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

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Abstract

This paper studies the online market for illegal drugs in which no legal institutions exist to alleviate buyer uncertainty. Trade takes place on platforms that offer rating systems for sellers, thereby providing an observable measure of reputation. The analysis exploits the fact that one of the two dominant platforms unexpectedly disappeared. Sellers were forced to switch platforms and thus reset their rating. The results show that on average a one percentage point increase in rating causes a unit price increase of 6.7%. Revealed 'good' types may charge prices 20% higher than entrants.

Keywords: Institutions, reputation, uncertainty, dark web, drugs
JEL-Classification: L14, L15, D82, K42

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1 Introduction

For individuals to engage in mutually beneficial exchange, they must trust the counterparty to fulfill its promised role in the transaction. One way to establish trust is to rely on the reputation of an individual as an honest trader. By making transactions conditional on the counterparties' reputation, past actions are linked to future trades. If the value of reputation for future trades is sufficiently high, short-run incentives to cheat can be overcome.

The use of a reputational mechanism to diminish uncertainty in trade has been shown to be an important factor in a variety of settings (e.g., Milgrom et al., 1990; Greif, 1989), and previous work has demonstrated that reputation can overcome uncertainty and allow markets to function when formal or legal institutions enforced by a (state) authority are absent (e.g., Greif et al., 1994; Leeson, 2007). However, while the theoretical mechanism is well-understood, empirical evidence on reputation in such unique settings in which legal institutions are absent is scarce. Reputation is inherently hard to measure and in many settings it is difficult to pin down the extent to which reputation substitutes or complements legal institutions. The rise of online trade has allowed reputation to be measured in the form of publicly observable ratings and a large literature has developed that estimates returns to reputation (e.g., Cabral and Hortacsu, 2010). But the role of the reputational mechanism in overcoming uncertainty is still difficult to disentangle from the effects of legal institutions.

In this paper, we provide empirical evidence on the value of reputation in a market devoid of contracting institutions deriving from a legal system. We make use of a unique dataset of the online market for illegal drugs. Due to the illegal nature of the transactions and strong need for market participants to remain anonymous, contracts are unenforceable. To overcome uncertainty and provide the necessary trust, trade is conducted on online sales platforms that provide a rating system for merchants in a form that is familiar to any user of e.g. Amazon. We focus our attention on the two dominant sales platforms from 2014 to 2015, jointly covering 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 value of a sellers' reputation in the absence of legal institutions.

We find substantial returns to reputation and document three key results. First, switching sellers went from the top 35% of sellers in the ratings distribution to the bottom 10%, causing a reduction in unit prices charged of around 20% on average. We find that a 1% improvement in rating causes an increase in unit prices of 6.7% on average. The effect size varies across the different types of drugs we analyze and lies between 0.5 USD and 5 USD of the respective unit price. Second, we document the difference in reputation between an established seller with a high rating and an entrant. The average rating of these two groups precisely corresponds to the average ratings of switchers prior to the platform exit and shortly after the migration. Hence, we find that a revealed high type (i.e. established highly-rated seller) may set prices 20% higher than a seller whose type is unknown. Third, our empirical approach implicitly shows that reputation is at least partially non-transferable across online marketplaces. We further provide evidence that as a switchers' rating recovers following the platform migration, the effect on prices reduces in size and may vanish.

The magnitude of the effects we find highlights the importance of reputation in a market in which contracts are unenforceable and no legal system is available. Similar analysis conducted for legal sales platforms generally finds significantly smaller effects (e.g., Cabral and Hortacsu, 2010; Cai et al., 2014; Resnick and Zeckhauser, 2002). The reputational cost of the forced re-entry for switchers can also be interpreted as the cost of being ostracized. Ostracism has been documented to be an important tool to enforce common rules for trade and honest behavior (Milgrom et al., 1990; Greif, 1989; North, 1991; Benson, 1989). However, ostracism as an enforcement mechanism is unlikely to be effective in our setting due to the degree of anonymity; voluntarily re-entering the market under a new pseudonym is always feasible. This suggests that our findings likely downplay the cost of being ostracized in markets in which sellers are not anonymous.

We also observe substantial variation in effect size across drug categories. We argue that this is driven by differences in the degree of product differentiation and quality uncertainty. Both the range of qualities that exist across the product spectrum for a given category of drug and the uncertainty buyers face based on reliability of information provided by the seller prior to the sale vary significantly across categories of drugs. For synthetic drugs, the purity of the product sold and hence the quality varies substantially and cannot be ascertained before receipt of the product. For example, LSD is commonly sold by being added to absorbent paper. It is impossible to know the amount of LSD placed in the paper, or if any LSD has been added at all, prior to the purchase. The quality variations for a non-synthetic drug such as Cannabis in turn are smaller and quality can even be partially observed from product images. Consequently, we find the largest effect for a synthetic drug such as LSD and the smallest effect for Cannabis.

To conduct our analysis, 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 seller's rating, size, name and public PGP ('pretty good privacy') key for encrypted communication.[1]

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 unexpectedly 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 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 then exploit the ratings reset these switchers experience as an instrument to estimate the causal effect of reputation in the form of online ratings.

Our work in this paper makes three contributions to the literature. One, we study a unique black market that has received limited 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), North (1991), 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. To the best of our knowledge, we are the first to investigate reputation empirically in a setting devoid of legal institutions and provide causal estimates.

As far as we are aware, only few authors have previously studied the online market for illegal drugs in economics.[2] Bhaskar et al. (2017) appear to be the first to analyze

[1] 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.

[2] However, there exists a larger literature in economics on the trade of illegal drugs offline, as well as on

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 (2019) investigates scamming of buyers on a smaller darknet platform. Both Espinosa (2019) and Bhaskar et al. (2017) also document estimates of reputational effects using fixed-effects regressions that are substantially smaller than our findings and which are broadly in line with results documented for legal markets. We investigate this difference to our findings and provide estimates of basic fixed effects regressions in which we do not make use of our instrument. We obtain effect sizes for the impact of rating that are in line with much of the literature, emphasizing the importance of our instrumental-variable approach. Finally note that 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 effects of reputation for sellers in online markets (see Tadelis (2016) and Cabral (2012) for surveys). Much of the literature documents that a high rating or a large number of positive versus negative feedback is generally associated with higher sales rates and completion rates for transactions (e.g. Cabral and Hortacsu, 2010; Cai et al., 2014), but that the effect on price is relatively small (e.g. Resnick and Zeckhauser, 2002; Cabral and Hortacsu, 2010; Houser and Wooders, 2006). However, some studies are exceptions to this pattern and document more substantial reputational premia (e.g. Jolivet et al., 2016; Fan et al., 2016). Our results are significantly more pronounced, demonstrating that the value of reputation in the absence of enforceable contracts and legal certainty increases. We further contribute a novel identification of the ratings effect on price that allows us to provide causal estimates.

Three, our estimates shed light on the value of playing a separating instead of a pooling equilibrium 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 (perfectly) signal their quality via prices. We further observe in our data that (i) identified low-reputation sellers tend to exit the market quickly, while identified high-reputation

the effects of drug liberalization policies (e.g. Galenianos and Gavazza, 2017; Jacobi and Sovinsky, 2016; Adda et al., 2014).

sellers tend to stay in the market long, and (ii) tracing back these two sets of sellers to their early days in the market does not reveal consistent price differences between 'good' and 'bad' types. In addition, the theoretical literature on quality signaling establishes that an important condition for signaling to occur in equilibrium is that low-quality sellers must prefer such a full-information equilibrium to a pooling one (e.g. Daughety and Reinganum, 2008; Janssen and Roy, 2015; Milgrom and Roberts, 1986). The fact that sellers that accumulate a low rating leave the market early strongly suggests 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 setup of the market. Section 3 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 4 details the empirical approach and discusses the identification of the ratings effect. Section 5 documents and discusses the results. Section 6 provides additional findings and sensitivity checks. Finally, Section 7 concludes.

2 The market

Trade in illegal drugs has moved online in the past decade to a significant degree. Foley et al. (2019) estimate that illegal trade conducted using bitcoin amounts to $76 billion per year, while 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). These online drug trades take place on sales platforms located on the dark web. Following a purchase on such a platform, the product is shipped by mail to the customer.[3]

These 'darknet platforms' are characterized by four features. First, they are 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, they enable and encourage their users to communicate using PGP ('pretty good privacy') encryption. Third, transactions can only be conducted using a cryptocurrency (usually bitcoin). Each seller or buyer can 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 is provided, in which buyers can leave feedback for sellers they have bought

[3] Soska and Christin (2015) study the first of these platforms, "Silk Road", and estimate that the website at its height in 2013 had an annual revenue of more than $100 million.

from. In addition, platforms often provide an escrow system that sellers can offer to customers. Instead of making the payment directly to the vendor's on-site wallet, the buyer sends his bitcoins to a wallet of the platform. Then, the vendor sends the merchandise and after the buyer confirmed its arrival, the platform transfers payment to the seller.[4] Sellers can also choose to forego this system and require buyers to send the funds directly prior to shipment of the merchandise.

On the surface, darknet platforms 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 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 previous sales made. Buyers in turn can browse the listings by selecting the relevant category of products, or using the sites' search function.

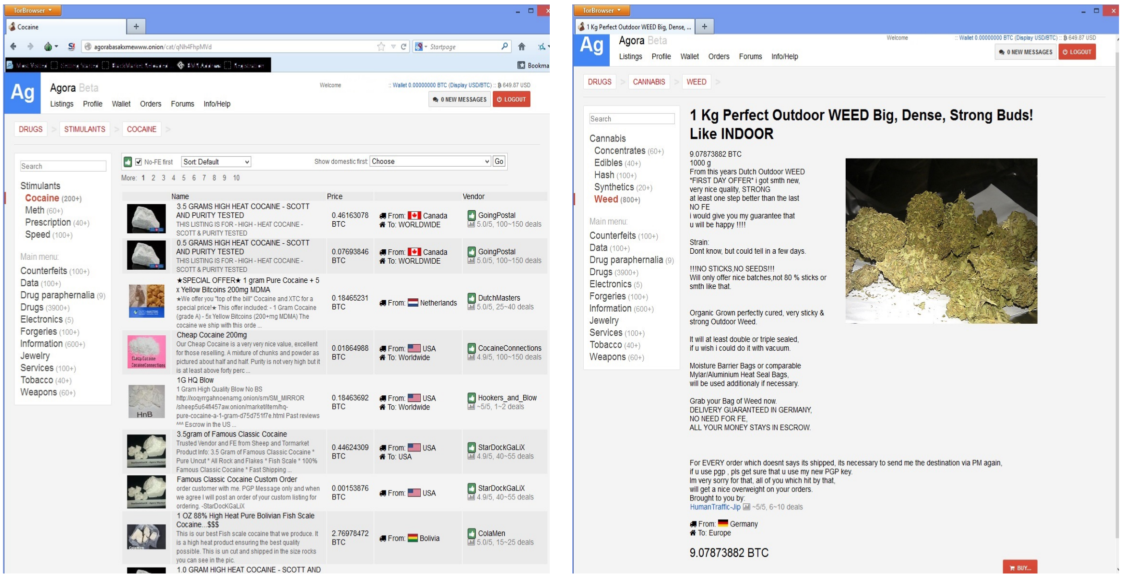


Figure 1: Screenshots from Agora

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

In contrast to clearnet markets, there is a great deal of darknet platform turnover. At any given point in time there may be dozens of different marketplaces active on the darknet.

[4]If the buyer does not signal the shipment to have concluded, the payment is 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 an escrow 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, 2020). See Figure 7 in the appendix for an overview of the escrow system on Silk Road.

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 large 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 8 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.[5] 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. 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 Cocaine. In this instance, we determine that the quantity sold in the offer is 1 gram.

We observe eight product categories of illegal drugs, namely Cannabis, MDMA, Cocaine, Amphetamine, Methamphetamine, Heroin, LSD, and Ketamine, and 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

[5] 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.

Figure 2: Screenshot of Evolution item

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

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 USD 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.[6]

Table 1: Summary statistics

Category	Mean unit price		# Vendors	# Offers	Median quantity
Cannabis	10.64	per 1g	1,314	5,902	14.00 g
MDMA	46.00	per 1g	721	3,368	7.00 g
Cocaine	109.19	per 1g	679	2,898	3.50 g
Amphetamine	15.88	per 1g	319	1,469	20.00 g
LSD	4.81	per $10 \times 100\mu g$	223	1,465	$31.25 \times 100\mu g$
Meth	158.15	per 1g	296	1,247	3.50 g
Heroin	152.00	per 1g	244	1,054	1.00 g
Ketamine	58.46	per 1g	127	531	5.00 g

Notes: The table reports summary statistics for the eight product categories 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.

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

[6] Detailed information on the distribution of price and quantity can be found in the appendix in Figures 9 and 10.

quantity, often shows stark differences by the shipping origin of the product. To illustrate this, Table 9 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 81.10 USD in the United States to 283.32 USD in Australia. 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.[7] 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 9 also illustrates that the largest share of vendors active ship their goods from the western world. Figure 11 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).

The second source of large price variations are quantity discounts. Vendors offer their potential customers significantly reduced prices for buying in bulk. Table 10 in the appendix 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. To account for both country differences and quantity discounts in our estimations, we include seller-, category- and quantity-specific interacted fixed effects which are unique to the country the product is shipped from for virtually all items.[8]

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

[7] 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.

[8] The handful of country changes in specific items sold we observe are driven by sellers from individual european countries changing the shipping origin to "European Union", as there are no customs procedures or checks between EU member states.

Evolution seller switched the platform following the exit. As we will show in section 4, 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 12 in the appendix documents the share uptime and speed in accessing the two sites in detail.

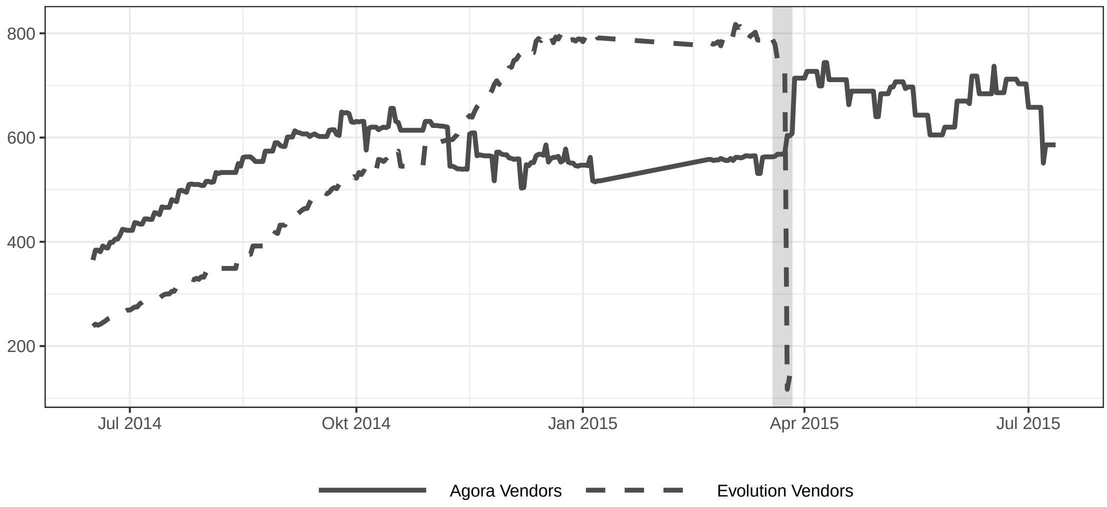


Figure 3: Platform size

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 12 in the appendix).

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).[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 13 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

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

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).

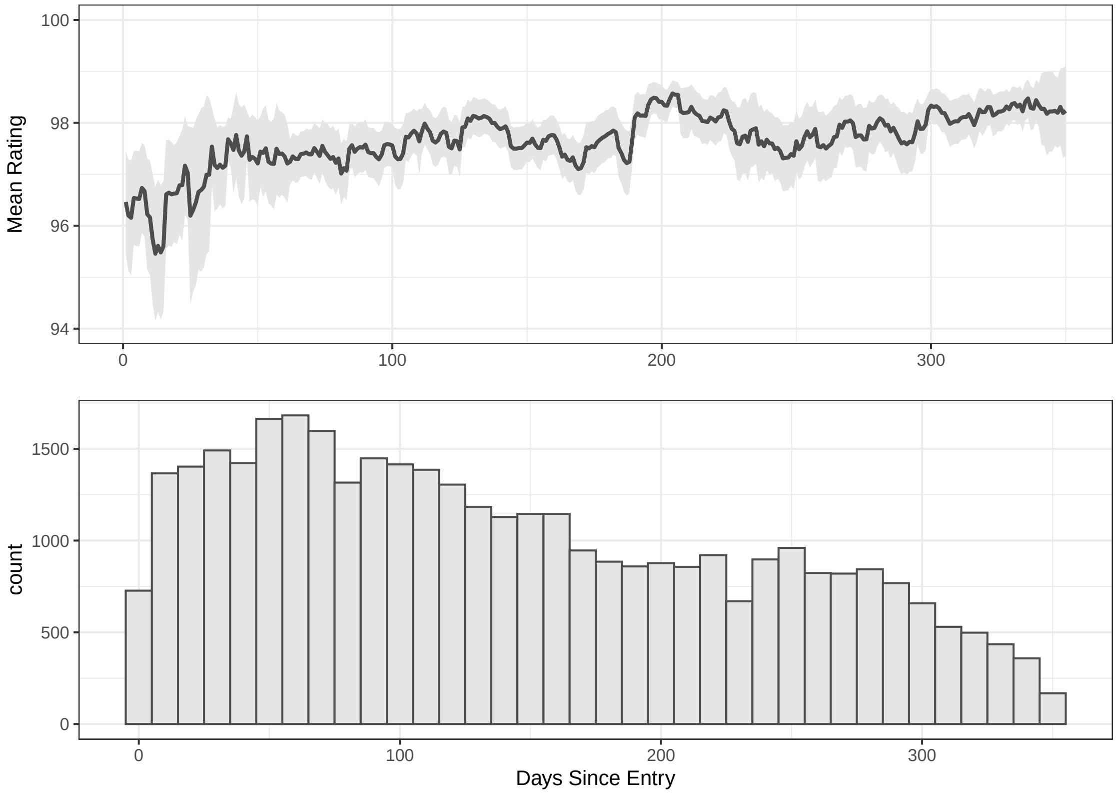


Figure 4: Vendor lifecycle

Notes: The figure shows the average rating at the top and the number of unique vendor accounts at the bottom 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 on the Agora platform. We track accounts that have been opened from the day of entry over time. Entry 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 significantly less volatile over the first 50-60 days. Within 100 days of activity it appears that sellers on average have matured. However, we

[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 vendors are observed for the first time.

continue to observe a slight further increase in the average rating as time progresses. This is particularly true for the small sample of vendors that are active for 300 days and more. The difference in the average rating between a new entrant and a mature vendor is very small in absolute numbers and around 2-3 (percentage) points. Figure 4 also indicates that a sizable fraction of new entrants drop out of the market within 80-200 days. 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). This is confirmed by the data, as the vast majority of sellers that drop out have a low rating and only few sellers with a low rating continue to stay in the market past 100 days. Since our dataset covers a time period of one year, the number of observations starts to become small and the ratings information more 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 and of a given quantity. We denote the individual items by the index i. We consider the following pricing equation:

$$Price_{t,i} = \beta_1 Rating_{t,j} + \beta_2 Escrow_i + \mu_i + \varepsilon_{t,i}, \tag{1}$$

where $Price_{t,i}$ denotes an item i's unit price at time t, $Rating_{t,j}$ the seller j of item i's aggregate rating at time t, and $Escrow_i$ whether the item requires use of the escrow system.[11] The variable μ_i represents the item-specific fixed effects of seller $\times$ category $\times$ quantity, and $\varepsilon_{t,i}$ 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. By conditioning on quantity in the item-specific fixed-effects, we explicitly allow for non-linear pricing of products. We documented previously in section 3 that quantity discounts are commonplace. Note that we implicitly account for country of origin without explicitly conditioning on it, as we do not observe sellers offering the same product (in the same quantity) in multiple locations.

Since 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

[11] In our estimations, we consider specifications with and without the escrow covariate. Exclusion of the variable leaves the results unaffected.

correspondingly higher expectation of its quality, which will impact the rating they leave. Then the ratings variable is correlated with past realizations of the error term. To overcome endogeneity concerns, we conduct an instrumental variable regression of Equation 1. We exploit the fact that the Evolution platform performed an exit-scam in the time frame we study and make use of a crucial aspect of darknet platforms: the publication of sellers PGP keys.

The illegal marketplaces we study strongly encourage buyers and sellers to encrypt their communication. When buyers 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 offerings 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 and highly complex. These features of PGP keys provide us with a unique identifier that allows matching vendor accounts across platforms and time. Figure 14 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 relatively 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 2 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

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

Table 2: 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.

platforms. Of the 2,344 unique sellers active, around 73% use only one account. This is in line with the previously documented estimates. Table 2 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.

By linking seller accounts over time and across platforms, we are now able to track sellers that are forced to switch platforms due to the exit-scam of the Evolution platform. In an exit-scam, the platform administrators steal the currency held by buyers and sellers on their respective platform accounts and take the platform offline. This is possible, because when traders conduct their business on one of the two darknet platforms we study, they place their bitcoins on their platform account in order to then make transactions. In addition, 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. 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, traders quickly migrated to other platforms. 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,

$$Rating_{t,i} = \delta_1 Switch_{t,j} \times \mathbb{1}\{t \geq Exit\}_t + \delta_2 Escrow_i + \eta_i + \xi_{t,i}, \tag{2}$$

to isolate the effect of rating on price, where η_i represents the item-specific fixed effects and $\xi_{t,i}$ the error term. 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 switching only affects prices via the reset in rating, ruling out direct effects of switching on price. However, this assumption need only hold conditionally within item types, i.e., within homogenous classes of drugs, for a specific seller, and a given quantity. Importantly, this implies that we can disregard seller-specific changes in pricing strategies that affect all items of a seller equally. 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, but only if the strategic behavior is item-class specific. While we cannot test for this possibility directly, we do not observe any change in the rate of sales made by switchers from before to after the exit (see Figure 16 in the appendix), that would indicate a fast recapturing of market share of switchers. As the sales information we have is very coarse, we also proxy sales by the number of feedbacks left for a seller and again observe no change in the rate of feedbacks left over time across the exit (see Figure 17 in the appendix). In addition, 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.

Figure 5 shows the placement of switchers in the ratings distribution in the month preceding the exit and the month following the exit. The shading of each bar corresponds to the share of switchers, with a darker tone indicating a higher share of switchers. The

[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. Table 12 in the appendix documents the average price, median quantity, and number of vendors and items prior to the exit on either platform. We do not observe any patterns or significant differences that would indicate variation in how the two platforms operated in the market.

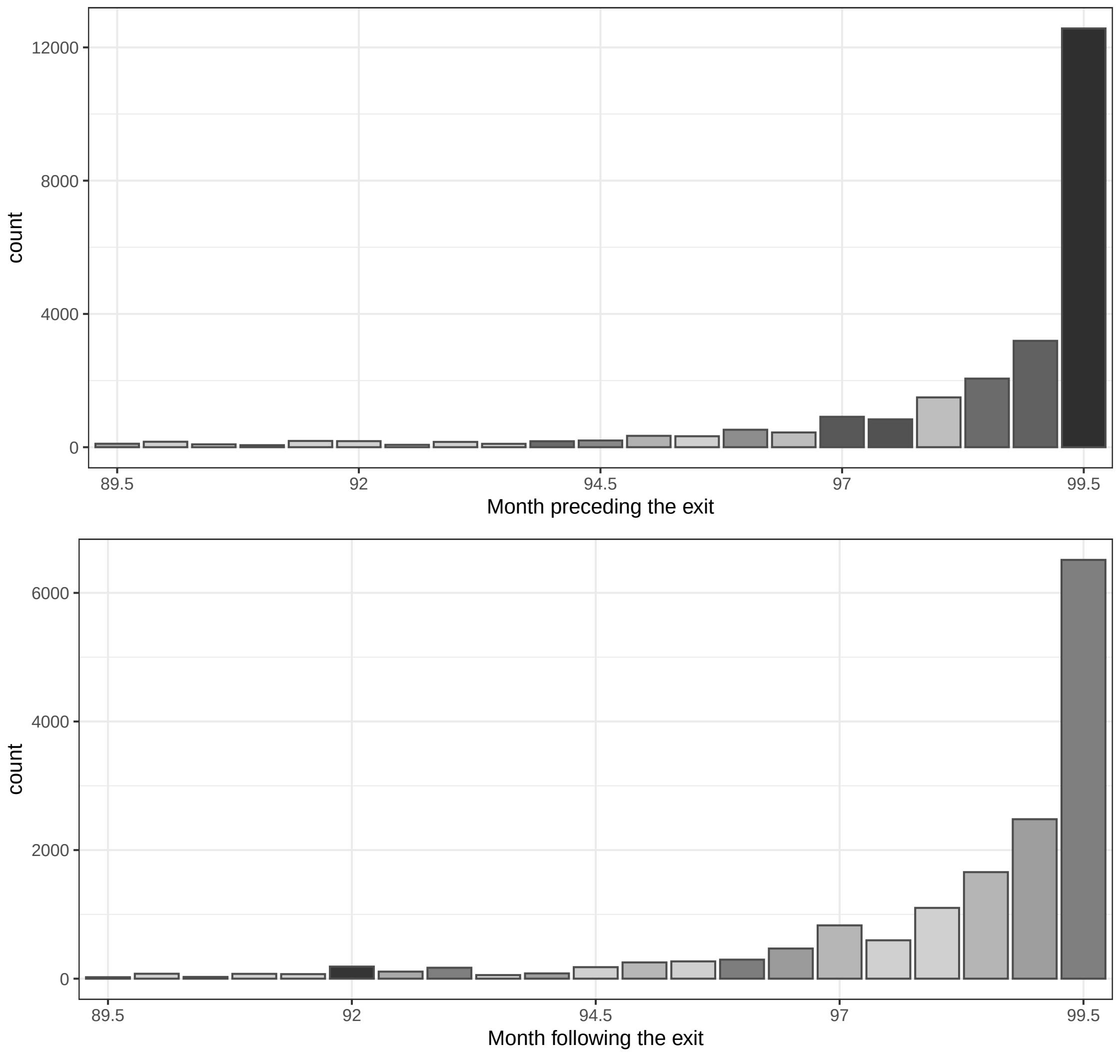


Figure 5: Move in the ratings distribution for switchers

Notes: The figure shows the top end of the distribution of seller rating. The shading corresponds to the share of switchers in each bar, with darker coloring indicating a higher share of switchers.

exit-scam and subsequent forced migration shifted switchers significantly down the ratings distribution. Prior to the exit, the highest share of switchers was in the top bar of the distribution with a rating of 99.5 or above. This corresponds to being in the top 50% of the ratings distribution, however most of these types have ratings that put them in the top 25% of the distribution. Remaining switchers mostly have ratings of 97 or higher, and little to no switchers are observed below a rating of 95. In the month following the exit on the other hand, the highest share of switchers are observed in the distribution at 92-92.5, corresponding to being in the bottom 10% of the distribution and a much smaller share is found in the upper parts of the distribution.

Figure 16 in the appendix shows this impact on the average rating and total sales of switchers compared to all other sellers over time. On average, switchers tended to have a higher rating than other sellers prior to the exit. The forced migration in March 2015 caused a ratings shock and lowered the average rating for switchers by around 3-4 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 all other sellers instead shows no reaction to the exit. Similarly, the average aggregate sales of switchers were slightly below those of the rest, 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 before, while the sales growth of all other sellers appears again unaffected by the exit. The average rating of switchers recovers within the three months following the exit, which is also in line with the approximately 100 days it takes for the average seller to mature.

The number of sellers and items that we observe and are able to track when switching the platform differs across the categories of drugs. For our estimations in section 5 we restrict the analysis to the categories of Cannabis, Cocaine, LSD, and Amphetamine, since the remaining categories do not contain a sufficient number of sellers that switch. We also exclude MDMA from the analysis. MDMA is sold both in powder and in pill form with varying advertised strength, and it is impossible to generate a uniform measure of quantity without incurring substantial measurement error. We further limit the sample to a time period around the Evolution exit date from 120 days prior to the exit to 45 days after the exit. We then extend the post-exit period. Moreover, we only include product offers from countries where we observe switching sellers. Since we have very few observations from developing countries, we restrict the sample to developed countries.

Table 3 documents how switchers price their products fourteen days before and fourteen days after the exit. It shows that the average unit price of switchers between the two dates strongly decreased across all categories of drugs, with the exception of LSD, indicating a clear adjustment to the large reputational loss suffered. The percentage change of prices is significant for all drugs and is approximately -7.5 USD on average. The market price change on the other hand between fourteen days prior to the exit and fourteen days after is negative for most categories, but significantly smaller, 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

Table 3: Switchers before and after the exit

	Mean # offers		Median quantity		Mean unit price change		
Category	Before	After	Before	After	Absolute	Percentage	Market
Cannabis	2.09	2.09	7.09	10	-0.83	-7%	-4%
Cocaine	3.11	2.47	3.50	3.50	-15.79	-15%	-3%
LSD	3.43	3.50	15.75	13.25	0.88	20%	-10%
Amphetamine	3.14	3.80	20	25	-2.92	-30%	$+24\%$

Notes: The table contrasts switchers fourteen days prior to the exit and fourteen 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. 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.

exit by adjusting the product portfolio.

Lastly, Table 11 in the appendix contrasts switchers to all other sellers present on Evolution a week prior to the exit. It demonstrates that 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. Switching sellers tend to offer slightly fewer different products on average than other Evolution sellers across most categories, while the median quantity of items offered is similar between the two groups. These patterns fit with the higher average rating we observe: switching sellers tend to be reputable, highly rated sellers that offer a somewhat smaller, higher quality portfolio compared to the average seller, but are present in the different product groups in the same share as the average seller and offer the same quantities as the average seller. That is, they are a representative sample of the high-quality sellers of the entire market. Indeed, when comparing switchers only to other highly-rated sellers, the difference in the number of offers decreases and the pattern disappears. 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, since switchers can on average be considered revealed high types prior to the exit and entrants whose type is uncertain following the exit.

5 Results

Table 4 presents the estimation results for the first stage of the linear model outlined in section 4. We find a consistent negative effect of switching on rating that lies approximately between 0.8% and 1% and is statistically significant at the 1% level for all categories of drugs with the exception of Amphetamines. We also provide results of the model estimated in a log-log specification as the distribution of rating is highly skewed and find a negative, statistically significant effect of switching markets on rating that ranges from 8% to 14%. Note that we transform rating with the inverse hyperbolic sine function instead of the standard logarithmic function as we have a non-trivial amount of observations with a rating of zero (e.g. Burbidge et al., 1988; MacKinnon and Magee, 1990). We further find a positive and statistically significant coefficient for escrow for all drugs except Cannabis. We would expect a positive effect, since the escrow system is meant to reduce the risk buyers face for paying for merchandise before receiving it, use of the system should allow a seller to set a higher price. In addition, it incurs small fees that need to be offset. Throughout our analysis we consistently document positive effects of escrow on the price charged. In Table 13 in the appendix we further document the results for the same estimations when excluding the escrow covariate. The results are unaffected by exclusion of the variable.

Table 5 presents estimation results of a reduced form model without our instrument of the effect of switching markets on prices. We find a strong negative effect across all categories. The effect is statistically significant at the 1% level. On average, switching is associated with reducing the unit price by around 1.6 USD. We find strong variation across categories in the size of our estimates that is aligned with the price level of each category. The largest effect in absolute terms is found for Cocaine, which is also the most expensive category of drug we consider. In relative terms the effect for Cannabis corresponds to 5.5% of the standard deviation of the unit price, while for Cocaine it is 14.8%, for LSD 17.7%, and for Amphetamines 2.1% respectively. The effect sizes in the log-log specification of the model show a similar pattern of effect sizes across the different categories of drugs and range from -5.2% for Cannabis to -9.5% for LSD. Table 14 in the appendix shows the results for the same estimations when excluding the escrow covariate. This does not affect our results.

Table 6 presents the estimation results for the full model outlined in section 4 where we exploit the switch instrument to estimate the ratings effect on price. We find a strong, positive and statistically significant effect of rating on price across all categories, with the exception of Amphetamines. These effects are also economically meaningful and significant. On average, a one percentage point improvement in rating causes an increase in the unit price of around 2.4 USD. As before, the effect size varies across drug categories in line with the different price levels for individual drugs and the associated price premium ranges from 0.5 USD for LSD to 5 USD for Cocaine. In our log-log specification, we find

Table 4: First stage: The effect of switching markets on rating

	Level-level				
	All	Cannabis	Cocaine	LSD	Amphetamine
Switch x post	−0.756***	−0.928***	−0.791***	−1.039***	−0.022
	(0.030)	(0.045)	(0.049)	(0.064)	(0.108)
Escrow	0.094***	−0.241***	0.128***	0.459***	0.661***
	(0.015)	(0.024)	(0.024)	(0.022)	(0.056)
	Log-log				
	All	Cannabis	Cocaine	LSD	Amphetamine
Switch x post	−0.010***	−0.014***	−0.008***	−0.011***	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Escrow	0.001***	−0.003***	0.001***	0.005***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Item-specific FE	✓	✓	✓	✓	✓
Num. obs.	298322	136437	79437	37713	44735
Num. switch items	190	87	52	28	23

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 120 days prior to the exit until 45 days post exit. 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 × category × quantity.

that the increase in prices corresponds to approximately 6.7% of the unit price on average and the effect size is smallest for Cannabis (4%) and larger for Cocaine (6.9%) and LSD (10.6%). We further find effects of requiring use of the escrow system that are statistically significant at the 1% level but substantially smaller than the impact of a ratings increase, emphasizing the importance of reputation in this market. We document in Table 15 in the appendix results for the same instrumental variable estimations when excluding the escrow covariate, showing that our results are robust to excluding the variable.

The effect size pattern we document is explained by the degree of product differentiation and quality uncertainty within different categories of drugs. The purity of synthetic drugs can vary substantially and buyers face a substantial amount of uncertainty regarding

Table 5: Reduced form: The effect of switching markets on price

	Level-level				
	All	Cannabis	Cocaine	LSD	Amphetamine
Switch x post	−1.640***	−0.800***	−3.772***	−0.384***	−0.765***
	(0.162)	(0.052)	(0.550)	(0.048)	(0.204)
Escrow	0.864***	0.169***	2.159***	0.369***	0.490***
	(0.081)	(0.028)	(0.270)	(0.017)	(0.108)
	Log-log				
	All	Cannabis	Cocaine	LSD	Amphetamine
Switch x post	−0.061***	−0.052***	−0.054***	−0.095***	−0.088***
	(0.002)	(0.003)	(0.004)	(0.008)	(0.006)
Escrow	0.025***	0.016***	0.018***	0.039***	0.061***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Item-specific FE	✓	✓	✓	✓	✓
Num. obs.	304050	139244	80549	38910	45347
Num. switch items	190	87	52	28	23

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 120 days prior to the exit until 45 days post exit. 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 $\times$ category $\times$ quantity.

the quality of the drugs they purchase. Cocaine is well-known for having cutting agents added to bulk up weight. LSD is typically added to absorbent paper and sold in a collection of small squares decorated with design and artwork ('blotters'), which can contain any amount from zero up to the advertised amount of the drug. Given the uncertainty about product quality which is only resolved after purchase, the importance of rating and its effect on price are larger for synthetic drugs. This pattern is reinforced by the fact that synthetic drugs are more expensive or purchased in greater quantities, hence purchases present a greater financial risk for buyers. In contrast, the quality variations for Cannabis are smaller, the price is limited and quality can already be partially ascertained from product images.

Table 6: IV: The effect of rating on price

	Level-level				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (% points)	2.384***	0.941***	5.063***	0.507***	42.181
	(0.240)	(0.074)	(0.762)	(0.058)	(209.489)
Escrow	0.693***	0.398***	1.659***	0.163***	−27.377
	(0.090)	(0.041)	(0.300)	(0.031)	(138.325)
	Log-log				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (ihs)	6.749***	4.100***	6.894***	10.648***	342.626
	(0.339)	(0.304)	(0.665)	(1.025)	(1429.080)
Escrow	0.019***	0.026***	0.011***	−0.009	−2.405
	(0.002)	(0.002)	(0.003)	(0.006)	(10.279)
Item-specific FE	✓	✓	✓	✓	✓
Num. obs.	298322	136437	79437	37713	44735
Num. switch items	190	87	52	28	23

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 120 days prior to the exit until 45 days post exit. 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 × category × quantity.

The overall effect implies a significant value to being identified as a reputable seller. We documented previously that switchers can be considered revealed high types prior to the exit and entrants whose type is uncertain following the exit and that the drop in rating experienced on average corresponds closely to the difference in rating we observe for new entrants in the market compared to established, reputable sellers. Then we find based on the log-log specification that being identified as a high type via the ratings sytem allows a seller to charge prices on average 20% higher than an entrant. For LSD, the return to being revealed as a high quality seller is even above 30%.

These returns translate into a large loss of revenue for sellers. Our data contains a coarse measure of the number of transactions a seller has made, which we can use to obtain an estimate of the overall loss. On average, switchers make approximately 87 transactions in the 45-day time period following the exit and offer a median quantity of five times the base unit quantity (1 gram for all categories except LSD, where it is 1,000 μg). As we cannot ascertain the proportion of sales associated with individual items offered by a seller, we assume that it is uniformly distributed. Then, the 87 transactions on average resulted in revenues of roughly 14,500 USD. According to our estimates, retaining their reputation would have allowed them to charge prices 20% higher, implying a relative revenue loss of around 2,900 USD. The same back-of-the-envelope calculation per category of drug shows losses of approximately 770 USD for Cannabis, 3,600 USD for Cocaine, and 10,000 USD for LSD. Note that the cost of procuring the drug for a seller similarly differ significantly across categories, making it difficult to compare these category-specific estimates. We also proxy the number of sales based on the number of feedbacks received and find that based on this measure sellers only lose around 1,650 USD on average. As not every transaction results in a review being left, this number is accordingly biased downward.

As sellers recover their rating following the exit period, the impact of the switch shock should decrease. We document the average effect in Figure 6 over time as we extend the time frame for our estimation in the post-exit window. As expected, the effect decreases over time. This decrease begins to occur roughly around 70 days after the exit, which is in line with the time it takes for a seller to re-establish a high rating.

6 Sensitivity Analysis

Table 7 presents estimation results for a naive estimation approach of the effect of rating on price using OLS without making use of the instrument. In the specification in levels, we only find a statistically significant effect for Cocaine. However, this effect is extremely small relative to the price level for Cocaine. In the log-log specification, we find statistically

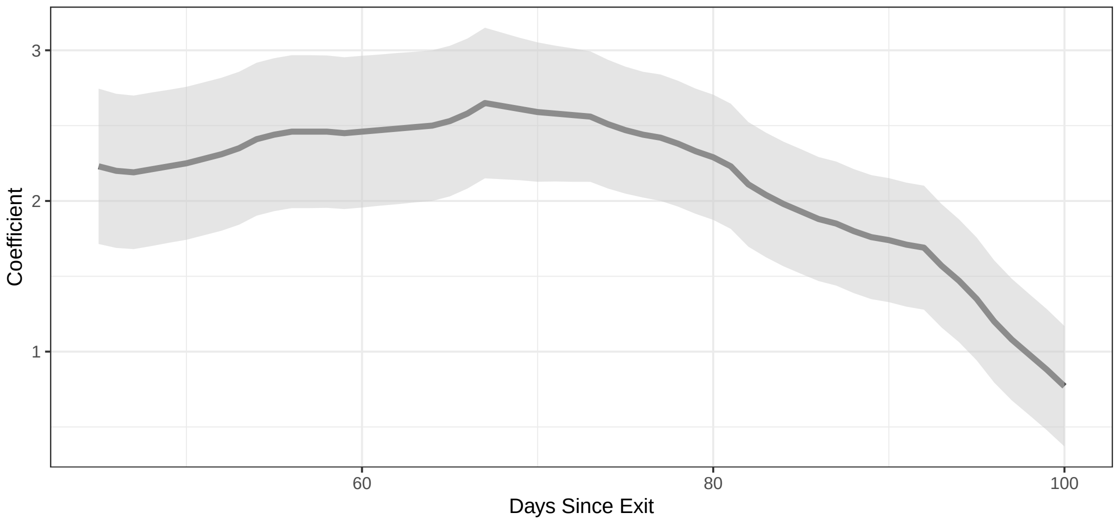


Figure 6: The effect of rating on price over time

Notes: The figure shows the estimated coefficient of rating on unit price based on the linear model specified in section 4. The time frame past exit is extended one day at a time and the effect re-estimated. The 95% confidence interval is shown in grey.

significant effects for all categories except LSD, but the effect for Cannabis is negative (though close to zero) and marginally significant. As in our level specification, these effects are very small and lie at 0.3% for Cocaine and 0.2% for Amphetamines. The estimates are basically unchanged when excluding the escrow covariate as shown in Table 16 in the appendix. These findings are broadly in line with previous literature on legal marketplaces that suggests that there are only small or no effects of rating on price (e.g. Resnick and Zeckhauser, 2002; Cabral and Hortacsu, 2010; Houser and Wooders, 2006; Cai et al., 2014). Our estimates in Table 7 and Table 16 are also in line with previous work on darknet marketplaces in Espinosa (2019) who investigates a smaller platform and finds that a 10% increase in positive evaluations is associated with 0.3-0.6% higher prices. Our main results shown in the previous section demonstrate that the finding that the impact of reputation on online platforms is not driven by increasing prices is misleading, as we find very large price premia for having a higher reputation once we account for the endogeneity of rating via our instrument.

Table 8 and Table 17 in the appendix present estimation results for a placebo exit in the period prior to the actual platform exit. We extend the time frame before the exit to the same split of 120 days before and 45 days after the assumed placebo exit takes place in line with our main estimation time frame and exclude the days immediately before the real platform exit. We find no statistically significant effects of rating on price in any specification.

Table 7: Naive OLS: The effect of rating on price

	Level-level				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (% points)	0.081***	–0.004	0.378***	–0.006	–0.008
	(0.010)	(0.003)	(0.041)	(0.004)	(0.009)
Escrow	0.847***	0.156***	2.063***	0.370***	0.476***
	(0.082)	(0.028)	(0.271)	(0.017)	(0.109)

	Log-log				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (ihs)	0.110***	–0.033*	0.315***	–0.031	0.225***
	(0.012)	(0.017)	(0.021)	(0.060)	(0.025)
Escrow	0.024***	0.015***	0.016***	0.037***	0.057***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Item-specific FE	✓	✓	✓	✓	✓
Num. obs.	298322	136437	79437	37713	44735

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 120 days prior to the exit until 45 days post exit. 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 $\times$ category $\times$ quantity.

Table 8: Placebo check: The effect of rating on price prior to the exit date

	Level-level				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (% points)	−1.529	−4.117	−16.559	0.691	0.703
	(2.301)	(8.342)	(36.228)	(0.993)	(0.753)
Escrow	1.356*	−2.511	−11.225	−1.084	−0.748
	(0.726)	(5.712)	(30.102)	(1.649)	(1.744)
	Log-log				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (ihs)	−0.331	−12.769	−22.757	17.841	3.186*
	(2.448)	(22.787)	(60.330)	(24.631)	(1.931)
Escrow	0.026***	−0.128	−0.264	−0.317	−0.026
	(0.003)	(0.271)	(0.720)	(0.448)	(0.049)
Item-specific FE	✓	✓	✓	✓	✓
Num. obs.	307465	140915	79410	37416	49724
Num. switch items	190	87	52	28	23

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 that ends one month before the evolution exit. We assume a placebo exit occurs 45 days prior and consider the period of 120 days leading up to the placebo date and 45 days after. 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 × category × quantity.

7 Conclusion

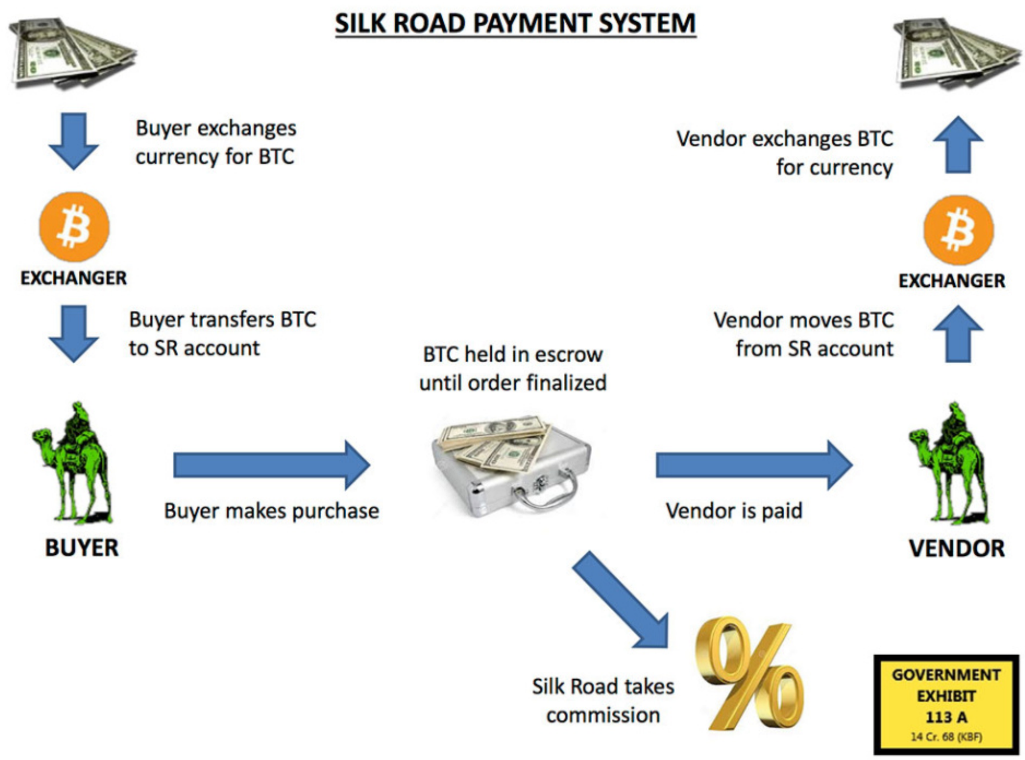
In this paper, we analyze the value of reputation in a market devoid of legal institutions. We examine the online market for illegal drugs, where market participants transact on online platforms that provide a rating system for sellers in a form familiar to any user of popular legal platforms such as Amazon, thus providing a publicly observable measure of reputation. The lack of legal institutions and strong need to stay anonymous suggests that reputation is the sole force to facilitate trade among market participants. We make use of a novel dataset of webscrape information of offers on the two dominant platforms during 2014/2015 that jointly covered more than 90% of the market. We exploit the fact that one of the two platforms suddenly exited the market in March 2015 and track sellers that were forced to migrate to the remaining platform. By necessity, these sellers must open a new account to continue selling, thereby resetting their rating. Using this exogenous variation in rating allows us to identify the causal effect of reputation in the form of online ratings on the price a seller may charge in the absence of legal institutions.

We document three key results. One, we find that a 1% increase in a sellers rating causes an increase in unit prices charged of 6.7% on average. This is a substantial estimate that is significantly greater than effects generally documented for legal markets. The impact of rating varies across different types of drugs, in line with the extent of product differentiation of and resulting quality uncertainty buyers face for a given drug. With larger quality differences, distinguishing yourself as a 'good type' by obtaining a high rating is more valuable. Two, we find that a revealed good type may set prices on average 20% higher than an entrant whose type is unknown. We provide evidence that the migrating sellers that we track are representative of established, highly rated sellers prior to the exit and argue that this result can be understood as a reduced form, causal estimate of the value of playing a separating equilibrium as a high type versus a pooling equilibrium. Three, our empirical approach implicitly shows that a sellers reputation is at least partially non-transferable across online marketplaces.

Our work in this paper corroborates previous literature which suggests that reputation may play a crucial role in facilitating trade when governmental or legal institutions are lacking. To the best of our knowledge we are the first to explicitly estimate the value of reputation in such a unique setting and provide causal estimates. Given the abundance of black markets for many types of goods, studying the dynamics of reputation in more detail in such an 'institutional void' is a promising pursuit for future research.

A Appendix

Figure 7: 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 8: Screenshot of the Grams search engine website

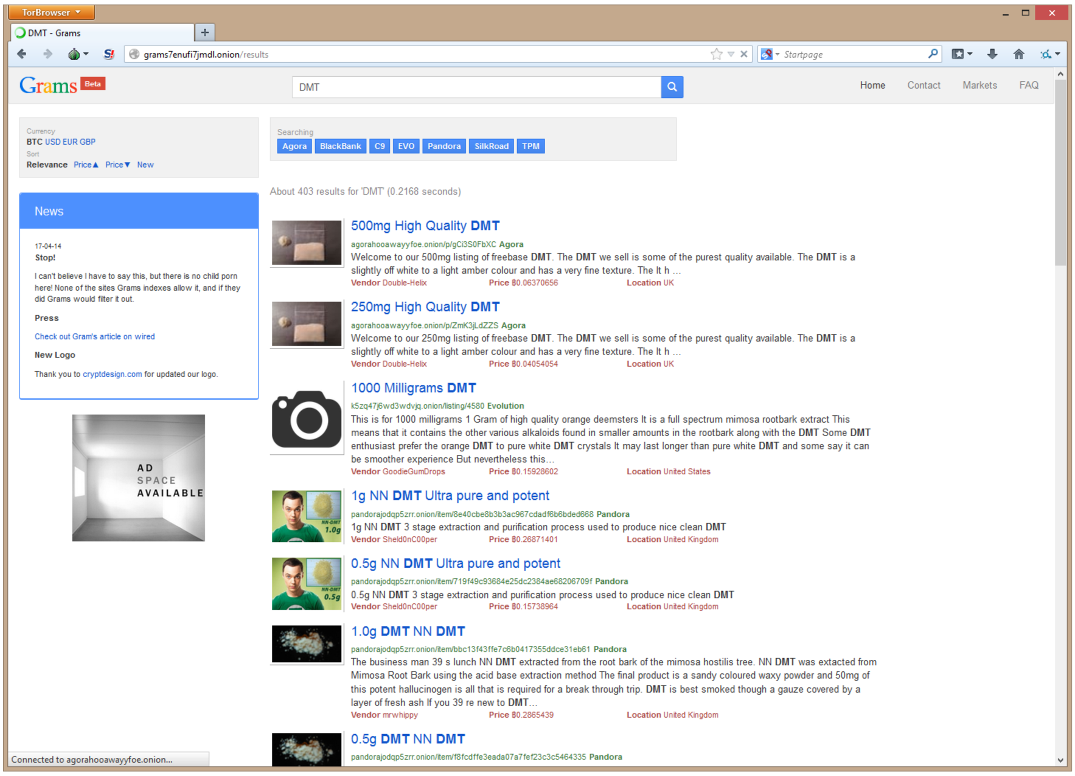
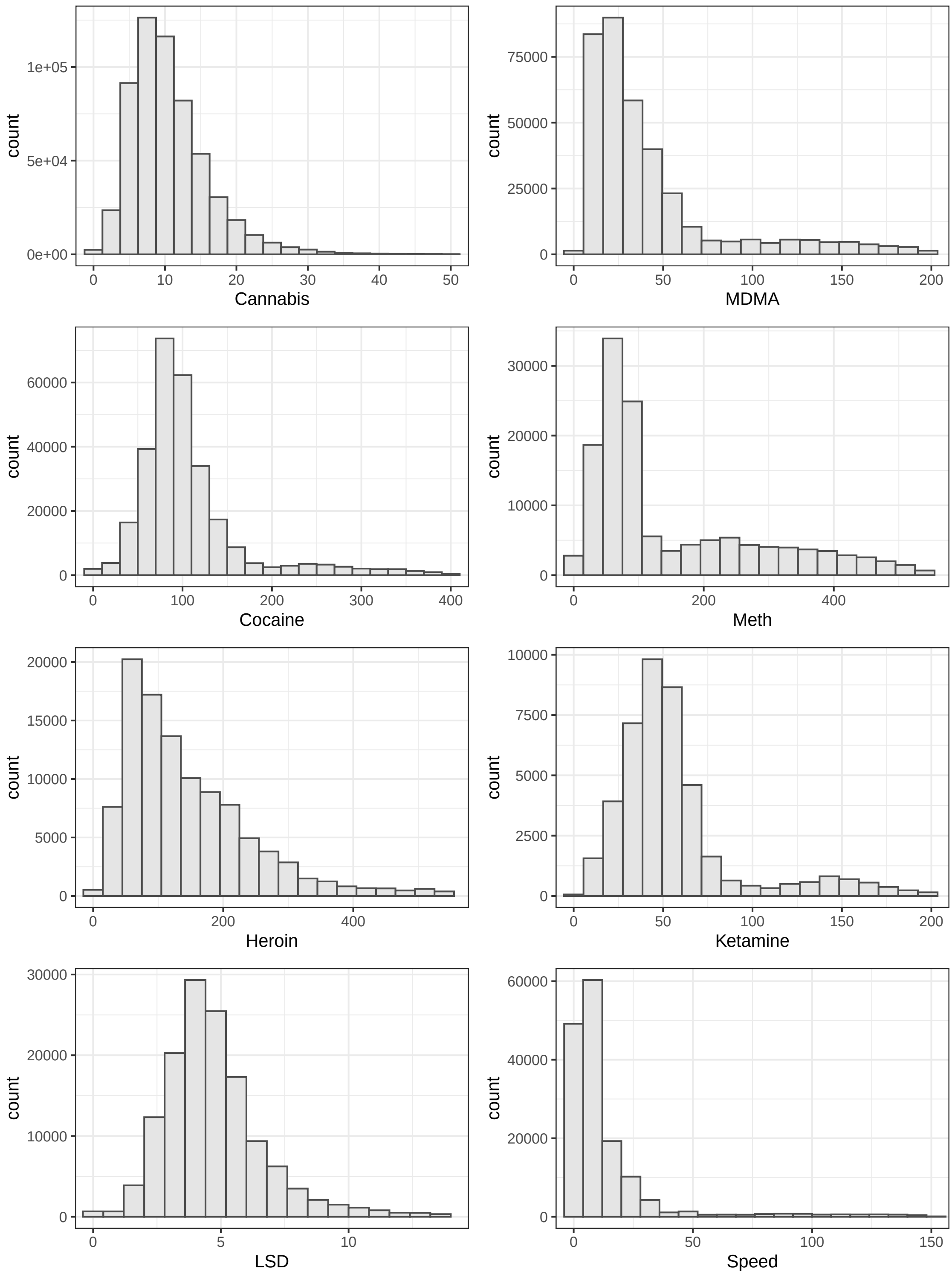


Table 9: Country differences for cocaine

Shipping origin country	Mean unit price	# Offers	# Vendors	Median quantity
United States	81.10	753	186	3.50
Netherlands	86.32	493	92	3.50
United Kingdom	110.58	461	108	3.00
Germany	93.52	276	57	5.00
Australia	283.32	272	77	2.00
Canada	94.56	201	41	3.50
France	105.54	74	18	1.00
Belgium	88.10	44	9	5.00
Sweden	128.36	41	12	2.00
Italy	101.43	32	5	5.00

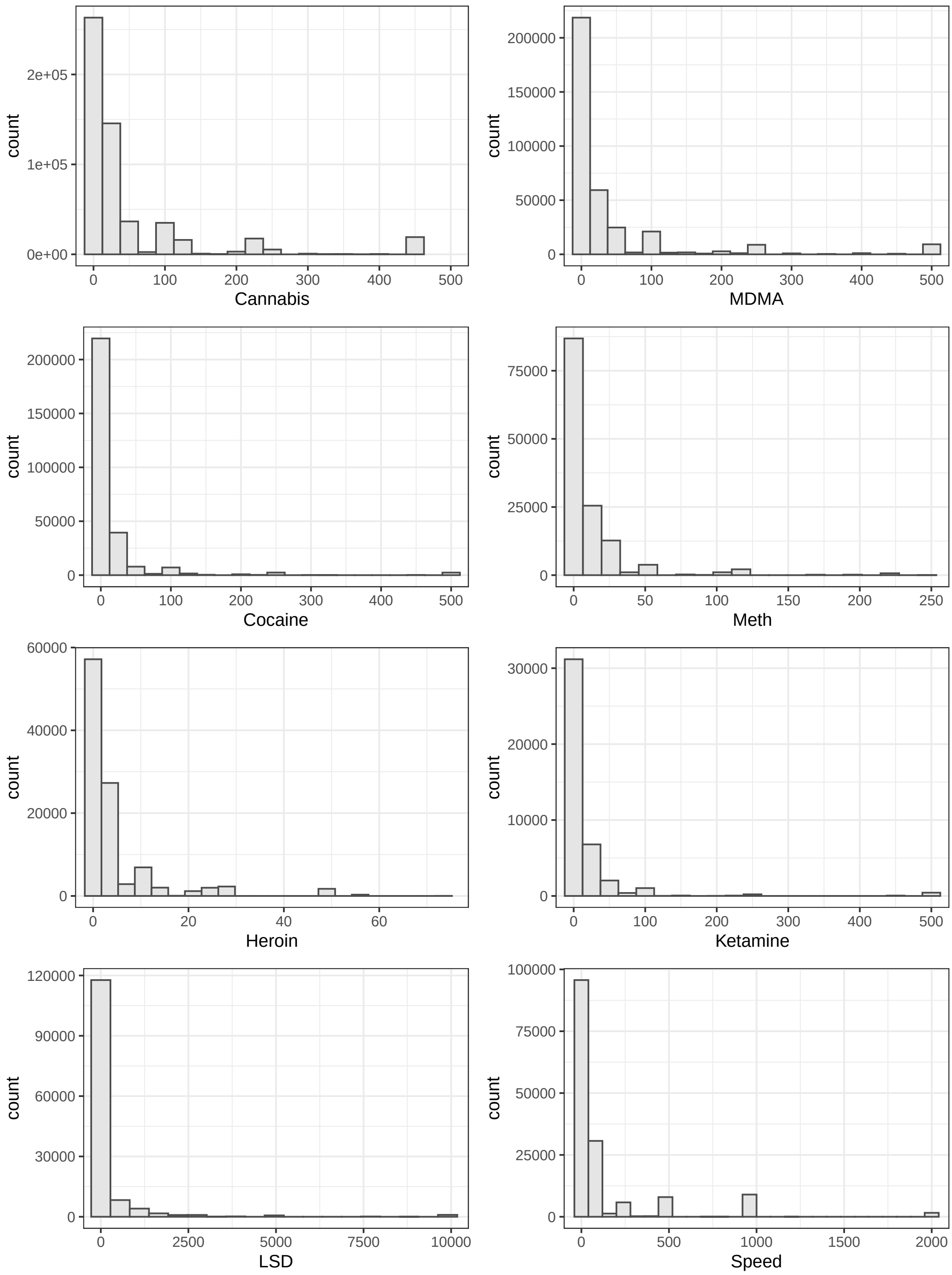
Notes: The table reports summary statistics for cocaine for the ten largest countries of origin as measured by the number of vendors active, sorted by size. Prices are reported in USD. The Bitcoin exchange rate used corresponds to the day on which the item price was observed. Unit price refers to the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

Figure 9: 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 10: Distribution of the quantity offered for all eight categories of drugs



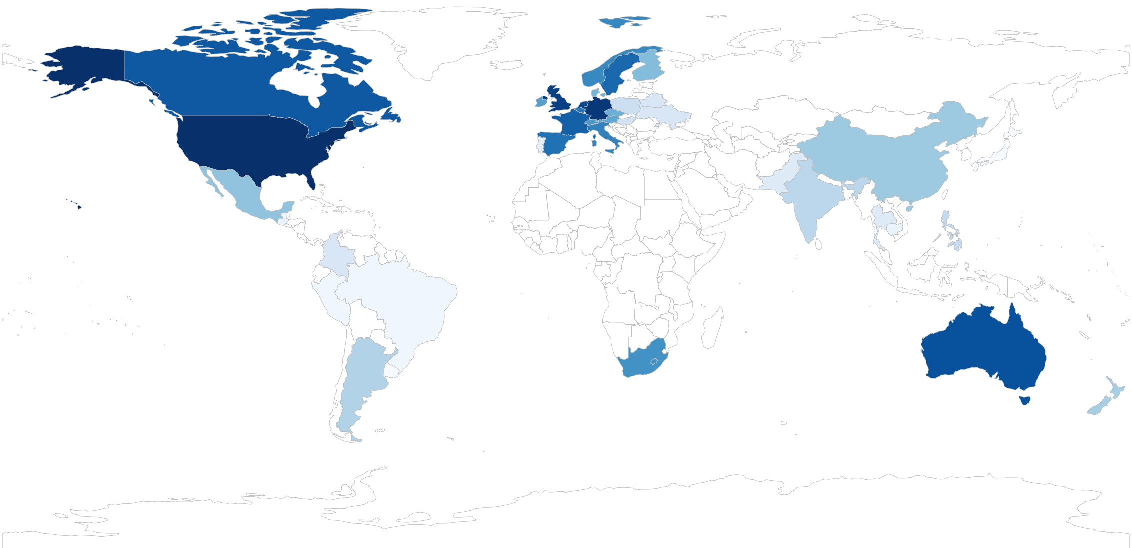
Note: The figure shows the distributions of the quantity of the eight drugs considered. The unit used is grams, except for LSD, where it is micrograms.

Table 10: Quantity discounts

Category	Single Unit	Discounts			
		$\times$ 5	$\times$ 10	$\times$ 50	$\times$ 100
Cannabis	17.53	0.77	0.67	0.49	0.42
MDMA	65.97	0.63	0.51	0.33	0.27
Cocaine	125.38	0.74	0.66	0.57	0.53
Amphetamine	42.54	0.37	0.25	0.14	0.10
Meth	172.79	0.61	0.43	0.21	0.15
Heroin	152.79	0.65	0.51	0.28	0.22
LSD	5.69	0.77	0.71	0.56	0.49
Ketamine	79.36	0.58	0.54	0.42	0.37

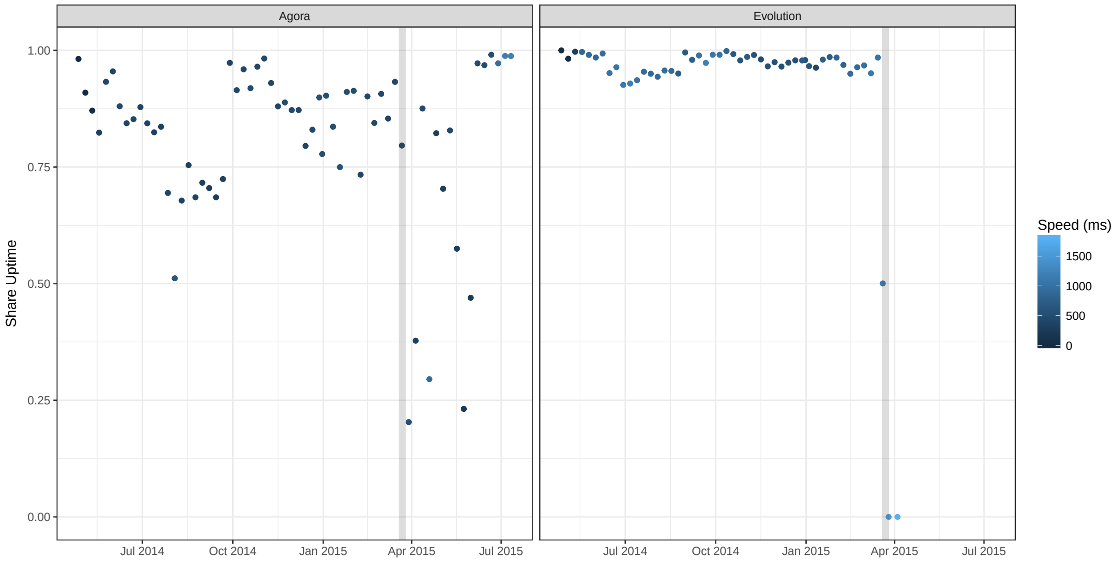
Notes: The table reports the discount rates for the eight product categories by quantity. Prices are reported in USD. The bitcoin exchange rate used corresponds to the day on which the item price was observed. Prices reported are the unit price, that is, the price per consumption unit, defined as 1 gram for all categories except LSD, where it is 10 $\times$ 100 μg.

Figure 11: 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 12: Platform uptime



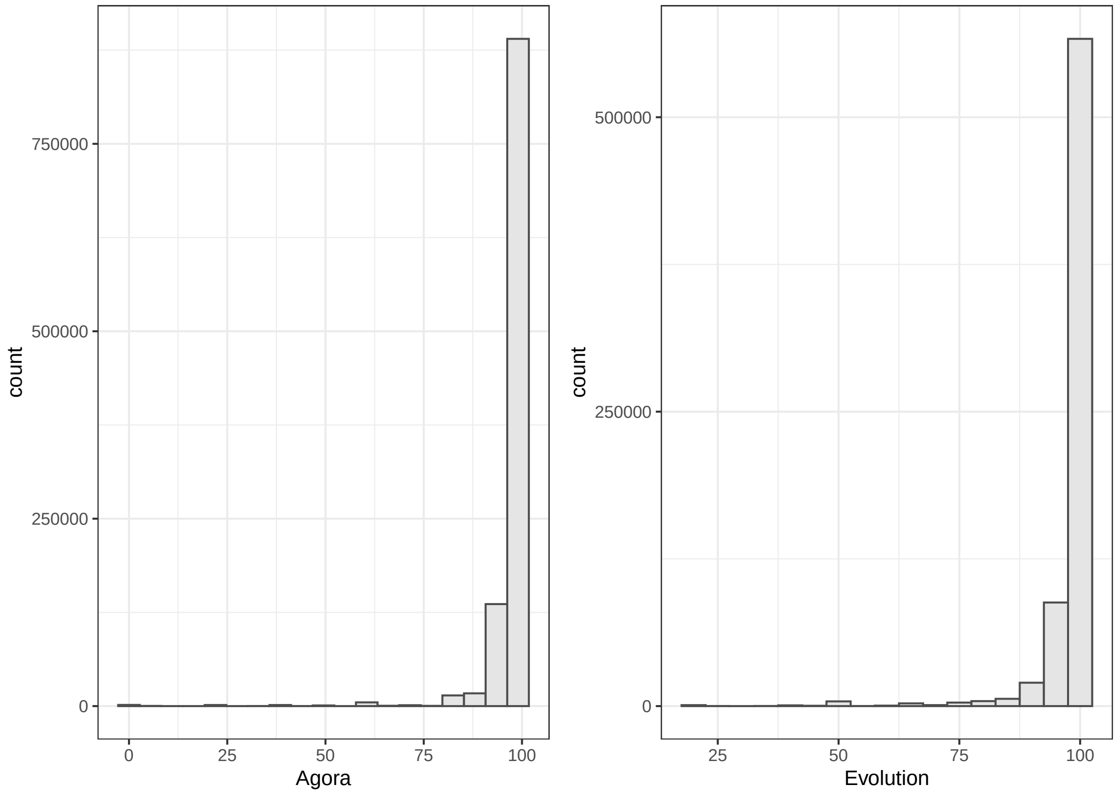
Notes: The figure shows the percentage share of uptime for each of the two platforms. The speed of accessing the site is indicated by the shading. The Evolution exit is indicated in grey.

Table 11: Sellers on Evolution seven days prior to the exit

	Share of sellers		Average # offers		Median quantity	
Category	Switchers	E-sellers	Switchers	E-sellers	Switchers	E-sellers
Cannabis	0.60	0.56	2.31	3.29	10	14
Cocaine	0.29	0.25	3.18	3.36	3.50	3.50
LSD	0.12	0.10	3.43	2.88	15.75	62.50
Amphetamine	0.14	0.16	2.88	3.73	15	20

Notes: The table contrasts switchers to all other Evolution sellers one week before the exit. It shows the share of the two groups in each category of drug, the average number of offers, and the median quantity sold.

Figure 13: 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.

Figure 14: 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
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J+3JmdwN/iwijE3Zy9ahCM4XTcelzxrJUmDZNcJuLfLDc9afsuOuJ4pFkfElrhZY
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LPvxPLutv5KkhETqQ5xqXjAnny+m7pQwNeFAKnFBcUsowEJIOXuGhoWFDTeR+T9b
9LstlHxCEtRVbyIu+03iOZ5vIl//3KCoTRgUuJcoIrMtbe+FQGmdYiGIp3nQKphy
vOpMGitVYv2RRc6ve1IpdAm9aBcLHf2CFUUEv5w896C/M4qTOvS+e1zQNTBgKjQK
GOz/0rXqGJPO1CA92PnTPILJOJ9W2e2lJTLyhN1P7SJ+oKSzzj5PrUgE/b5BuAvd
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ihU2sh/rQVqhMoHxz6CkC2Hb73Gb
=SgOE
-----END PGP PUBLIC KEY BLOCK-----
```
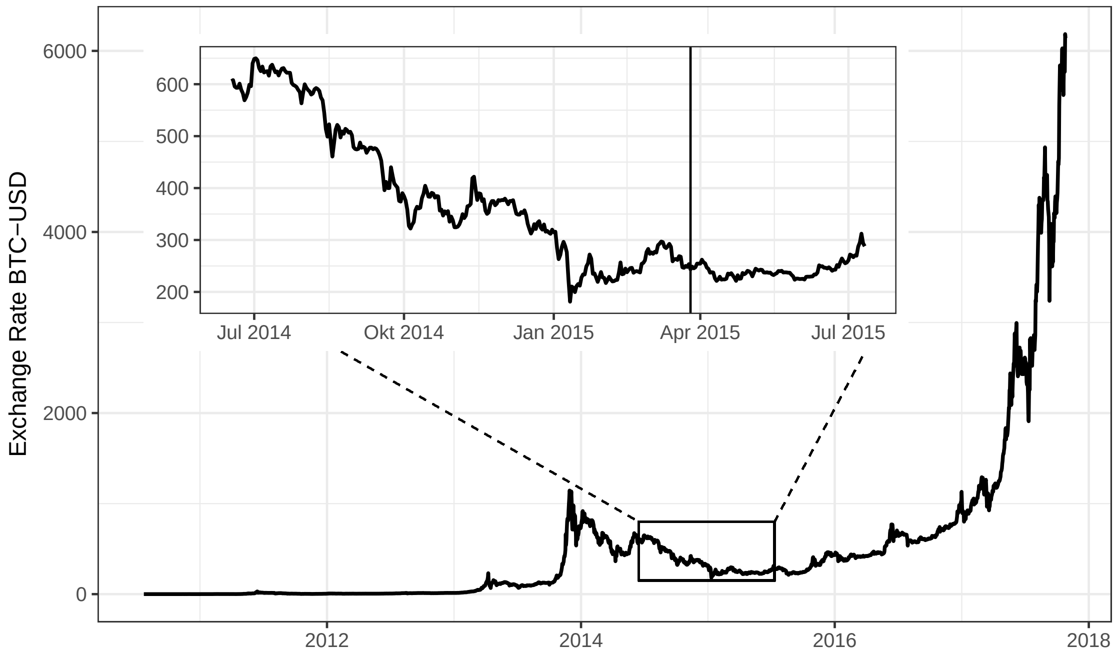


Notes: The figure shows an example of a public PGP key block. The key can be used to encrypt information sent to the owner of the private PGP key. These PGP key blocks are provided by the sellers on their account information and directly visible to buyers.

Figure 15: 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.

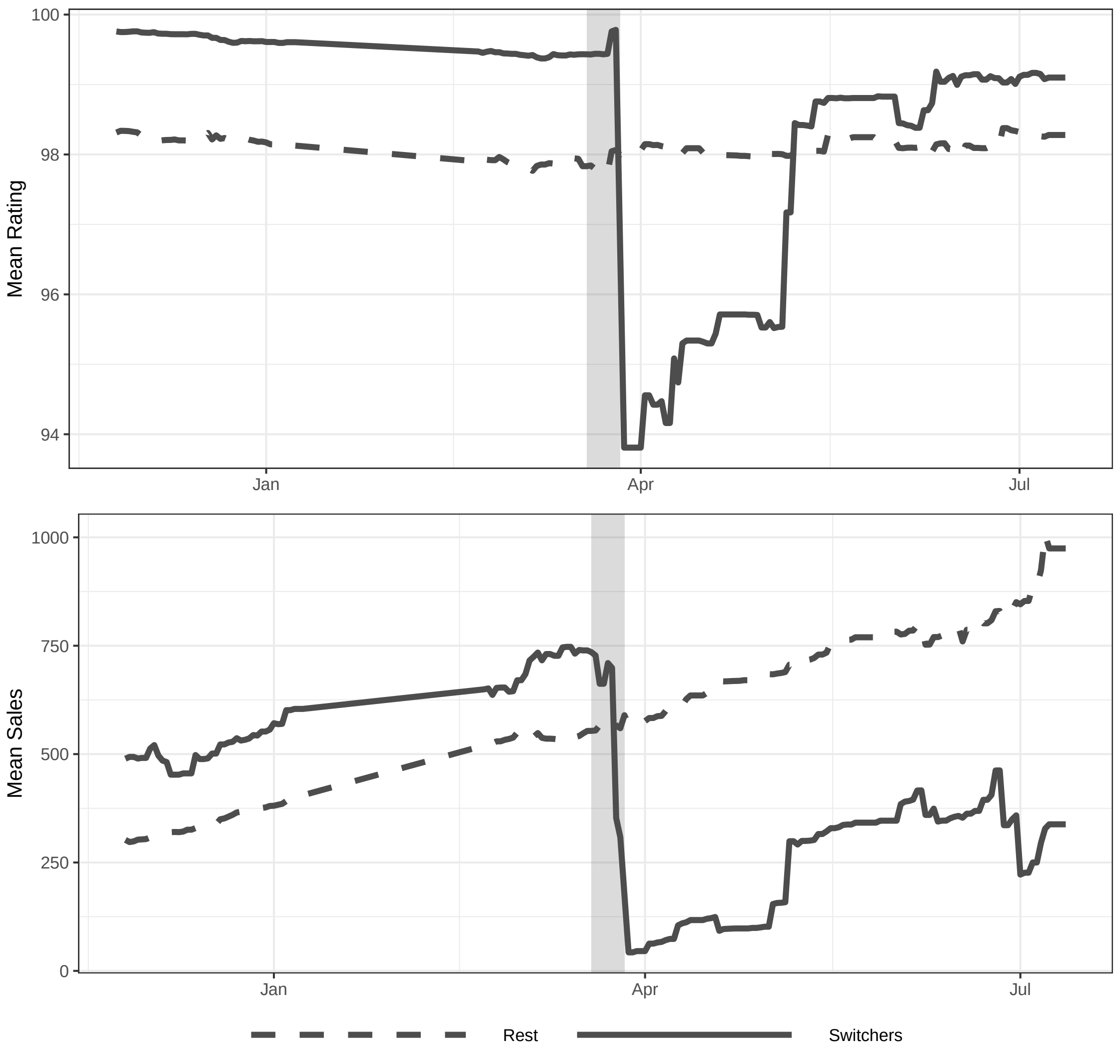


Figure 16: Ratings shock for switchers

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.

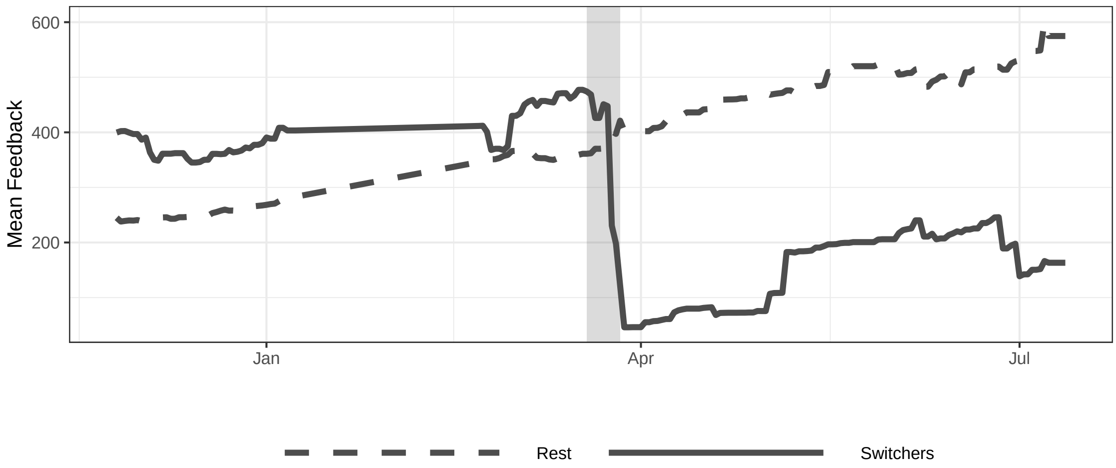


Figure 17: Feedback change for switchers

Notes: The figure shows the mean feedback count of switchers (sellers that sold exclusively on Evolution before the exit and migrated to Agora following the exit) and all other sellers both before and after the exit. The Evolution exit period is highlighted in grey.

Table 12: Platform Differences

	Mean Price		Median Quantity		# Sellers		# Items	
Product	Ago	Evo	Ago	Evo	Ago	Evo	Ago	Evo
Cannabis	10.77	10.52	14.17	10.00	646	713	2628	2832
MDMA	55.31	38.74	7.00	7.00	345	396	1348	1751
Cocaine	121.15	103.42	3.50	3.50	321	366	1219	1443
Amphetamine	20.11	12.67	20.00	20.00	122	206	467	900
Meth	181.47	145.00	2.40	3.50	148	159	580	611
Heroin	173.41	140.92	1.00	1.00	112	132	366	525
LSD	4.76	5.14	31.25	30.00	91	136	564	741
Ketamine	56.28	62.63	5.00	4.00	55	53	186	176

Notes: The table shows the mean unit price, median quantity, number of sellers and number of items observed on either platform prior to the Evolution exit. 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, except for LSD where it is per 10×100 microgram.

Table 13: First stage: The effect of switching markets on rating

	Level-level				
	All	Cannabis	Cocaine	LSD	Amphetamine
Switch x post	–0.742***	–0.941***	–0.763***	–0.836***	0.051
	(0.030)	(0.045)	(0.049)	(0.064)	(0.108)

	Log-log				
	All	Cannabis	Cocaine	LSD	Amphetamine
Switch x post	–0.010***	–0.014***	–0.008***	–0.009***	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Item-specific FE	✓	✓	✓	✓	✓
Num. obs.	298322	136437	79437	37713	44735
Num. switch items	190	87	52	28	23

Notes: Results based on a linear model as specified in section 4 but excluding the escrow covariate. The sample is restricted to countries with switching vendors and a time period around the evolution exit, from 120 days prior to the exit until 45 days post exit. 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 × category × quantity.

Table 14: Reduced form: The effect of switching markets on price

	Level-level				
	All	Cannabis	Cocaine	LSD	Amphetamine
Switch x post	–1.530***	–0.794***	–3.332***	–0.232***	–0.713***
	(0.162)	(0.052)	(0.547)	(0.048)	(0.204)
	Log-log				
	All	Cannabis	Cocaine	LSD	Amphetamine
Switch x post	–0.057***	–0.051***	–0.051***	–0.079***	–0.081***
	(0.002)	(0.003)	(0.004)	(0.008)	(0.006)
Item-specific FE	✓	✓	✓	✓	✓
Num. obs.	304050	139244	80549	38910	45347

Notes: Results based on a linear model as specified in section 4 but excluding the escrow covariate. The sample is restricted to countries with switching vendors and a time period around the evolution exit, from 120 days prior to the exit until 45 days post exit. 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 $\times$ category $\times$ quantity.

Table 15: IV: The effect of rating on price

	Level-level				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (% points)	2.247***	0.918***	4.578***	0.420***	−16.765
	(0.241)	(0.072)	(0.774)	(0.068)	(35.384)

	Log-log				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (ihs)	6.456***	3.996***	6.592***	11.107***	−181.229
	(0.336)	(0.298)	(0.668)	(1.291)	(430.523)
Item-specific FE	✓	✓	✓	✓	✓
Num. obs.	298322	136437	79437	37713	44735

Notes: Results based on a linear model as specified in section 4 but excluding the escrow covariate. The sample is restricted to countries with switching vendors and a time period around the evolution exit, from 120 days prior to the exit until 45 days post exit. 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 × category × quantity.

Table 16: Naive OLSD: The effect of rating on price

	Level-level				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (% points)	0.081***	–0.005	0.382***	0.002	–0.006
	(0.010)	(0.003)	(0.041)	(0.004)	(0.009)

	Log-log				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (ihs)	0.112***	–0.036**	0.317***	0.044	0.250***
	(0.012)	(0.017)	(0.021)	(0.060)	(0.025)
Item-specific FE	✓	✓	✓	✓	✓
Num. obs.	298322	136437	79437	37713	44735

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 120 days prior to the exit until 45 days post exit. 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 $\times$ category $\times$ quantity.

Table 17: IV: The placebo effect of rating on price

	Level-level				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (% points)	−1.220	−13.619	−28.958	0.536	0.691
	(2.103)	(97.125)	(110.050)	(0.667)	(0.723)

	Log-log				
	All	Cannabis	Cocaine	LSD	Amphetamine
Rating (ihs)	0.219	−61.077	−61.540	13.319	3.148*
	(2.388)	(566.390)	(441.567)	(14.794)	(1.855)
Item-specific FE	✓	✓	✓	✓	✓
Num. obs.	307465	140915	79410	37416	49724
Num. switch items	190	87	52	28	23

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 that ends one month before the evolution exit. We assume a placebo exit occurs 45 days prior and consider the period of 120 days leading up to the placebo date and 45 days after. 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 × category × quantity.

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