time t, while $Escrow_i$ indicates whether an item i requires using the escrow services for payment. Finally, $\varepsilon_{t,i}$ is a scalar unobserved seller/item-specific shock at time t that is assumed to be mean-independent of the remaining right-hand side

[10]We also require that the vendor has not made any sales yet, since it is possible for a vendor to be missed in previous scrapes due to technical difficulties. We further exclude the first few scrapes in our dataset when many sellers are observed for the first time.

variables. Note that by conditioning on quantity in the item-specific fixed-effects, we explicitly allow for non-linear pricing of products and for the pricing structure to vary across categories (and countries). We documented previously in section 3 that quantity discounts are commonplace.

To estimate the above equation, we need to deal with two possible concerns of endogeneity in the ratings variable. The first is unobserved seller heterogeneity. This has been noted before in the literature several times (e.g. in Resnick and Zeckhauser (2002)) and it has been argued that it may explain the sometimes puzzlingly small effect that ratings appears to have on price on legal sales platforms (e.g. in Cabral and Hortacsu, 2010). Due to the required anonymity in the market that we study however, all information available to buyers is available to us as well. There is no offline presence for vendors or information on the darknet platforms that we do not observe which may provide buyers with additional information about sellers. The second concern however is more severe. Since the ratings information is a summary measure of past buyers feedback, it is likely to be a function of past prices. Buyers who purchase an expensive product may have a correspondingly higher expectation of its quality which will impact the rating they leave for the seller. Then the aggregate ratings variable in Equation 1 is likely to be correlated with past realizations of ε. We tackle this issue by making use of an instrument for rating available to us, in order to obtain a causal estimate of the value of reputation.

Specifically, we make use of two crucial features of darknet platforms in order to conduct an instrumental variable regression of Equation 1: the publication of sellers public PGP keys and the ability of platforms to perform so-called exit-scams. Consider the two characteristics in turn.

The first aspect we exploit is the nature of encrypted communication on darknet platforms. These illegal marketplaces highly encourage buyers and sellers to encrypt their communication. When consumers choose to make a purchase, they must provide the seller with an address for the shipping of the merchandise. Doing so in the clear given the illegal nature of the trade poses an additional risk for buyers. Consequently, vendors are required to provide their public PGP key for buyers to use in their advertisements on the platform, so that each vendor account on a platform is linked to a specific public PGP key. PGP ('pretty good privacy') is a popular encryption program that makes use of public-key cryptography. Each user of PGP has two keys, one private and one public. Communication with a user can be conducted by encrypting the information prior to sending with the public key of the receiver. Decrypting the message can then only be done by using the private key which is only known to the receiver.[11] Private and public keys

[11]Technically, it is only computationally infeasible to decrypt without knowledge of the private key.

are unique and highly complex. These features of PGP keys provide us with a unique identifier that allows matching vendor accounts across platforms and time. PGP keys also make it possible for potential buyers to verify the true identity of a seller on a new platform. Figure 13 in the appendix shows an example of a public PGP key.

We exploit our knowledge of sellers' account names and public PGP keys to link all vendor accounts across both time and platforms. Previous work on darknet marketplaces suggests that only a small fraction of sellers operate across platforms. For example, Soska and Christin (2015) measure the number of unique 'aliases' (account and marketplace pair) a seller uses and show that more than 75% of sellers only use one. Similarly, Buskirk et al. (2014) suggest that more than 78% of sellers are only present on a single platform as of September 2014.

Table 3: Unique sellers in the market

		Unique sellers				
	accounts	total	one account	two accounts	three accounts	four accounts
N	3,005	2,344	1,718	620	23	3

Notes: The table shows the number of vendor accounts and the number of unique sellers present in total and by the number of accounts sellers use on the two platforms. There are no sellers active on only one platform with multiple accounts.

Table 3 shows the number of vendor accounts and of operating unique sellers on the two platforms, as well as the number of accounts unique sellers use. There are significantly fewer actual unique sellers in the market than the number of vendor accounts on the two platforms. Of the 2,344 unique sellers active, around 73% use only one account. This is in line with the previously documented estimates. Table 3 also shows how many accounts a seller that is active on both platforms uses. Almost all sellers use only one account on both platforms respectively, while only 23 sellers use three accounts spread across the two platforms, and three sellers operate with four separate accounts. There are no sellers that only sell on one of the platforms, but use multiple accounts to do so.

The second aspect we exploit is the Evolution exit-scam. When traders conduct their business on the darknet platform, they place their bitcoins on their platform account in order to then make transactions. Furthermore, when making use of the escrow system, they place the payment temporarily on a wallet of the platform operator. In either case, the funds are nominally controlled by the platform operators as soon as they are transferred

Public key cryptographic systems rely on mathematical problems that make it easy to generate a private and public key pair, but very difficult to re-engineer the private key based on the public key. This allows the public key to be broadcast and communication remains secure as long as the private key is secret. The great advantage is that no key must be secretly exchanged prior to communication commencing. Almost all secure communication (such as online banking) makes use of a public key cryptography system.

to the site's account. Even though users can exercise control over the funds in their own accounts, this is at the operators' discretion. This gives an incentive to the platform administrators to shut down the site unexpectedly and abscond with all the money in platform accounts. In mid-March of 2015, Evolution began to disallow withdrawals of bitcoins from wallets and accounts on the platform, citing technical difficulties. Escrow accounts were similarly frozen and inaccessible. Within a week the site went offline. Estimates suggest that the site administrators stole around 130,000 bitcoins from their users, worth at the time approximately \$34 million. The exit was highly unexpected, since Evolution was the largest platform in the market and was known for stability and professionalism. Cursory examination of discussion forums on darknet platforms at the time suggests that it took 2-3 days for traders to start to become aware of the scam occurring.

However, buyers quickly migrated to other platforms to continue purchasing. Similarly, sellers wishing to continue their business were forced to migrate to a different platform. At the time, Agora was the only remaining large and dominant marketplace and saw a sudden increase in sellers following the Evolution exit (see Figure 3). Sellers forced to 'switch' the marketplace had to create a new account and hence lost their reputation in the process.[12] We exploit this ratings 'reset' of 'switchers' to estimate the effect of ratings on price and we track sellers switching by linking their accounts as described before. Hence, we augment Equation 1 with the following first-stage regression,

$$Rating_{t,i} = \delta_1 Switch_{t,j} \times \mathbb{1}\{t \geq Exit\}_t + \eta_i + Month_t + \xi_{t,i}, \tag{2}$$

to isolate the effect of rating on price, where η_i represents the item-specific fixed effects and $\xi_{t,i}$ the error term.

Figure 5 shows the impact of the exit-scam and subsequent forced move to Agora on the aggregate rating and sales of switchers and of sellers selling on Agora both before and after the exit-scam. The Evolution exit period is indicated in grey. On average, switchers tended to have a higher rating than sellers selling on Agora prior to the exit. The forced migration in March 2015 caused a ratings shock and lowered the average rating for switchers by around 3 percentage points. Recall from section 3 that a three-point-difference in the rating was generally found when comparing the average entrant to the average mature seller. The rating of the continuously present Agora sellers instead

[12] Agora and Evolution operated in the exact same way and offered the same services to their users. They also had the same fee structure for operating a seller account. Figure 15 in the appendix documents the average price difference between the two platforms over time, showing that there is no sizable or consistent difference that would indicate variation in how the two platforms operated in the market.

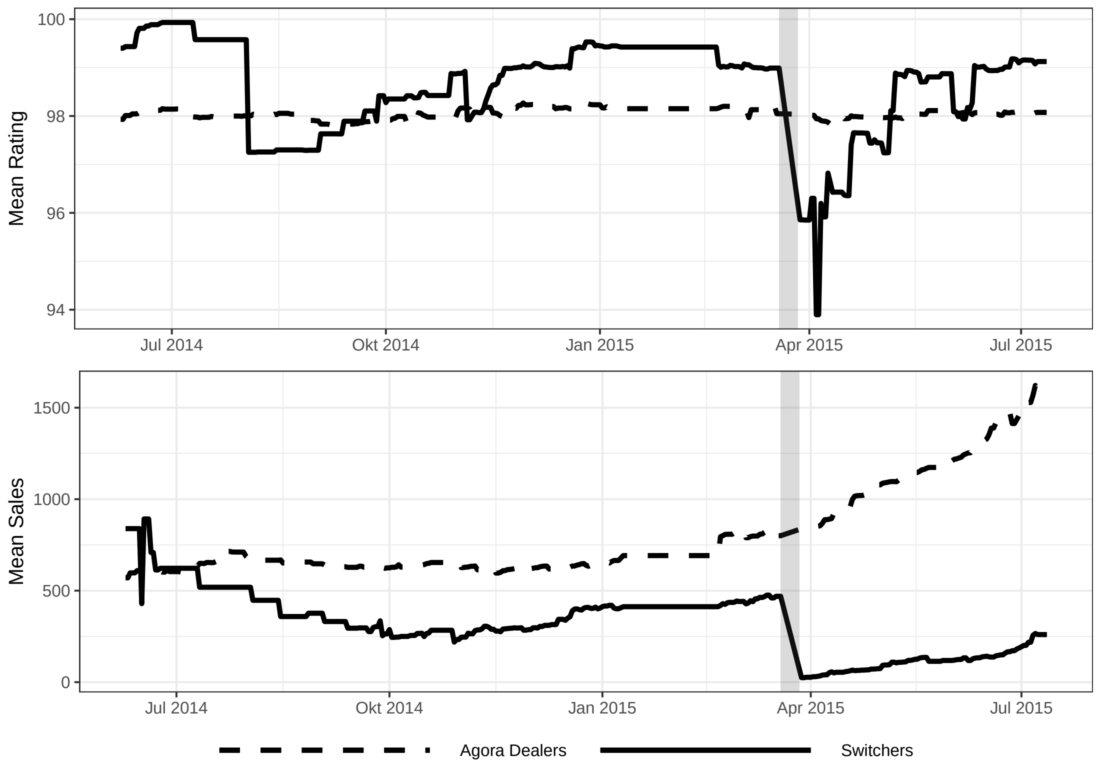


Figure 5: Ratings shock for switchers

Notes: The figure shows the mean aggregate rating and mean total sales of switchers (sellers that sold exclusively on Evolution before the exit and migrated to Agora following the exit) and sellers present on Agora both before and after the exit. The Evolution exit period is highlighted in grey.

shows no reaction to the exit. Similarly, the average aggregate sales of switchers were slightly below those of Agora sellers, but dropped to approximately zero in the wake of the Evolution exit-scam. Following the exit, sales began to grow at a very similar rate to the Agora seller sales, which again were unaffected by the exit. The average rating of switchers appears to recover within the three months following the exit, which is also in line with the approximately 100 days it appears to take for the average seller to mature.

Table 4 documents how switchers price their products seven days before and two days after the exit. It shows that the average unit price of switchers between the two dates strongly decreased across all categories of drugs, indicating a clear and immediate adjustment to the large reputational loss suffered. Taking into account the market price one week prior to the exit, the percentage change of prices is significant for all drugs and is above 20% for most categories. The largest change we document occurs for Ketamine, however we only observe a single switcher in this category. The market price on the other

Table 4: Switchers immediately before and after the exit

	Mean # offers		Median quantity		Mean unit price change		
Category	Before	After	Before	After	Absolute	Percentage	Market
Cannabis	4.96	4.00	7	7	-1.34	-12%	$+4\%$
MDMA	5.17	3.42	20	5	-10.72	-24%	$+9\%$
Cocaine	4.08	3.55	2	2	-14.86	-13%	$+7\%$
Amphetamine	4.25	5.00	17	25	-1.21	-6%	$+5\%$
Heroin	3.86	5.60	1	1	-36.11	-22%	$+6\%$
LSD	4.88	4.33	27	23	-0.99	-21%	$+12\%$
Meth	10.00	10.00	1	1	-37.88	-23%	$+5\%$
Ketamine	6.00	5.00	1	3	-28.03	-45%	$+11\%$

Notes: The table contrasts switchers seven days prior to the exit and two days after the exit. It shows across categories i) the average number of offers per seller at the two dates, ii) the median quantity of offers at the two dates, iii) the absolute average change in prices charged and percentage change relative to the market price seven days prior to exit, as well as the overall market price increase in percentage. The price changes shown for switchers are averages of country differences. Only one switcher is observed for Ketamine. Prices are reported in $US. The Bitcoin exchange rate used corresponds to the day on which the item price was observed. Unit price refers to the price per consumption unit, defined as 1 gram for all categories except LSD, where it is 100 μg.

hand increased across all categories between the week prior and two days after the exit, further reinforcing that switching has a powerful, negative effect on the prices a seller may charge. The table also provides information on the average number of offers for products made by switchers and the median quantity of the offers. It demonstrates that there is little variation in product offerings before and after the exit by switchers, indicating that there is no reaction to the exit by adjusting the product portfolio.

Lastly, to gain a better understanding of switchers, Table 5 contrasts them to all other sellers present on Evolution a week prior to the exit. It shows the proportion of sellers across the different categories of drugs, the average number of items on offer per seller, and the price differences between switchers and other Evolution sellers. Switchers are representative for the average Evolution seller prior to exit and found in almost identical proportion across the different categories to the average seller. Once adjusting for country differences, the average price differences between switchers and other sellers are quite small. In addition, they tend to offer fewer different products on average than other Evolution sellers across most categories, but this is not universally the case. In Table 10 in the appendix, we provide a similar comparison of switchers to Agora sellers one week after the exit. As before, switchers are found in similar proportions across the categories as all other Agora sellers.

However, we also observe that switchers tend to have a higher average rating (99.2) the week prior to the exit, compared to all other Evolution sellers (97.9). It appears that

Table 5: Sellers on Evolution seven days prior to the exit

	Proportion of sellers		Average # offers		
Category	Switchers	Evo sellers	Switchers	Evo sellers	Price difference
Cannabis	0.44	0.46	5.12	10.46	1.09
MDMA	0.28	0.29	5.56	5.86	-3.67
Cocaine	0.21	0.25	4.33	6.17	-4.25
Amphetamine	0.14	0.14	4.25	5.43	-0.15
Heroin	0.11	0.10	4.16	7.32	0.61
LSD	0.11	0.09	4.83	7.82	-0.19
Meth	0.04	0.09	10.00	4.68	4.53
Ketamine	0.02	0.02	6.00	2.67	5.76

Notes: The table contrasts switchers to all other Evolution sellers one week before the exit. It shows the proportion of the two groups in each category of drug and the average number of offers. The price difference displayed is the average of the difference of the mean price of the two groups by country in each category.

'better', more mature sellers that tend to have a more narrow offering of products of likely high quality stay in the market and switch platforms in response to the exit. It is not surprising then that the average rating for this group of sellers recovers within the 100 days range after switching.

Before we proceed to the results, we discuss how the functioning of this market and our empirical approach relates to theoretical frameworks. There exists an extensive literature on seller reputation that investigates the building up of reputation and corresponding decline in uncertainty for buyers over time (see a review of this strand of literature in Bar-Isaac and Tadelis, 2008). Classic papers usually focus on a long-lived, monopolistic seller facing a single or sequence of buyers over time (e.g. Fudenberg and Levine, 1989; Mailath and Samuelson, 2001; Benabou and Laroque, 1992). This literature highlights conditions under which learning may be efficient, whether 'convergence to the truth' actually occurs and seller types are correctly revealed, and emphasizes that results may often hinge on for example the size of the discount factor, the degree of uncertainty about seller types, and more broadly the relative sizes of the 'carrot' and 'stick' when sellers may benefit short-term from cheating their buyers but may be punished for it by buyers to induce cooperative behavior (Bar-Isaac and Tadelis, 2008; Mailath and Samuelson, 2006).

However, in our analysis we do not investigate in detail the specific mechanism that allows a seller to convey information on the quality and reliability of his/her product to potential buyers, the 'reputation-building' aspect, instead we focus on the value of having been identified reliably as a seller of good quality, compared to the outcome for new sellers where buyers face great uncertainty. Our analysis is therefore more closely related to the literature on disclosure and signalling of product quality. Disclosure refers to a seller making a credible direct claim about his/her quality (e.g. via independent certification), while signalling refers to a sellers actions that can influence buyers' beliefs about said sellers quality (e.g. via the posted prices). It seems reasonable to exclude the possibility to disclose quality ex-ante in the particular black market that we study in this paper.

The literature on quality signalling is generally concerned with establishing the conditions under which signalling may occur in equilibrium and competing sellers strategically distort their price to signal their true quality to buyers (Daughety and Reinganum, 2008a; Milgrom and Roberts, 1986; Bagwell and Riordan, 1991; Sobel, 2009). What is often documented (among other conditions), is that in order for such a separating signalling equilibrium to be played, low-quality sellers must not prefer this full-information equilibrium to a pooling one (Daughety and Reinganum, 2008b; Janssen and Roy, 2015). Intuitively, if low-quality sellers obtain a greater profit from mimicking the price setting of a high-quality seller under uncertainty than when being identified by buyers as a low type, prices across the different types will be chosen equally and buyers cannot tell sellers apart simply from observing posted prices.

Indeed, our analysis can be interpreted as shedding light on the value of playing a full-information, separating equilibrium in a setting with extreme uncertainty: the forced migration to the Agora platform for switchers and ratings 'reset' turns these sellers from identified types into entrants, who may be good or bad types in the eyes of buyers. Since we find that there are substantial returns to reputation, a full-information signalling equilibrium appears not to exist in this market. Furthermore, our descriptive analysis above highlighted that sellers that build up a bad reputation tend to leave the market relatively soon, indicating that it does not pay off to be identified as a bad type. This is further underlined by the fact that such a seller may always choose to re-enter the market under a new pseudonym. Arguably, there exists cut-throat competition among both lower-rated and new sellers. Similarly, we showed that sellers with good reputation tend to stay in the market for a (relatively) long time, clearly indicating that it does pay off to play a separating equilibrium, if you are a good type. This is also in line with findings documented in Janetos and Tilly (2017) who study the Agora market and argue that there are indeed two types of sellers, good and bad, where low-rated sellers tend to exit the market as more bad reviews start to come in. We take this as strong evidence that in this market 'bad types' will prefer to imitate the price setting of 'good types' when reputation has not been established sufficiently and quality is unobservable.

To investigate in more detail whether signalling is possible in this market, we take a closer look at entrants. We trace these vendors back to their date of entry into the market and investigate two specific groups: (i) vendors that were later identified to be of a 'good type', that is, vendors that build up a high rating and stay in the market long-term, and (ii) 'bad types', which are vendors that are observed with a (relatively) low rating and do not improve on it. These types also tend to leave the market early. Table 9 in the appendix contrasts these two types at their time of entry into the market to the competing vendors present. There does not appear to be a visible pattern of distorted price setting by either 'good' or 'bad' types, relative to all other competitors, suggesting that without type revelation via the ratings system, sellers play a pooling equilibrium. In this case, our estimates can be interpreted as showing the value of being in a separating, full-information equilibrium relative to a pooling one.

5 Results

Table 6 presents the main estimation results, corresponding to the model outlined in section 4. We consistently find that a better rating is associated with a higher price. A one percentage point increase in rating increases the price for all drugs except Heroin by a substantial and statistically significant amount. The associated price premium is about $2 for Cannabis, $12 for Cocaine, $6 for MDMA and $3 for Amphetamine. These results are also economically significant in their relative magnitude—a one percentage point increase in rating in the respective estimation sample is associated with up to a 45% of a standard deviation increase in the respective unit price (45% for Cannabis, 15% for Cocaine, 13% for MDMA and 7% for Amphetamine). The insignificant result for Heroin should be interpreted with caution, as we only observe six switching vendors for Heroin. Our main results demonstrate that the returns to reputation are indeed substantial in such a black market. Based on the estimates in Table 6, we find that a mature and highly-rated seller, whose 'good type' has been revealed via the ratings system, may set a price on average around 60% of the standard deviation of the unit price greater than an entrant.

In addition, the coefficients for the other variables show the expected sign. An increase in competition as measured by the number of competitors has a negative effect on the asking price of sellers, while use of the escrow service increases the unit price of the item on offer. The size of the parameters emphasizes the special role reputation plays in this black market: a one percentage point increase in rating consistently yields a greater price premium than offering escrow and more than offsets an increase in competitors (with the exception of Heroin).

As previously documented, ratings for switching sellers recover quickly. This implies that the ratings effect should disappear over time. Indeed, the more we extend the post-exit

Table 6: Results

	Cannabis	Cocaine	Heroin	MDMA	Amphetamine
Rating	1.87***	11.63***	0.19	6.42***	2.90***
	(0.45)	(1.89)	(0.14)	(0.85)	(0.69)
Nr. of competitors	–0.02***	0.02	–4.38***	–0.19***	–0.48***
	(0.00)	(0.06)	(0.24)	(0.03)	(0.05)
Escrow	0.27***	6.45***	20.89***	2.59***	0.49***
	(0.03)	(0.89)	(1.86)	(0.50)	(0.06)
Item-specific FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
N	113,198	36,613	11,573	38,942	14,653

Notes: Results based on a linear model as specified in section 4. The sample is restricted to countries with switching vendors and a time period around the evolution exit, from one month prior to the exit until two weeks afterwards. Heterocedasticity-robust standard errors given in parentheses. *, ** and *** denote p<0.1, p<0.05 and p<0.01, respectively. Item-specific fixed effects are seller × country × category × quantity.

sample observation period, the more the effect weakens. The results in Table 7 are based on a sample in which the post-exit cutoff was extended by a week. All coefficients are consistently smaller. The estimate for Cannabis is indistinguishable from zero, while for Cocaine, MDMA, and Amphetamine, we observe reductions in parameter size between 25% and 48%. The exception is the estimate for Heroin which is now marginally significant and slightly larger, but still negligible in economic terms.

As a robustness check, we perform a placebo test. We assume a pseudo-exit to occur on 23.02.2015 (before the actual exit) and use similar time restrictions as previously. The results are given in Table 12 in the appendix. We find that the coefficients are always insignificant, with the exception of Amphetamine, for which we find a very small positive effect. However, the estimates are very noisy. We are confident that our main results identify the effect of rating on price induced by the platform exit for switching vendors.

The results from our preferred models in Table 6 are based on a flexible within-item specification, including fixed effects based on the intersection between country, vendor and item quantity. We also report results in Table 11 in the appendix that rely on a model including country, vendor, item quantity and month specific effects. The choice of specification and the level of fixed effects does not influence the results.

Table 7: Results with extended post-exit sample

	Cannabis	Cocaine	Heroin	MDMA	Amphetamine
Rating	−0.39	8.71***	0.36**	3.38***	2.20**
	(0.40)	(2.42)	(0.16)	(0.64)	(0.92)
Nr. of competitors	−0.01***	0.03	−5.43***	−0.07***	−0.15**
	(0.00)	(0.06)	(0.26)	(0.02)	(0.07)
Escrow	0.02	3.85***	5.32***	1.21***	−0.23*
	(0.03)	(0.78)	(1.39)	(0.24)	(0.13)
Item-specific FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
N	131,419	42,265	13,417	45,205	16,967

Notes: Results based on a linear model as specified in section 4. The sample is restricted to countries with switching vendors and a time period around the evolution exit, from one month prior to the exit until three weeks afterwards. Heterocedasticity-robust standard errors given in parentheses. *, ** and *** denote p<0.1, p<0.05 and p<0.01, respectively. Item-specific fixed effects are seller × country × category × quantity.

6 Conclusion

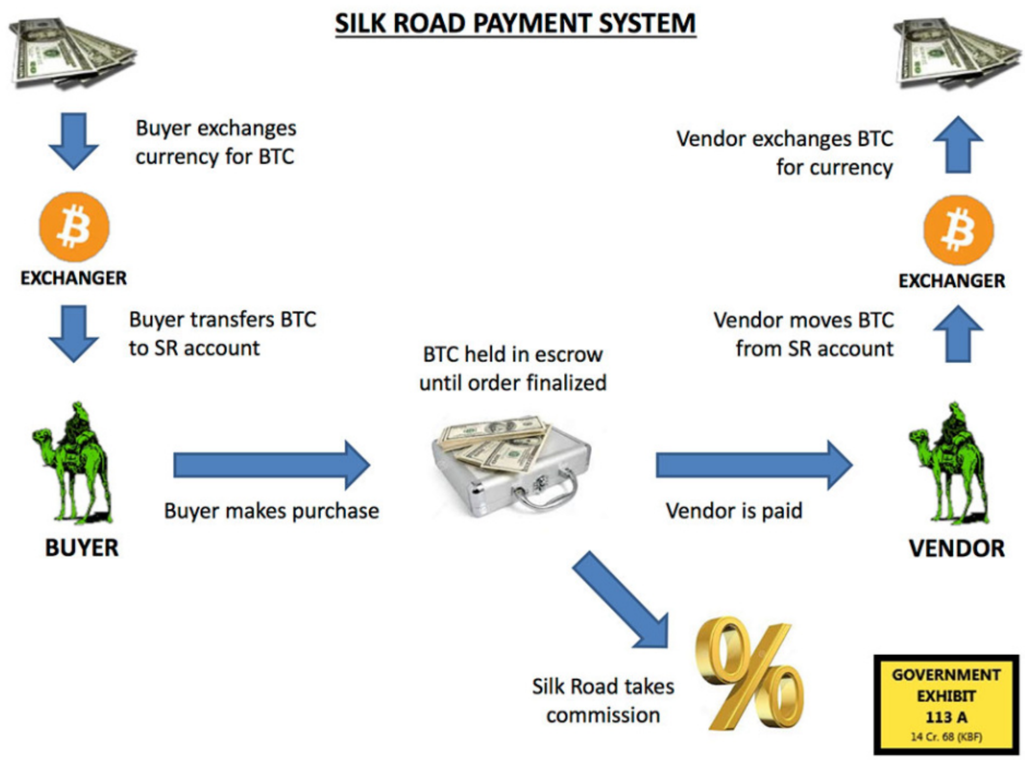
In this paper, we examine the role that seller reputation plays in the online market for illegal drugs. Similar to legal online marketplaces, these 'darknet platforms' offer a ratings system for sellers operating in the market. The institutional void and strong need for traders to remain anonymous in this black market suggests that reputation is a driving force to facilitate trade among market participants. We make use of a novel dataset of webscrape information of offers on the two dominant sales platforms during 2014/15. Our descriptive analysis highlights several stylized facts about darknet markets. First, sellers offer large quantity discounts for bulk offers. Second, drug prices vary considerably across countries. Third, the ratings distribution exhibits the commonly observed 'J-shape'. Fourth, ratings of sellers typically stabilize within 90 days and mature sellers on average have a three percentage point higher rating than entrants.

In our main analysis, we exploit the fact that one of the two platforms suddenly disappeared in March of 2015 and track sellers that are forced to migrate to the remaining marketplace in the aftermath. By necessity, these sellers must register a new account and therefore experience a ratings reset. Using this exogenous variation in ratings allows us to identify the effect of rating on the unit price a seller may charge. We consistently find a large, positive effect of rating on price across drug categories. We find a price premium of 2$ for Cannabis, 12$ for Cocaine, 6$ for MDMA, and 3$ for Amphetamine for each percentage point increase in rating. On average, this effect corresponds to an increase of about 20% of a standard deviation of the respective unit price. As the ratings shock subsides over time, the effect decreases. We find that an established seller may set prices on average around 60% of a standard deviation higher than an entrant.

Our work in this paper demonstrates that rating has a large influence on price in the absence of legal institutions. A sellers rating appears to be the key determinant of prices. The magnitudes of the estimates are substantially larger than most documented in the literature on legal online marketplaces. This corroborates previous literature which suggests reputation may play a crucial role in facilitating trade when governmental or legal institutions are lacking. Our results further document that it is difficult to transfer reputation across different online marketplaces, even when doing so would be to the sellers' advantage. Studying the dynamics of reputation in more detail in such an institutional void is a promising pursuit for future research.

A Appendix

Figure 6: Silk Roads payment system



Notes: The figure shows the payment system originated by Silk Road. Using the escrow system of the platform, buyers may transfer payment onto the escrow account instead of sending directly to the seller. Finalizing the order refers to buyers signalling receipt of the goods. Source: US government diagram used in the Silk Road trial, arstechnica.com.

Figure 7: Screenshot of the Grams search engine website

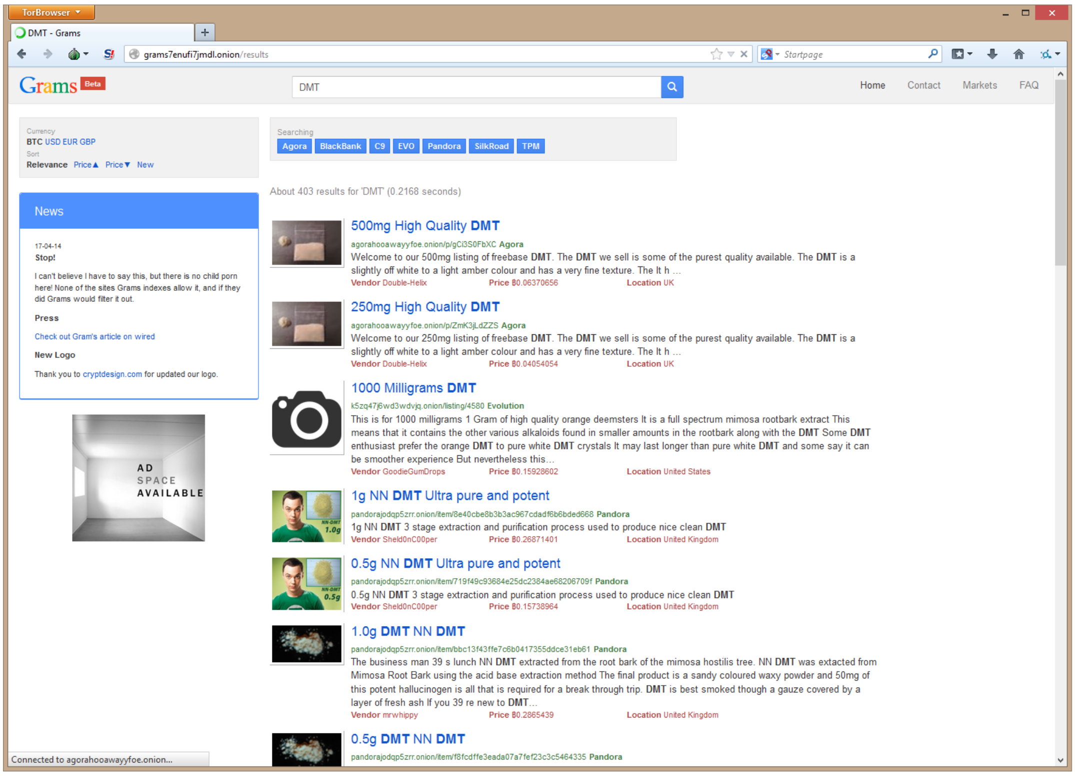
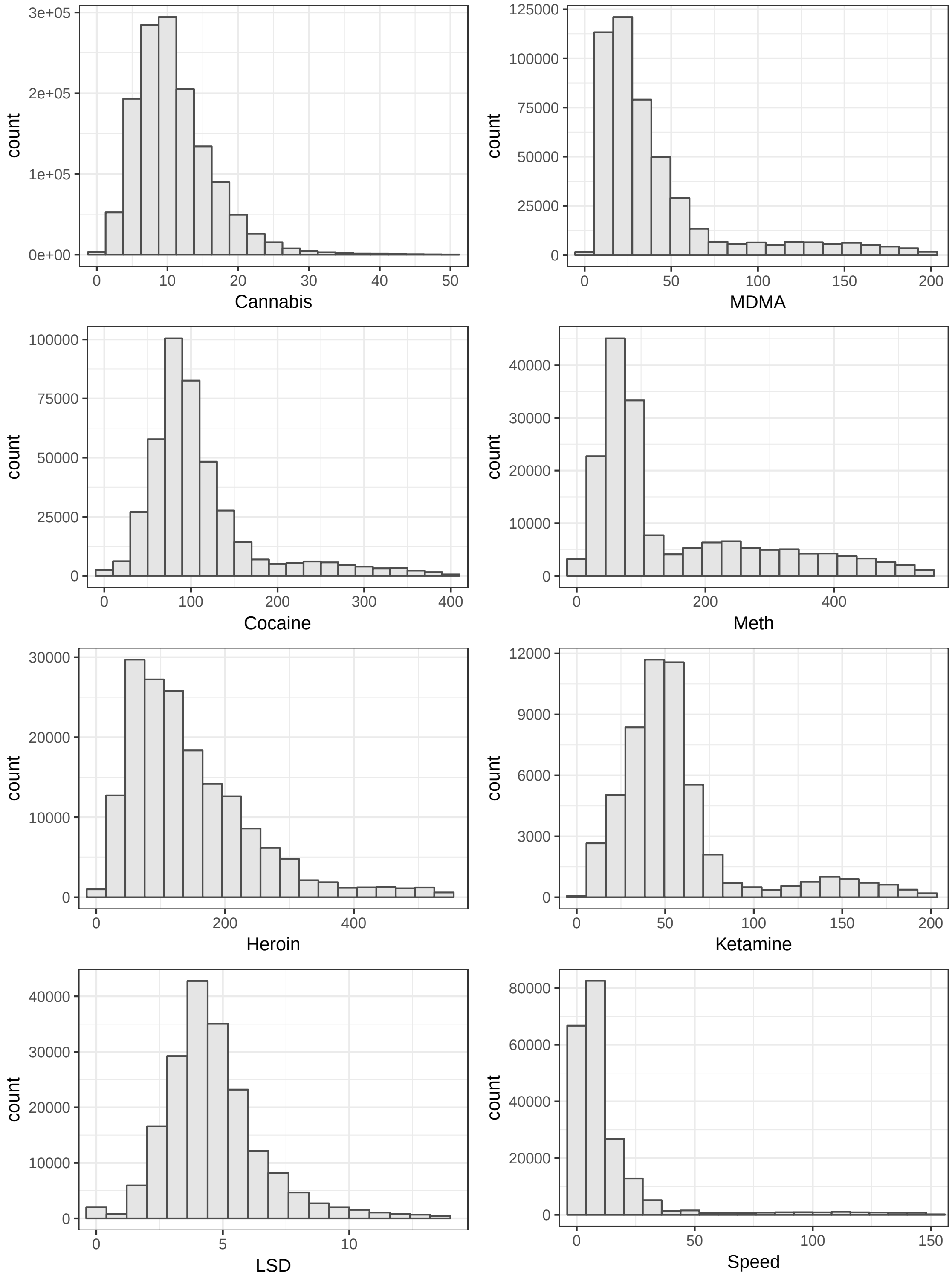


Table 8: Country differences for cocaine

Shipping origin country	Mean unit price	# Offers	# Vendors	Median quantity
United States	79.95	1,177	200	3.50g
United Kingdom	105.57	776	120	2g
Netherlands	86.05	733	101	3g
Australia	267.47	507	84	2g
Germany	92.86	466	62	5g
Canada	93.69	265	44	3.50g
France	107.18	106	18	1g
Sweden	124.52	73	14	2g
Belgium	84.63	62	10	5g
Italy	97.21	42	6	5g

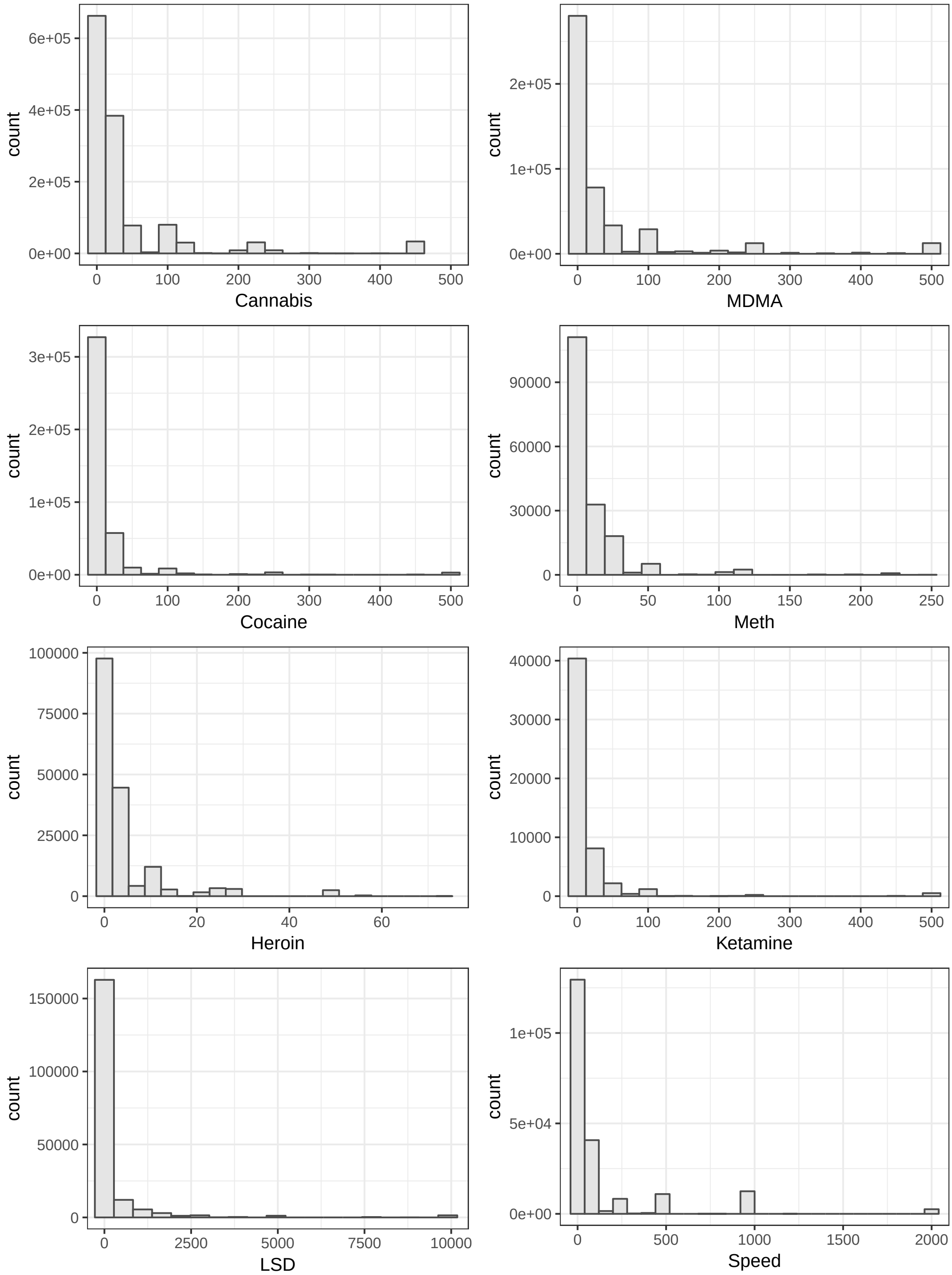
Notes: The table reports summary statistics for cocaine for the ten largest countries of origin as measured by the number of vendors active, sorted by size. Prices are reported in USD. The Bitcoin exchange rate used corresponds to the day on which the item price was observed. Unit price refers to the price per 1 gram.

Figure 8: Distribution of the unit price demanded for all eight categories of drugs



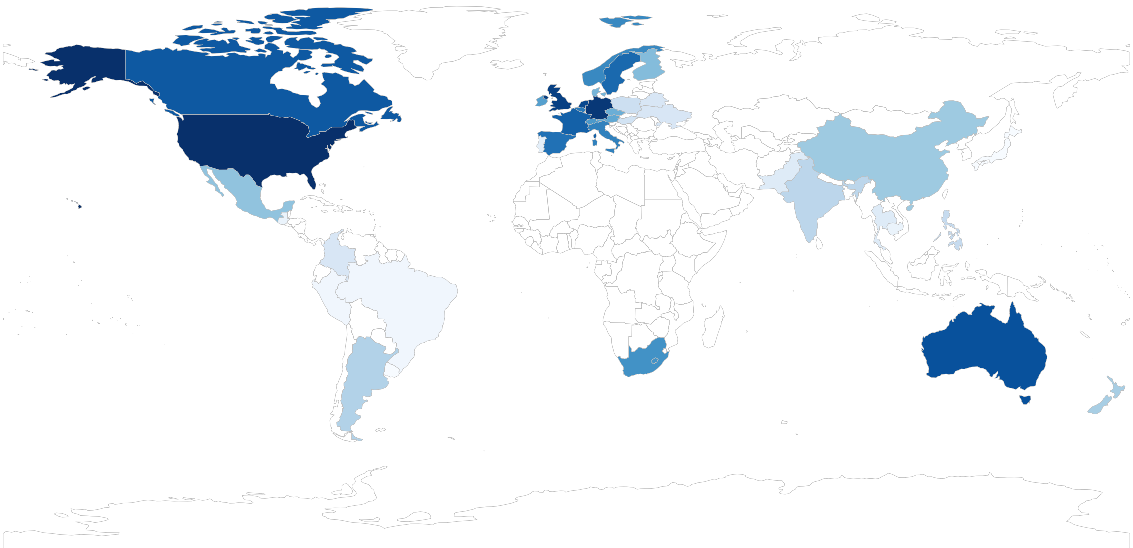
Notes: The figure shows the distributions of the unit price of the eight drugs considered. Prices are reported in USD. The Bitcoin exchange rate used corresponds to the day on which the item price was observed. Unit price refers to the price per consumption unit, defined as 1 gram for all categories except LSD, where it is 100 μg.

Figure 9: Distribution of the quantity offered for all eight categories of drugs



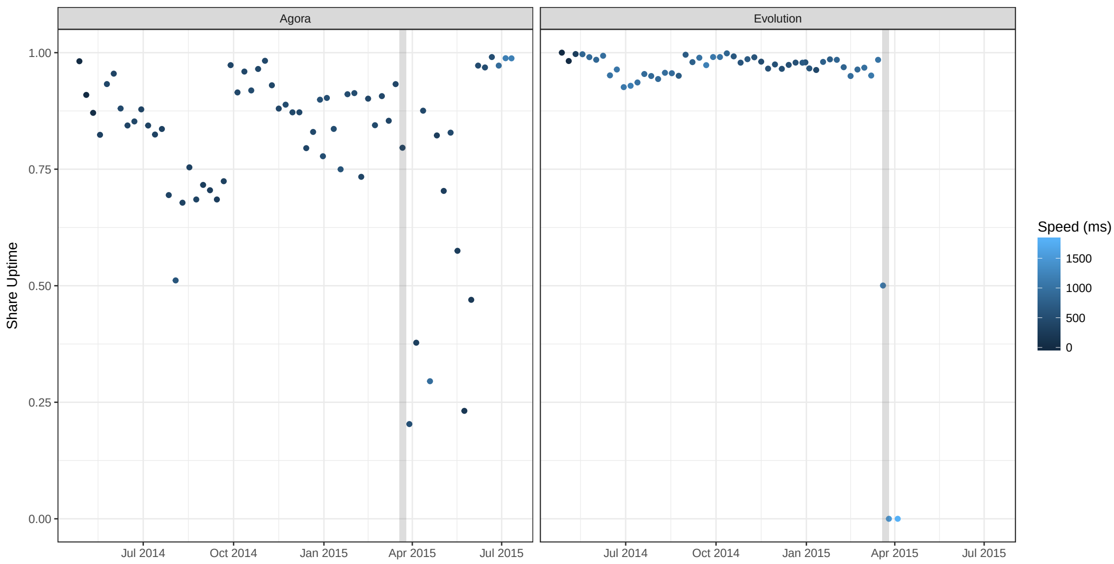
Note: The figure shows the distributions of the quantity of the eight drugs considered. The unit used is grams, except for LSD, where it is micrograms.

Figure 10: Number of unique offers for illegal drugs by shipping origin



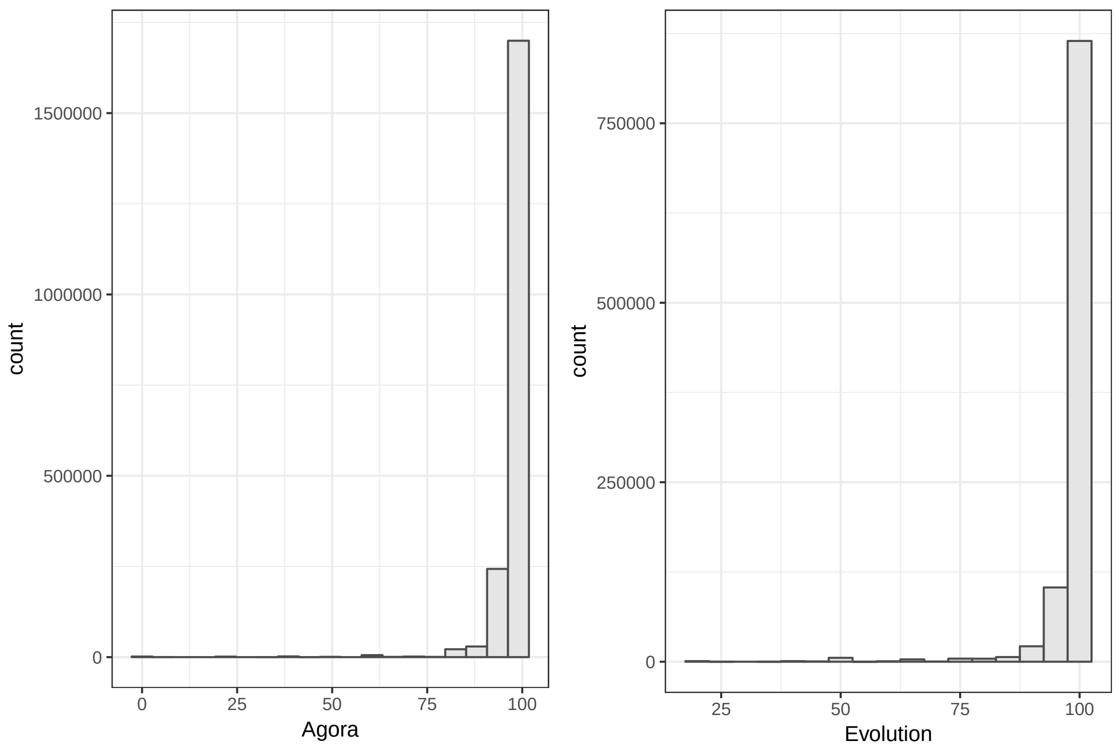
Notes: The figure shows the total number of unique items shipped from each country on both platforms. The largest market is the United States. Most of the offers originate in North America, (Western) Europe, and Australasia.

Figure 11: Platform uptime



Notes: The figure shows the percentage share of uptime for each of the two platforms. The speed of accessing the site is indicated by the shading. The Evolution exit is indicated in grey.

Figure 12: Distribution of seller rating



Notes: The figure shows the distribution of ratings of the individual vendor accounts. The rating is scaled for both platforms from 0 to 100, where a higher number indicates a better rating.

Table 9: Highly-rated and lowly-rated vendors at date of entry

	Price difference		Number of vendors active		
Category	‘Good’ types	‘Bad’ types	‘Good’ types	‘Bad types’	Average
Cannabis	0.39	−0.39	130	44	772
MDMA	−0.13	5.11	62	27	378
Cocaine	0.49	3.24	48	23	365
Speed	−0.24	−2.69	32	13	141
Heroin	−39.07	−41.22	13	10	124
LSD	−1.68	−0.01	25	8	102
Ketamine	−0.88	−12.32	8	5	56
Meth	12.25	−1.97	23	10	162

Notes: The table contrasts ‘good’ types (vendors observed to build up a high rating over time) and ‘bad’ types (vendors observed with a low rating) at their time of entry into the market to the average of all other vendors at the date of entry across categories of drugs and shows (i) the difference in the average unit price by type to all competing vendors, (ii) the number of identified types, and (iii) the average number of competing vendors at the date of entry. The price difference displayed is the average of the difference of the mean price of the two groups by country in each category.

Figure 13: An example of a PGP key


```
-----BEGIN PGP PUBLIC KEY BLOCK-----
Version: GnuPG v2.0.21 (MingW32)

mQINBFMEu2UBEADghDvg13Cn1yEF7Lv8twfBKBe4rLd5BEepZKMS5hi5R0xSdIqh
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9LstlHxCEtRVbyIu+03iOZ5vIl//3KCoTRgUuJcoIrMtbe+FQGmdYiGIp3nQKphy
vOpMGitVYv2RRc6ve1IpdAm9aBcLHf2CFUUEv5w896C/M4qTOvS+e1zQNTBgKjQK
GOz/0rXqGJPO1CA92PnTPILJOJ9W2e2lJTLyhN1P7SJ+oKSzzj5PrUgE/b5BuAvd
f1mt9FCljX1n62PSPf6mZEvIyhShqEA7kkS5zHi6pLFZYB6uivaN3rtNLrPlgCCJ
ihU2sh/rQVqhMoHxz6CkC2Hb73Gb
=SgOE
-----END PGP PUBLIC KEY BLOCK-----
```
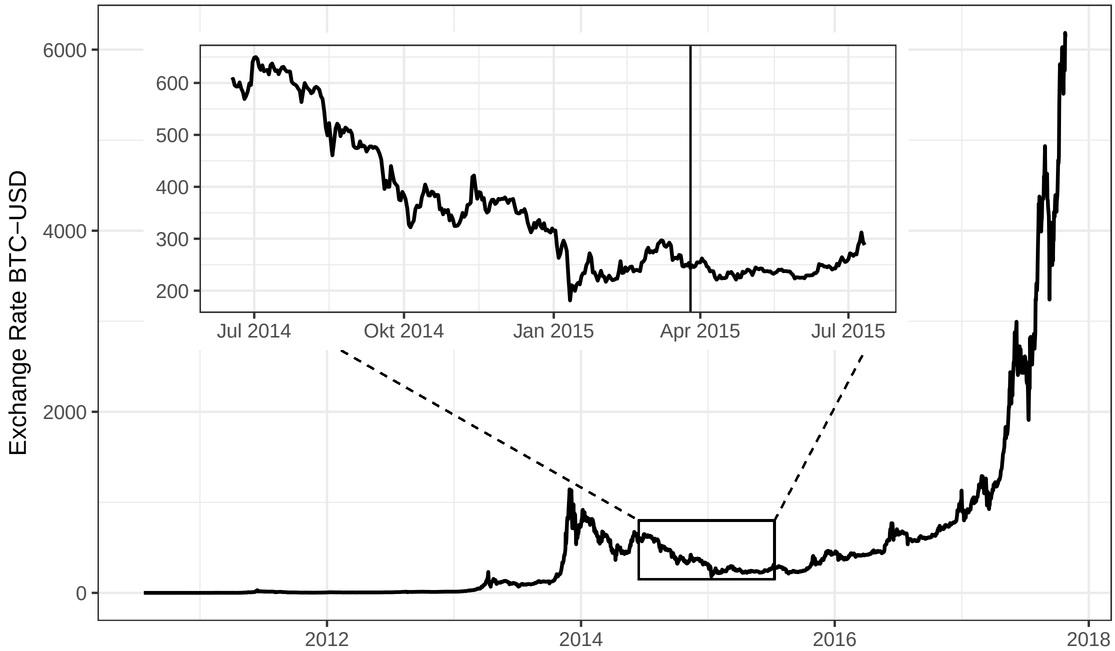


Notes: The figure shows an example of a public PGP key block. The key can be used to encrypt information sent to the owner of the private PGP key. These PGP key blocks are provided by the sellers on their account information and directly visible to buyers.

Figure 14: The bitcoin exchange rate



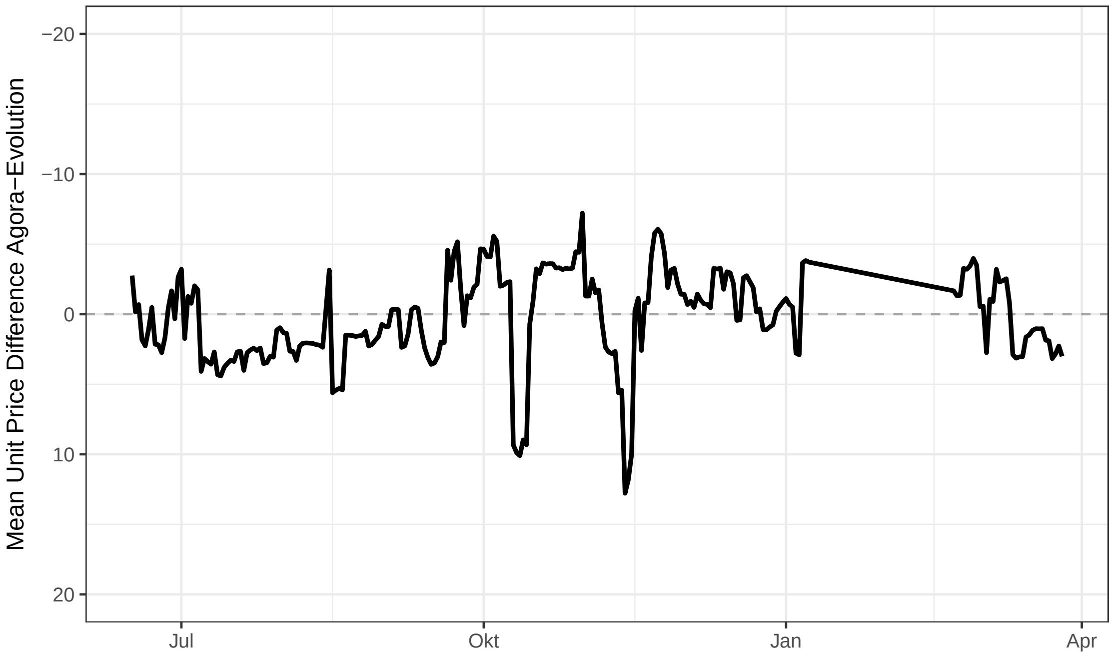
Note: The figure depicts the bitcoin-USD exchange rate from 2011 to November 2017. The highlighted segment shows the exchange rate in the timeframe studied in this paper. The Evolution exit is indicated by the vertical line.

Table 10: Sellers seven days after the exit

	Proportion of sellers		Mean unit price		
Category	Switchers	Ago sellers	Switchers	Ago sellers	Price difference
Cannabis	0.40	0.52	11.64	10.48	-0.62
MDMA	0.25	0.29	34.67	44.32	-6.17
Cocaine	0.15	0.26	106.55	111.65	10.12
Speed	0.12	0.12	6.18	21.16	-1.77
Heroin	0.10	0.10	142.77	169.05	21.23
LSD	0.06	0.08	3.67	4.66	1.39
Ketamine	0.04	0.04	47.91	54.15	6.91
Meth	0.04	0.11	274.20	147.96	-27.04

Notes: The table contrasts switchers to all other Agora sellers one week after the exit. It shows the proportion of the two groups in each category of drug and the average unit price. The price difference displayed is the average of the difference of the mean price of the two groups by country in each category.

Figure 15: Price difference between the platforms



Notes: The figure depicts the mean unit price differences between the two platforms. Prices are reported in USD. The Bitcoin exchange rate used corresponds to the day on which the item price was observed. Unit price refers to the price per consumption unit, defined as 1 gram for all categories except LSD, where it is 100 μg.

Table 11: Results for alternative specification

	Cannabis	Cocaine	Heroin	MDMA	Amphetamine
Rating	2.03***	12.50***	0.20	5.64***	4.67***
	(0.48)	(2.34)	(0.18)	(0.95)	(1.26)
Nr. of competitors	−0.02***	0.00	−5.78***	−0.16***	−0.39***
	(0.00)	(0.07)	(0.26)	(0.03)	(0.08)
Escrow	0.03	4.81***	7.39***	0.94***	−0.25*
	(0.04)	(0.86)	(1.43)	(0.33)	(0.14)
Country FE	✓	✓	✓	✓	✓
Vendor FE	✓	✓	✓	✓	✓
Quantity FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
N	113219	36636	11578	38973	14671

Notes: Results based on a linear model as specified in section 4. The sample is restricted to countries with switching vendors and a time period around the evolution exit, from one month prior to the exit until two weeks afterwards. Heterocedasticity-robust standard errors given in parentheses. *, ** and *** denote p<0.1, p<0.05 and p<0.01, respectively.

Table 12: Results for placebo

	Cannabis	Cocaine	Heroin	MDMA	Amphetamine
Rating	3.60	–95.45	–8.64	16.40	0.28***
	(5.41)	(143.48)	(7.25)	(18.69)	(0.08)
Nr. of competitors	0.02	–0.30	–2.22**	–0.92	–0.16***
	(0.05)	(0.85)	(1.07)	(1.07)	(0.03)
Escrow	–0.12	–5.74	24.46***	3.34***	0.58***
	(0.57)	(13.06)	(2.33)	(0.85)	(0.06)
Item-specific FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
N	77163	23541	7767	25226	9953

Notes: Results based on a linear model as specified in section 4. The sample is restricted to countries with switching vendors and a time period around a placebo evolution exit on 23.02.2015. Heterocedasticity-robust standard errors given in parentheses. *, ** and *** denote $p<0.1$, $p<0.05$ and $p<0.01$, respectively. Item-specific fixed effects are seller $\times$ country $\times$ category $\times$ quantity.

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