Dealing with Uncertainty: The Value of Reputation in the Absence of Contracting Institutions*

Nicolas Eschenbaum and Helge Liebert†

This draft: June 5, 2019

Abstract

This paper analyses an online black market in which no legal institutions exist to alleviate buyer uncertainty. Traders make use of platform rating systems, thereby providing an observable measure of reputation in the absence of contracting institutions. The analysis exploits the sudden market exit of one of the two dominant platforms. Sellers were forced to migrate to the competing platform and experienced a ratings 'reset.' The results show that on average a one percentage point improvement in rating causes a unit price increase of 20% of a standard deviation and revealed high-quality sellers may set prices 60% higher than entrants.

Keywords: Institutions, reputation, dark web, drugs, uncertainty

JEL-Classification: L14, L15, L81, K42

*We are grateful to Berno Buechel, Stefan Buehler, Maximilian Conze, Philemon Kraehenmann, Giovanni Mastrobuoni, Frank Pisch, and seminar participants at EARIE 2018 (Athens), IIOC 2019 (Boston), Workshop on the Economics of Digitization 2019 (Louvain-la-Neuve), Swiss IO Day 2019 (Bern), at the University of Konstanz, and the University of St. Gallen for helpful discussions and comments. The usual disclaimer applies.

†Nicolas Eschenbaum: University of St. Gallen, Institute of Economics (FGN), Varnbüelstrasse 19, 9000 St. Gallen, Switzerland (nicolas.eschenbaum@unisg.ch). Helge Liebert: Harvard University, Center for Disability and Insurance (CDI), Rosenbergstrasse 51, 9000 St. Gallen, Switzerland (helge.liebert@unisg.ch).

1 Introduction

For individuals to engage in mutually beneficial exchange, they must trust the counterparty to fulfill its promised role in the transaction. Without good 'economic governance' that ensures the ability for market participants to commit to fulfill contractual terms agreed upon, markets cannot function well (Dixit, 2009). Formal contracts that are enforced by a legal system provide the necessary structure to ensure said trust. But legal systems may not always be available or be too costly to rely on. This is particularly the case in modern online markets. Consider for example a buyer purchasing on an online platform from a seller located in a different country and jurisdiction. Legal enforcement of the contract would likely be very costly or downright impossible.

Despite these difficulties, online markets have been booming. The key factor behind their sucesss story is often argued to be the existence of ratings systems, which provide an informal reputational mechanism to foster trust (Tadelis, 2016). Reputational mechanisms have often been documented to be able to alleviate a limited availability of 'contracting institutions' (Acemoglu and Johnson, 2005) or even act as an alternative to such institutions provided by legal systems (Greif, 1989). Such ratings systems have been of great interest to researchers, as they allow reputation to be explicitly quantified and studied. However, online markets generally continue to operate within the context of existing contracting institutions that are provided by the state. Their presence obscures the value of these informal reputational mechanisms. It is ex-ante hard to say if ratings systems act as a substitute to legal institutions or as a complement, and the effect of reputation is difficult to disentangle from the impact legal institutions have.

In this paper, we study the role of reputation in a market devoid of contracting institutions deriving from a legal system. We make use of a unique dataset of the entire online market for illegal drugs. Due to the illegal nature of the transactions and powerful need for market participants to remain anonymous, contracts are effectively unenforceable and instead individuals must rely on the reputational mechanism provided on the online sales platform. Here, reputation replaces contracting institutions provided by courts of law. We focus our attention on the two dominant sales platforms present at the time that jointly covered more than 90% of the market. We exploit the fact that one of the two platforms unexpectedly exited the market and track sellers that 'switch' to the remaining platform in the aftermath. These sellers were forced to open a new account and hence reset their rating in the process. This exogenous shock to switchers' ratings provides us with an instrument to obtain causal estimates of the impact of a sellers' reputation, as measured by the aggregate rating.

Online sales platforms for illegal products and services have been a similar success story as platforms for legal products over the past decade.[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 markets.' 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.

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 dominant 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 so-called 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.[2]

In mid-March 2015, the administrators of Evolution executed what is known as an "exit-scam" and absconded with an estimated $34 million in bitcoins (at the time) stolen from their traders. That is, they shut down access of buyers and sellers to their respective bitcoin wallets on the platform and took the website offline. Vendors selling exclusively on the Evolution platform were subsequently forced to migrate to 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 sellers that sold on Evolution prior to the exit and migrated to Agora following the exit.

We proceed to estimate the effect a sellers rating has on prices charged and document three key results. First, we find a large, positive, causal effect of a sellers' aggregate rating on the unit price he/she charges. The effect varies across the different types of drugs we consider and lies between $2 and $12 of the respective unit price. Specifically, in our main

[1]Foley et al. (2019) estimate that illegal trade conducted using bitcoin amounts to $76 billion per year. The 2017 Global Drug Survey documents that in the UK in 2017, around a quarter of respondents report purchasing drugs online (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.

[2]In addition, 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. Note that these darknet platforms only provide a rating system for the sellers, not for buyers.

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) – approximately 20% on average. Second, we document the difference in observable reputation between an established seller with a high rating and an entrant, and find that such an established seller that is a 'good' type according to his/her reputation may set prices on average around 60% of a standard deviation higher. Third, our empirical approach implicitly documents that reputation is at least partially non-transferrable across online marketplaces. We further provide evidence that as a switchers' rating recovers following the migration, the effect on prices charged reduces in size and may even vanish. Finally, the impact of rating is significantly larger than other important factors, such as the impact on prices due to increased competition or the use of the escrow system.

The size of the effects we document shows the importance of reputation in a market in which contracts are de-facto unenforcable and no legal systems are available. Similar analysis conducted for legal sales platforms generally finds significantly smaller effects (Tadelis, 2016; Cabral, 2012). However, we also observe large variation in effect size across drug categories. We argue that this is driven by differences in the degree of product differentiation, i.e. when competing offers of a given drug are closer substitutes, the value of being recognized as a 'good' type increases. We illustrate the pricing of sellers with a standard, stylized model of imperfect competition with product differentiation, in which reputation simply reveals to buyers the level of quality of the seller. When sellers cannot be distinguished in type, prices are chosen equally among sellers with different levels of quality. Whereas if the type of the seller has been revealed via the reputational mechanism, the 'good' type chooses a higher price and this 'markup' is increasing when products become closer substitutes. Seen in this light, our second key result can be interpreted as showing the return to a good type of playing a separating equilibrium instead of a pooling one in a setting with unobservable quality.

Our work in this paper makes three 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 a reputational mechanism. Our estimates provide empirical evidence on the role reputation plays in overcoming a lack of contracting institutions. This possibility has been emphasized before in, among others, Acemoglu and Johnson (2005),Greif (1989),MacLeod (2007), and explicitly documented in a variety of unique settings, such as emerging markets (Gao et al., 2017), medieval merchant guilds (Greif et al., 1994), a private code of law for merchants in the middle ages (Milgrom et al., 1990), or pirate organizations (Leeson, 2007). The existence of the observable ratings system allows us to quantify the effects and provide causal estimates.

To the best of our knowledge, only few authors have previously studied the online market for illegal drugs in economics.[3] Bhaskar et al. (2017) appear to be the first to analyze this unique market. The focus of these authors lies on documenting the evolution of the online drug trade and the darknet platforms over time. Janetos and Tilly (2017) in turn also analyze the Agora platform and develop a structural model of reputation-formation. In contrast, we do not focus on the mechanics of reputation-building by sellers, but on the ability of the reputational mechanism in overcoming the uncertainty buyers face and the corresponding value of reputation for sellers. Lastly, Espinosa (2018) investigates scamming of buyers on a smaller darknet platform. Both Espinosa (2018) and Bhaskar et al. (2017) also document estimates of reputational effects using basic fixed-effects regressions that are substantially smaller than ours and which are not as distinct in size from those generally documented for legal platforms, emphasizing the importance of our instrumental-variable approach. In addition, there exists a larger literature in computer science and criminology on darknet marketplaces (e.g. Soska and Christin, 2015; Aldridge and Decary-Hetu, 2014; Barratt et al., 2016).

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) and Cabral (2012) for surveys). Much of the literature documents a relatively small, but positive and statistically significant effect of reputation on price. We document effects that are significantly more pronounced than the reputational effects generally found in previous work on legal sales platforms, showing that the value of reputation in the absence of enforcable contracts and legal certainty increases. In addition, we contribute a novel identification of the ratings effect on price that allows us to provide causal estimates.

Third, as stated above our estimates can be interpreted as shedding light on the value of playing a separating equilibrium instead of a pooling one in a setting with unobservable quality. The large returns to reputation we find show that separation can be attained at least partially and that sellers cannot signal their quality perfectly via prices. In addition, the variation in effect sizes we find is closely in line with the predictions of a standard model of imperfect competition with product differentiation in which reputation acts as a reveal

[3] However, there exists a larger literature in economics on the trade of illegal drugs offline, as well as on the effects of drug liberalization policies (e.g. Galenianos and Gavazza, 2017; Jacobi and Sovinsky, 2016; Adda et al., 2014).

of seller quality and signalling is impossible. We further vindicate this assumption by documenting evidence that sellers are unable to signal quality and that new entrants indeed appear to choose a pooling price. Specifically, we observe that identified low-reputation sellers tend to exit the market quickly, while identified high-reputation sellers tend to stay in the market (relatively) long, and that tracing back established sellers to their early days in the market does not reveal consistent price differences between 'good' and 'bad' types among entrants. The theoretical literature on quality signalling establishes that an important condition for signalling to occur in equilibrium, is that low-quality sellers must prefer such a full-information equilibrium to a pooling one (Daughety and Reinganum, 2008; Janssen and Roy, 2015; Milgrom and Roberts, 1986). Our findings strongly suggest that this condition is not satisfied in our setting. Then, our second key result shows how valuable it is to be identified as a 'good' type and play a separating equilibrium, instead of a pooling one.

The remainder of this paper is structured as follows. Section 2 discusses the institutional setup of the market and its evolution. Section 4 explains how the data was collected and processed, and establishes important stylized facts about the nature of seller ratings and the determination of prices. Section 5 details the empirical approach and discusses the identification of the ratings effect. Section 6 documents and discusses the results. Finally, Section 7 concludes.

2 The darknet marketplaces

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.[4] 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 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.

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.

[4] 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.

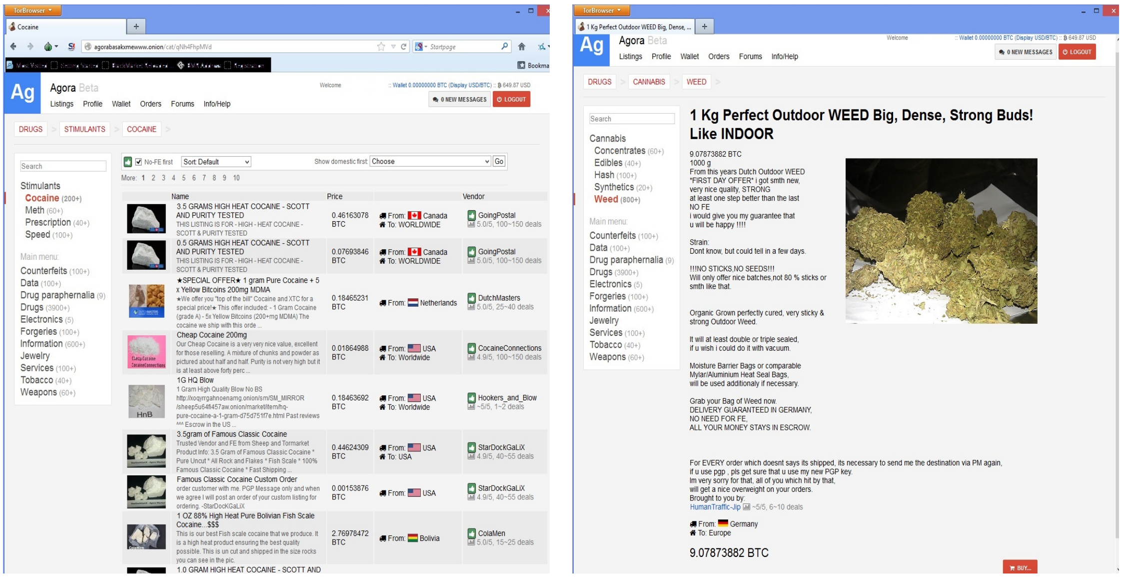


Figure 1: Screenshots from Agora

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

3 A simple pricing model

To illustrate the key elements of pricing by sellers, we consider a simple, stylized model in the spirit of Singh and Vives (1984). In line with our identification strategy, we abstract from the dynamics of reputation-building. Instead, we aim to understand the basic patterns of 'markups' in price that result from the ratings system overcoming the uncertainty buyers face. Suppose there are two sellers indexed by 1 and 2 respectively that each produce a differentiated good. There is a continuum of consumers with a quasi-linear utility function, where the representative consumer maximizes his/her utility $U(q_1,q_2) = \alpha_1 q_1 + \alpha_2 q_2 - (\beta q_1^2 + 2\gamma q_1 q_2 + \beta q_2^2)/2$ subject to the prices of the two goods. Under some conditions on the parameters α_i, β, γ, where $i = 1,2$, the inverse demand function is given by $p_i = \alpha_i - \beta q_i - \gamma q_j$, where $i \neq j$.[5] Since sellers of illegal drugs are very likely to be capacity constrained, we assume that sellers in our model choose their quantity q_i, taking as given the choice of the competitor q_j. Then we find that in equilibrium, prices satisfy $p_i = \beta q_i = \beta \left(\frac{2\alpha_i \beta - \alpha_j \gamma}{4\beta^2 + \gamma^2} \right)$.[6]

Specifying the model in this way allows us to capture both a fixed quality difference

[5] Specifically, we need that α_i, β, γ are positive, $\beta^2 - \gamma^2 > 0$, and $\alpha_i \beta - \alpha_j \gamma > 0$. We further require quantities and prices to be positive.

[6] We ignore marginal cost for simplicity. As long as they are constant, this is without loss of generality, as prices can be considered to be net of marginal cost.

between sellers, i.e. $\alpha_1 \neq \alpha_2$, and any range of substitutability given by γ in a very simple manner. We will assume that $\gamma > 0$ and hence the two goods are substitutes. Allowing for different degrees of substitutability is important, as we will show in section 4 that there exist large differences in the number of competing offers across categories and likely ease of finding close substitutes for buyers. In addition, the ratio of γ/β can be interpreted as an inverse measure of the degree of product differentiation. For our purposes, we can further simplify and normalize β to 1. Then, prices chosen in equilibrium satisfy $p_i = (2\alpha_i - \gamma\alpha_j)/(4+\gamma^2)$.

This highly stylized model makes the following straightforward predictions about what we should observe in the market for a given type of drug. First, if buyers are unable to distinguish between sellers of different quality levels, $\alpha_1 = \alpha_2$ in the demand function, and prices are chosen equally across quality levels. That is, the equilibrium consists of a pooling price. However, if buyers are able to distinguish between the qualities of sellers, the high-quality seller sets a higher price. This difference is increasing in the degree of quality differentiation. Hence there are returns to reputation if it reveals the type of the seller. Second, the closer substitutes the two products are, the greater the effect of being able to distinguish different quality levels. That is, the 'markup' in price that can be charged by revealing onself as a 'good' type in the market increases if offers by competing sellers are close substitutes. As it turns out, the sizes of our estimates will indeed show patterns that closely fit the predictions of this simple model.

However, sellers may be able to convey their quality to buyers without resorting to the reputational mechanism. In particular, sellers might disclose or signal their product quality to individuals. 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). Due to the properties of the black market and the illicit nature of the goods we study, it seems reasonable to exclude the possibility that sellers can reliably disclose quality ex-ante.

If prices are also uninformative about quality, our analysis can be interpreted as shedding light on the value of playing a full-information, separating equilibrium in a setting with quality uncertainty: the forced migration to the Agora platform for switchers and ratings 'reset' turns these sellers from identified types in a separating equilibrium into entrants, who may be good or bad types in the eyes of buyers. The literature on quality signalling documents that in order for price signalling to occur in equilibrium, low-quality sellers must prefer a full-information equilibrium to a pooling one (Daughety and Reinganum, 2008; 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.

Our descriptive analysis provides several indications in support of this condition. We highlight that sellers who 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 reinforced 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. 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 an indication that 'bad types' will prefer to imitate the price setting of 'good types' when reputation has not been established sufficiently and quality is unobservable. Similarly, we show 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.

To investigate in more detail whether signalling is possible in this market, we take a closer look at sellers. We trace vendors who are in the market for several weeks 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, do not improve on it and tend to leave the market soon after. 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. If entrants cannot signal quality via posted prices and established sellers reputation correctly reveals their type, our estimates allow us to calculate the value of being in a separating, full-information equilibrium relative to a pooling one for 'good' types by considering the difference in rating between a revealed good type and the average entrant and the value of each percentage-point in rating according to the estimates. As we will show in section 4, the difference in rating turns out to be three percentage-points.

4 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.[7] 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.

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

[7] 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.

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.[8]

Table 1: Summary statistics

Category	Mean unit price		# Vendors	# 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 $10\times100\mu$g	241	2,374	$100\times100\mu$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 $79.95 in the United States to $267.47 in Australia (both measured in US dollars). 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.[9] 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 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

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

[9]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.

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	× 5	× 10	× 50	× 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. Vendors 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 vendors 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 section 5, 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.

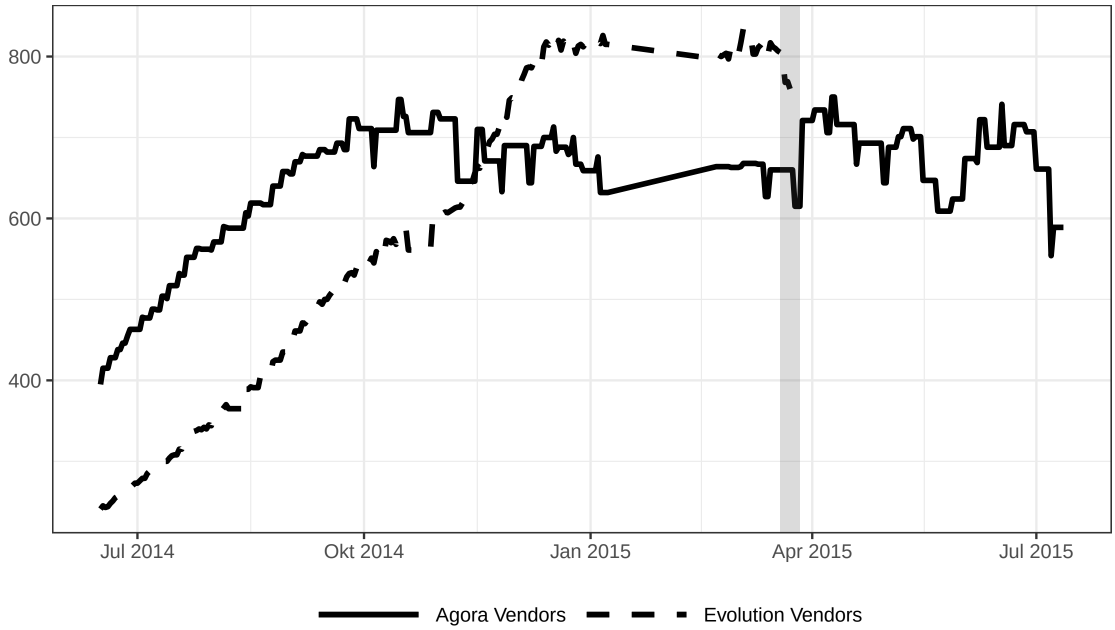


Figure 3: Platform size

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 6 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 sellers.

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 in absolute terms (for example in

Cabral and Hortacsu, 2010).[10] 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 vendors. 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).

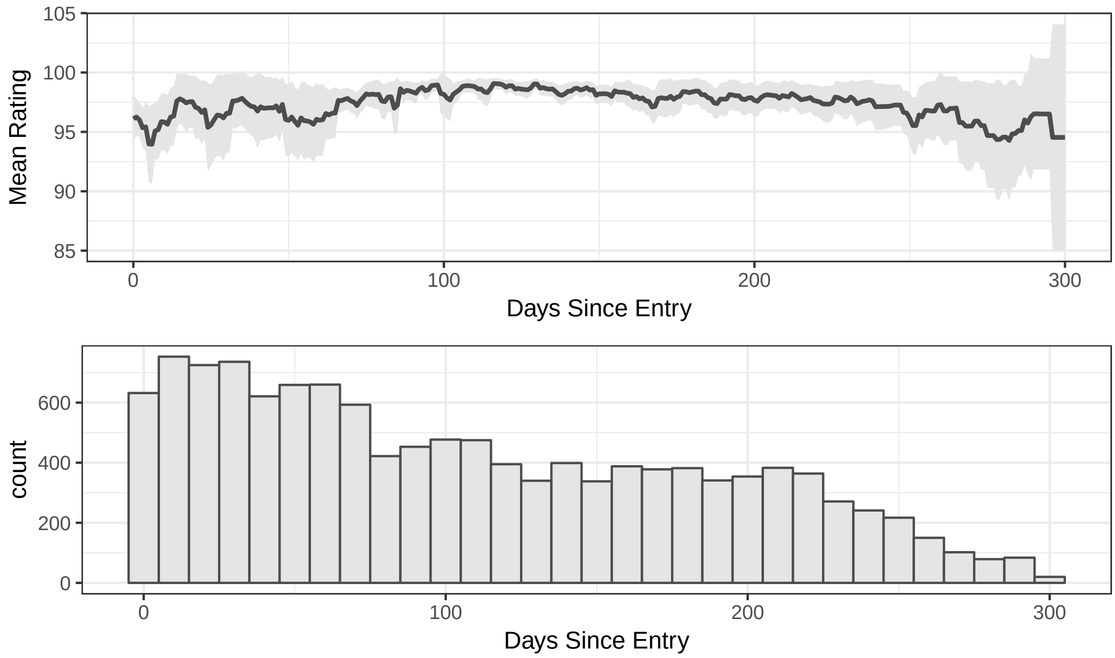


Figure 4: Vendor lifecycle

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 is defined as the date on which the vendor is observed for the first time.[11] As vendors

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

[11] 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 vendors are observed for the first time.

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.

5 Empirical approach

Our aim is to estimate the impact of a sellers rating on the prices charged for his/her products on offer. An individual item that is sold is determined 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:

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

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 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 4 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.[12] Private and public keys are unique

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

and highly complex. These features of PGP keys provide us with a unique identifier that allows matching vendor accounts across platforms and time. 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 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.[13] 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,

$$Rating_{t,i} = \delta_1 Switch_{t,j} \times \mathbb{1}\{t \geq Exit\}_t + \delta_2 Nsellers_{t,k,c} + Escrow_i + \eta_i + Month_t + \xi_{t,i}, \quad (2)$$

to isolate the effect of rating on price, where η_i represents the item-specific fixed effects and $\xi_{t,i}$ the error term. Due to the item-specific effects, this specification exploits the shift in the most flexible way, controlling for both unobserved product quality and seller-specific time-constant effects. Identification relies on an exclusion restriction for switchers. We assume that the only effect of switching on price is driven by the reset in ratings

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 4 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 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

[13] 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.

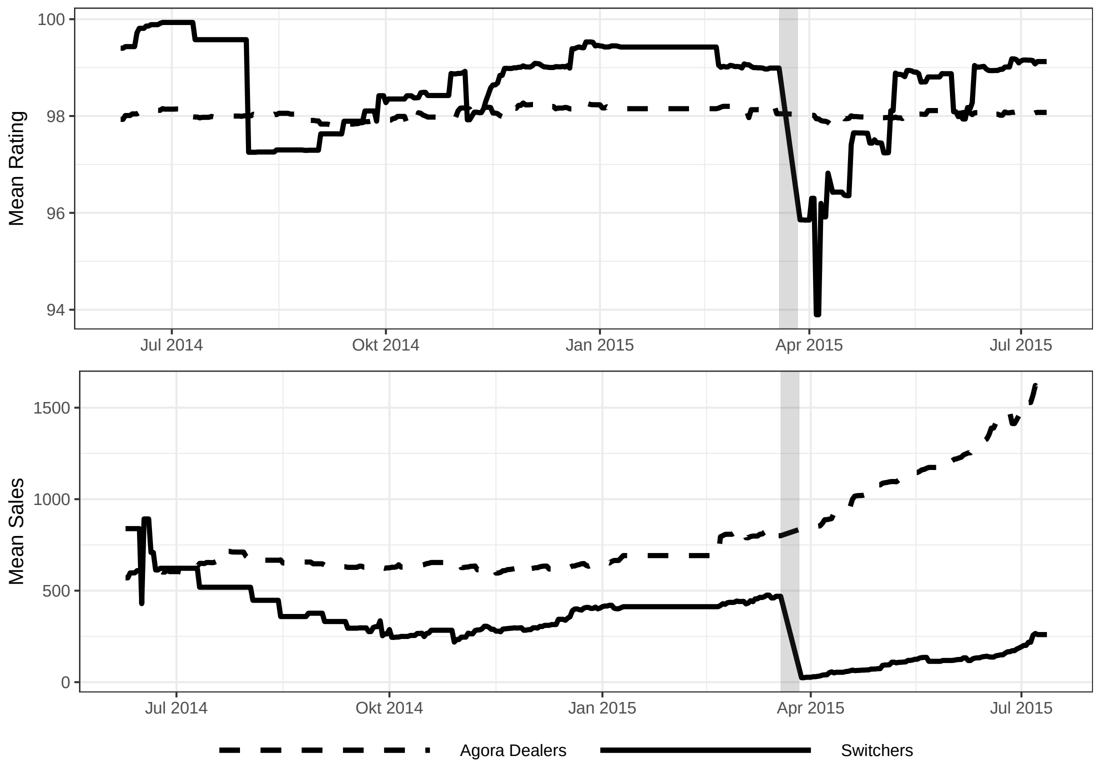


Figure 5: Ratings shock for switchers

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.

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 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

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.

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. One possible mechanism that could potentially confound our interpretation of the rating effect is if sellers react to changing platforms by adjusting prices to recapture market share. In this case, the effect of rating on price would be driven by strategic pricing behavior. However, recent work documents that firms do not make use of markups to increase their market share (Fitzgerald and Priolo, 2018). This is further reinforced by the institutional structure of the market and the high degree of competition we observe.

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.

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.

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 '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. Note that differences in seller-specific time-invariant latent quality will not confound our ratings estimate. Moreover, as we point out in the remainder of this section, this aspect provides a unique interpretation of our results that sheds light on the value of information reveal about seller types in a market with quality uncertainty.[14]

6 Results

Table 6 presents the main estimation results, corresponding to the model outlined in section 5. 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

[14] An alternative approach to estimate the value of rating for the average seller is to implement a semiparametric weighting approach that balances residual differences in observable characteristics between switchers and evolution sellers.

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 sellers 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. This shows a substantial return to being reliably identified as a reputable seller.

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 5. 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. Heteroscedasticity-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.

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 sample observation period, the more the effect weakens. The results in Table 7 are based

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 5. 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 $\times$ country $\times$ category $\times$ quantity.

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.

7 Conclusion

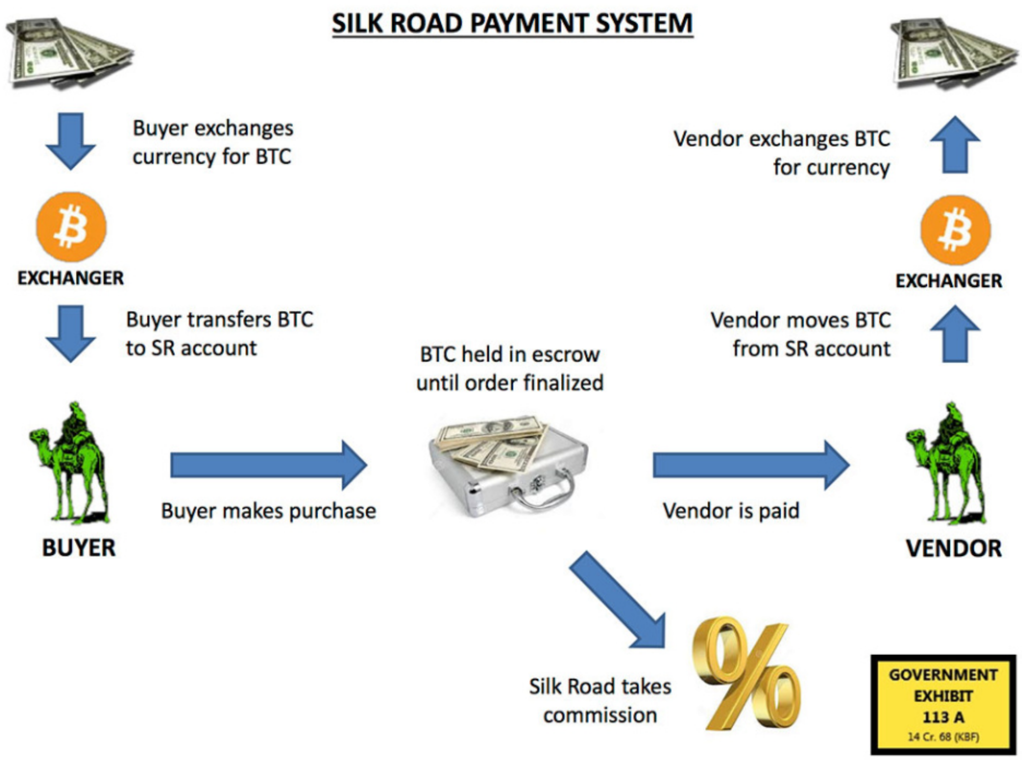
In this paper, we analyse the reputational effects arising in a market devoid of legal and governmental institutions. We examine the online black market for illegal drugs, in which market participants transact via centralized platforms akin to legal online markets. These 'darknet marketplaces' offer a ratings system for sellers operating in the market, thereby providing a publicly observable measure of reputation. 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. In our descriptive analysis, we highlight 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 document three key results. One, we consistently find a large, positive effect of rating on price across drug categories. We estimate 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. Two, we find that an established seller may set prices on average around 60% of a standard deviation higher than an entrant. We provide further evidence that this result can be interpreted as the value for a 'good' type of playing a separating equilibrium, instead of a pooling one, in a market with uncertainty about product quality. Three, our empirical approach implicitly establishes that reputation is at least partially non-transferrable across online marketplaces, even when doing so would be to the sellers' advantage.

Our work in this paper demonstrates that reputation indeed has a large role to play 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. 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

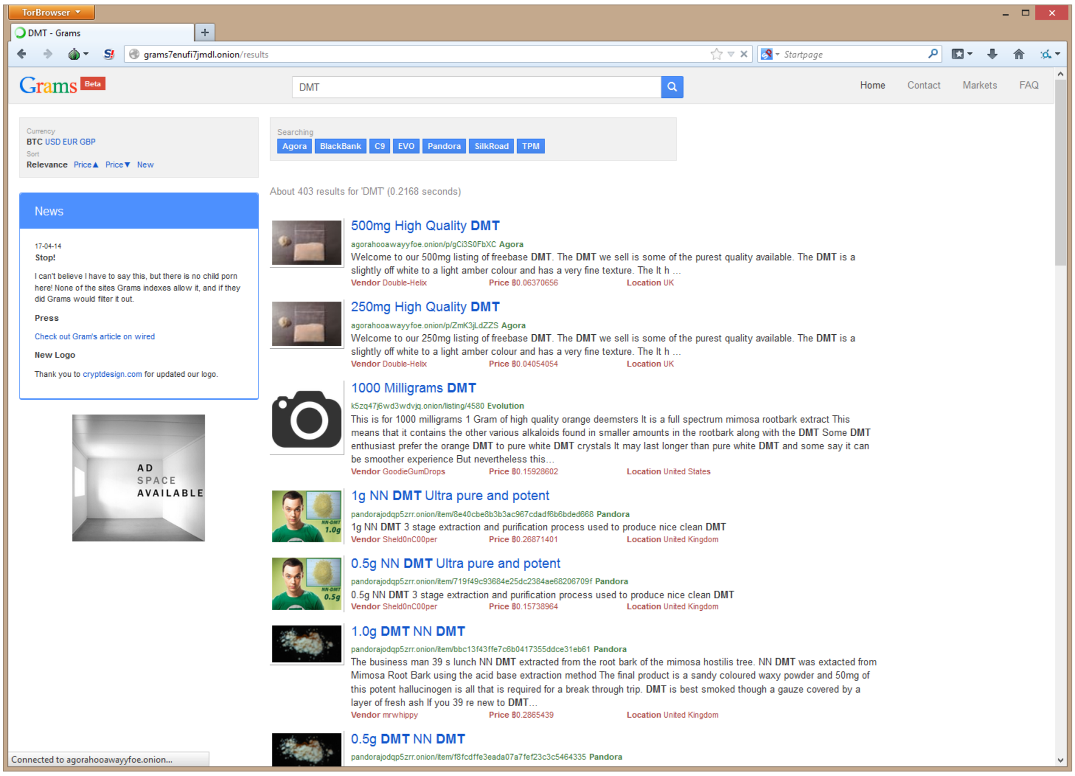
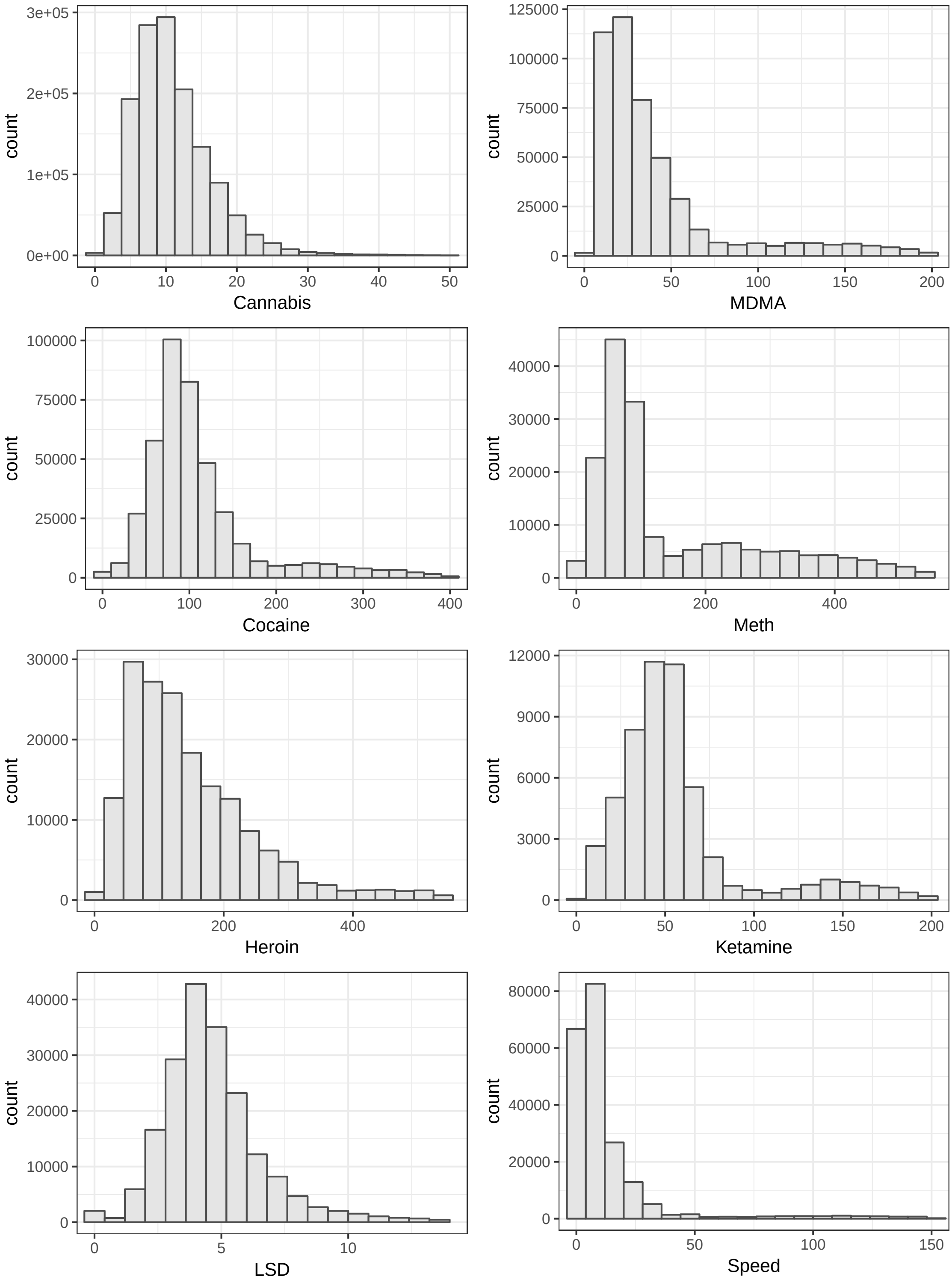


Table 8: Country differences for cocaine

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

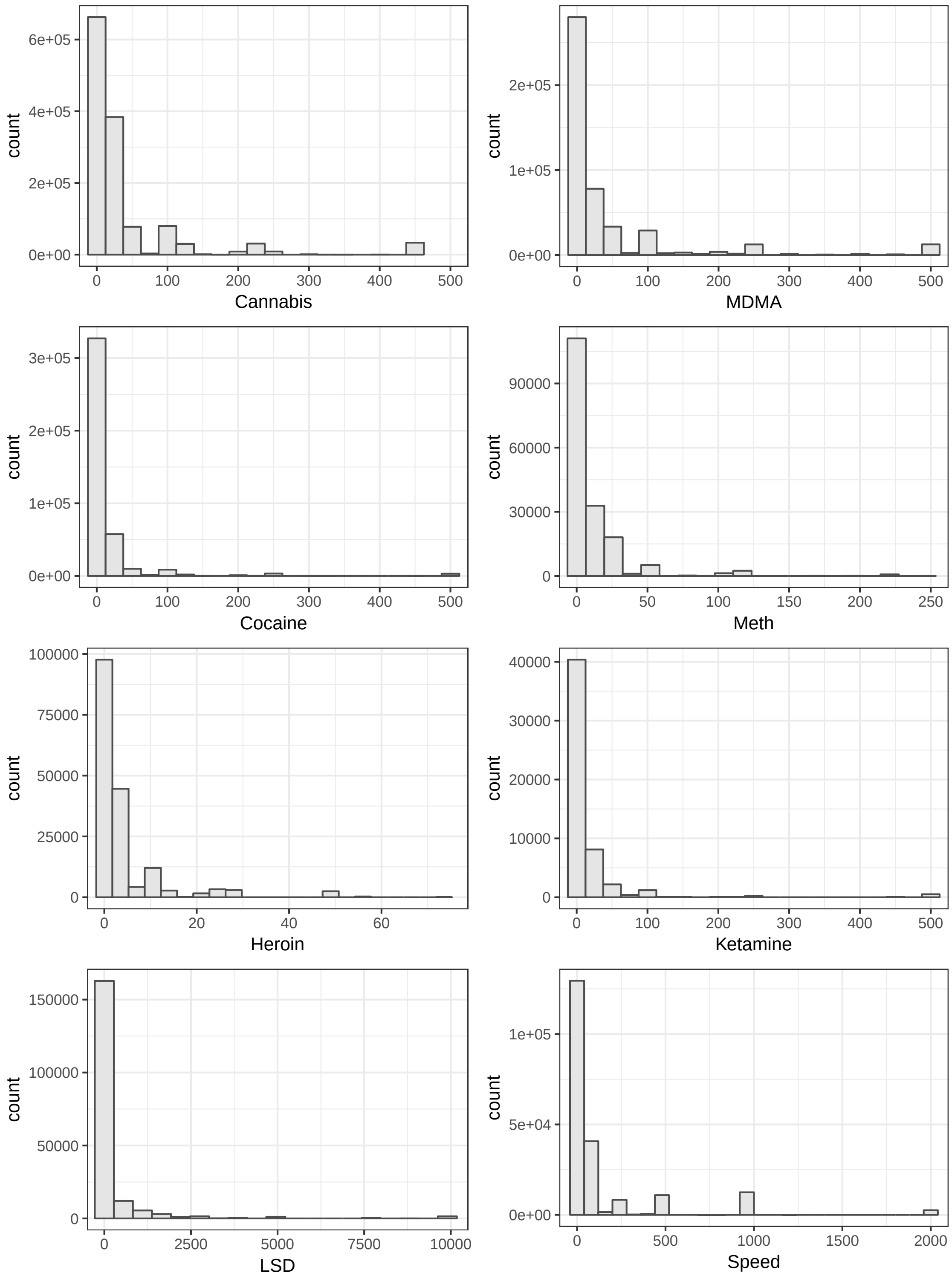
Notes: The table reports summary statistics for cocaine for the ten largest countries of origin as measured by the number of vendors active, sorted by size. Prices are reported in USD. The Bitcoin exchange rate used corresponds to the day on which the item price was observed. Unit price refers to the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

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



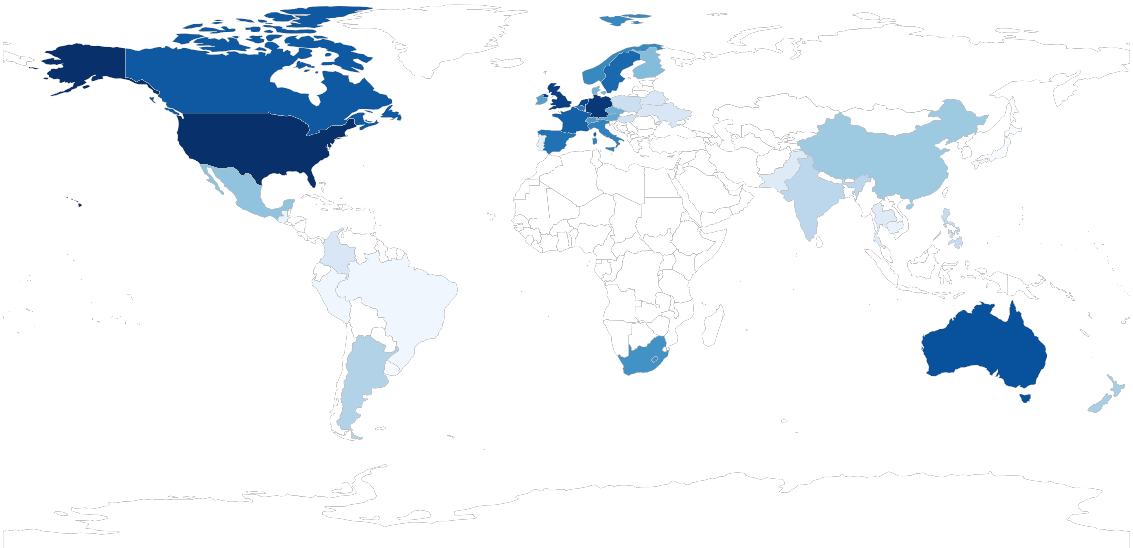
Notes: The figure shows the distributions of the unit price of the eight drugs considered. Prices are reported in USD. The Bitcoin exchange rate used corresponds to the day on which the item price was observed. Unit price refers to the price per consumption unit, defined as 1 gram for all categories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

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



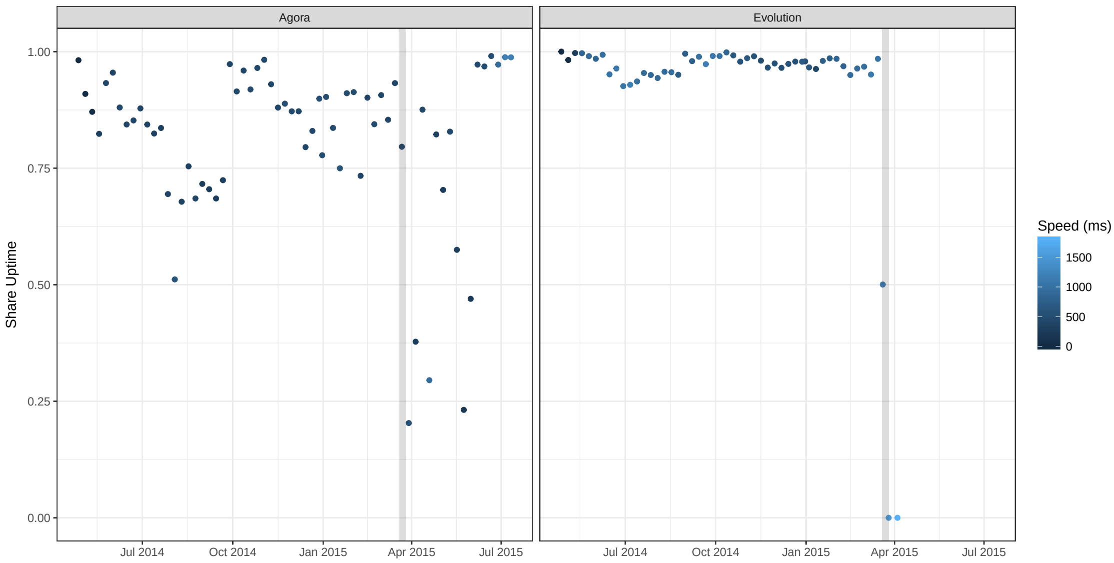
Note: The figure shows the distributions of the quantity of the eight drugs considered. The unit used is grams, except for LSD, where it is micrograms.

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



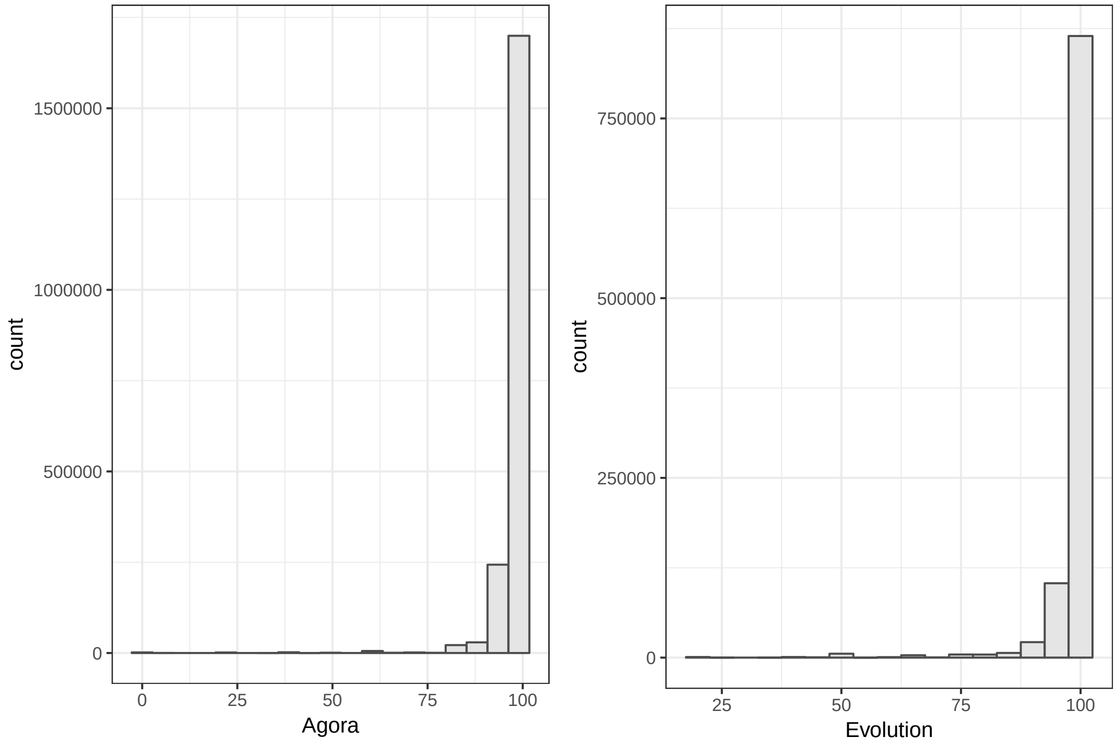
Notes: The figure shows the total number of unique items shipped from each country on both platforms. The largest market is the United States. Most of the offers originate in North America, (Western) Europe, and Australasia.

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 that do not improve on it and tend to drop out early) 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.

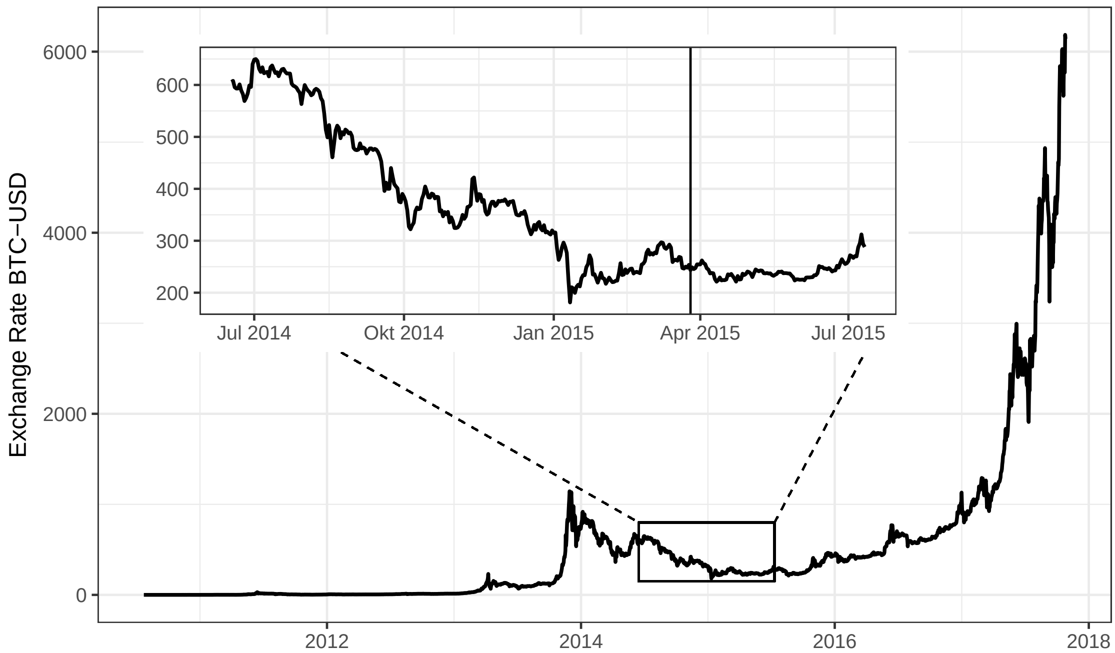
Figure 13: An example of a PGP key


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

mQINBFMEu2UBEADghDvg13Cn1yEF7Lv8twfBKBe4rLd5BEepZKMS5hi5R0xSdIqh
tiHo0eJgHR0OaOFCEWBk1Xo95ADZm0G9AJTRcAMNdTk6V9owDjvq2JdUegEwE7/r
o7teVYmXBvP6ltBwXEGnTgrCPPi+7Sspt+Wizmi60PFPxEao7bHVL6x/uMJhPk9O
Ktblpp25FYRbvOLzcgaOgf4mz3nRhks889e/cPLzglhnZH1QGW0oaurDW0cTU5zE
k18SD0ukDrCq6az2Mfs0f9MmSk7KxLHdiPHQCQ1T5gzu2D5aNtrnM6U2tFsT0jPv
0Yd0ewQcHLwX+LC7ZZBq0a8fNwRWQK60iw7X7E918Hz5wHcvaF1ablyvPVDI/BB1
INpaVNR9aKAkfWpJFIYV/RfSURVF/JZbzROj+NSSPGJ5xH4r0/T38MclqMmUB4H7
YiZu11rQt2qFVO1LUcH+0IFxpmT8D/jWt7vt9f46arM6/S7fAtxL9Ms7RLB1X2UF
FOEuQI93d4eX05AmNZtjHt6qyB3PFyfc/97lm7DoOR+l8SzFFgP3gbXnXMy89/O9
UbprZKTTEH4iZBYZ7tnPL4zOp9qQc1QCPWYQZVl1Ip9HUae0Nu2yajntvjgpJW9d
WROkTzQGWC/LlsOEPMOQ4DLwcT+PQFnB4cGTRfDnboMxvw4DaETSAbuu3wARAQAB
tBdKb2huIERvZSA8am9obkBkb2UuY29tPokCOQQTAQIAIwUCUwS7ZQIbLwcLCQgH
AwIBBhUIAgkKCwQWAgMBAh4BAheAAAoJEONC+EAjiUrQaxkP/jFGqSuMQXY9P1BN
KrDeYWeSmvCrexzoZf0fl8OWAuNY2qto4yx8OHAVXsk6zRRQaenN2DjzBibpHUzC
ueDrK6iax4ojpTePpHzAUexDUQdlYqXBdX7cY4/f+5A6Xpf5Y+ttpqDn5Jtte0iS
zo68UfU1JxJbXui6RWKlGjYbzCfw17aYEj9k9Bj2dcEan4O/y7LSOyYGJpGQp5Wv
J+3JmdwN/iwijE3Zy9ahCM4XTcelzxrJUmDZNcJuLfLDc9afsuOuJ4pFkfElrhZY
OhDzCLJiuSiJkNb14Cak6P6bFsXR1KuKu+G6TKEl1xMF2/6DF7AVCrp2Eas6MChH
LPvxPLutv5KkhETqQ5xqXjAnny+m7pQwNeFAKnFBcUsowEJIOXuGhoWFDTeR+T9b
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



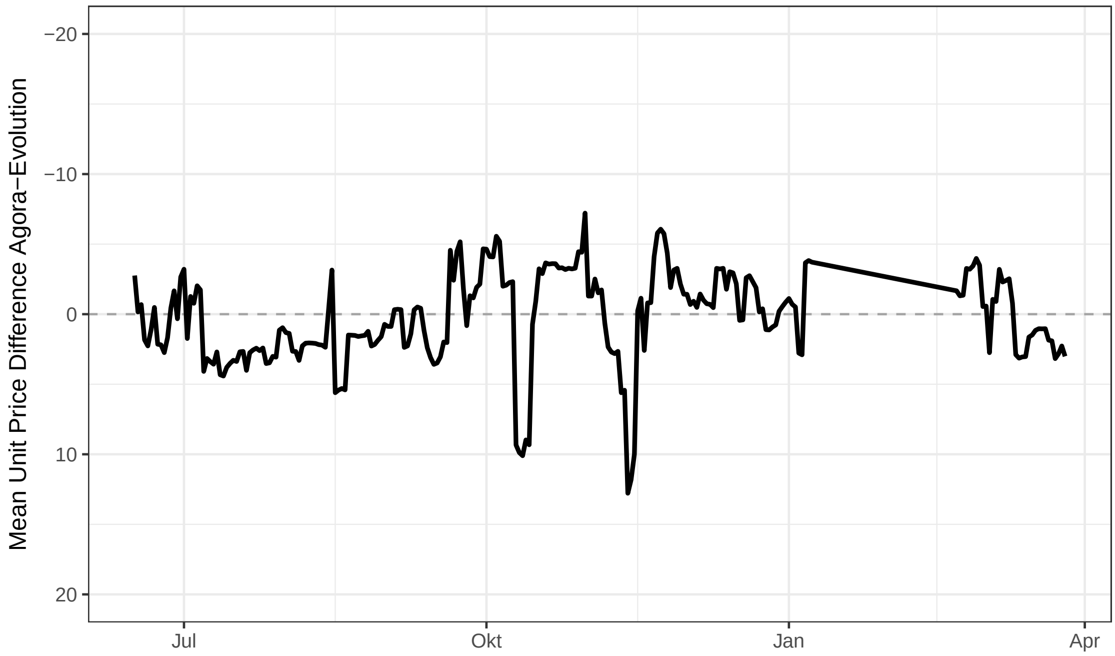
Note: The figure depicts the bitcoin-USD exchange rate from 2011 to November 2017. The highlighted segment shows the exchange rate in the timeframe studied in this paper. The Evolution exit is indicated by the vertical line.

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 5. 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 5. 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 × country × category × quantity.

References

Acemoglu, D. and Johnson, S. (2005). Unbundling institutions. *Journal of Political Economy* 113(5), 949–995.

Adda, J., McConnell, B. and Rasul, I. (2014). Crime and the depenalization of cannabis possession: Evidence from a policing experiment. *Journal of Political Economy* 122(5), 1130–1202.

Airbnb (2017). When am i charged for a reservation? `https://www.airbnb.com/help/article/92/when-am-i-charged-for-a-reservation`.

Aldridge, J. and Decary-Hetu, D. (2014). Not an 'ebay for drugs': The cryptomarket 'silk road' as a paradigm shifting criminal innovation. Mimeo. Available at SSRN: https://ssrn.com/abstract=2436643.

Barratt, M. J., Ferris, J. A. and Winstock, A. R. (2016). Safer scoring? cryptomarkets, social supply and drug market violence. *International Journal of Drug Policy* 35(Supplement C), 24 – 31.

Bhaskar, V., Linacre, R. and Machin, S. (2017). The economic functioning of online drugs markets. *Journal of Economic Behavior & Organization* .

Buskirk, J. V., Roxburgh, A., Bruno, R. and Burns, L. (2014). Drugs and the internet. *Bulletin 3*, National Drug and Alcohol Research Centre Sydney.

Cabral, L. (2012). *The Oxford Handbook of the Digital Economy*, Oxford University Press, chap. Reputation on the internet.

Cabral, L. and Hortacsu, A. (2010). The dynamics of seller reputation: Evidence from ebay*. *The Journal of Industrial Economics* 58(1), 54–78.

Cai, H., Jin, G. Z., Liu, C. and Zhou, L.-a. (2014). Seller reputation: From word-of-mouth to centralized feedback. *International Journal of Industrial Organization* 34(Supplement C), 51 – 65.

Daughety, A. F. and Reinganum, J. F. (2008). Imperfect competition and quality signalling. *The RAND Journal of Economics* 39(1), 163–183.

Dixit, A. (2009). Governance institutions and economic activity. *American Economic Review* 99(1), 5–24.

Espinosa, R. (2018). Scamming and the reputation of drug dealers on darknet markets. Mimeo.

Fitzgerald, D. and Priolo, A. (2018). How do firms build market share? *Working Paper 24794*, National Bureau of Economic Research.

Foley, S., Karlsen, J. R. and Putniņš, T. J. (2019). Sex, Drugs, and Bitcoin: How Much Illegal Activity Is Financed through Cryptocurrencies? *The Review of Financial Studies* 32(5), 1798–1853.

Galenianos, M. and Gavazza, A. (2017). A structural model of the retail market for illicit drugs. *American Economic Review* 107(3), 858–96.

Gao, C., Zuzul, T., Jones, G. and Khanna, T. (2017). Overcoming institutional voids: A reputation-based view of long-run survival. *Strategic Management Journal* 38(11), 2147–2167.

Greif, A. (1989). Reputation and coalitions in medieval trade: Evidence on the maghribi traders. *The Journal of Economic History* 49(04), 857–882.

Greif, A., Milgrom, P. and Weingast, B. R. (1994). Coordination, commitment, and enforcement: The case of the merchant guild. *Journal of Political Economy* 102(4), 745–776.

Jacobi, L. and Sovinsky, M. (2016). Marijuana on main street? estimating demand in markets with limited access. *American Economic Review* 106(8), 2009–45.

Janetos, N. and Tilly, J. (2017). Reputation dynamics in a market for illicit drugs. Mimeo. Available at: https://arxiv.org/pdf/1703.01937.pdf.

Janssen, M. C. and Roy, S. (2015). Competition, disclosure and signalling. *The Economic Journal* 125(582), 86–114.

Jolivet, G., Jullien, B. and Postel-Vinay, F. (2016). Reputation and prices on the e-market: Evidence from a major french platform. *International Journal of Industrial Organization* 45(C), 59–75.

Leeson, P. T. (2007). An-arrgh-chy: The Law and Economics of Pirate Organization. *Journal of Political Economy* 115(6), 1049–1094.

MacLeod, W. B. (2007). Reputations, relationships, and contract enforcement. *Journal of Economic Literature* 45(3), 595–628.

Milgrom, P. and Roberts, J. (1986). Price and advertising signals of product quality. *Journal of Political Economy* 94(4), 796–821.

Milgrom, P. R., North, D. C. and Weingast*, B. R. (1990). The role of institutions in the revival of trade: The law merchant, private judges, and the champagne fairs. *Economics & Politics* 2(1), 1–23.

Resnick, P. and Zeckhauser, R. (2002). *The Economics of the Internet and E-commerce (Advances in Applied Microeconomics)*, Emerald Group Publishing Limited, Vol. 11, chap. Trust among strangers in internet transactions: Empirical analysis of eBay' s reputation system. 127–157.

Singh, N. and Vives, X. (1984). Price and quantity competition in a differentiated duopoly. *The RAND Journal of Economics* 15(4), 546–554.

Soska, K. and Christin, N. (2015). Measuring the longitudinal evolution of the online anonymous marketplace ecosystem. *In Proceedings of the 24th USENIX Conference on Security Symposium*. SEC'15, Berkeley, CA, USA, USENIX Association, 33–48.

Tadelis, S. (2016). Reputation and feedback systems in online platform markets. *Annual Review of Economics* 8, 321–340.