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Research Paper

Reputation transferability across contexts: Maintaining cooperation among anonymous cryptomarket actors when moving between markets

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ABSTRACT

Background: Buyers and sellers of illegal drugs in cryptomarkets have been found to overcome trust issues created by anonymity and the lack of legal protection with the help of reputation systems. Cryptomarkets rarely operate for longer than a year before closing or getting shut down due to external shocks, such as law enforcement operations. This results in large flows of users migrating between market platforms. An important question in order to better understand why cryptomarkets recover quickly after external shocks is: to what extent can reputation be carried over between different markets? This problem is non-trivial given the anonymity of cryptomarket users and the fact that reputation is tied to a user's online identity. Here we analyze conditions under which sellers choose to migrate with the same identity and whether reputation history from previous cryptomarkets yields benefits in new contexts.

Methods: We analyze sellers' migration in three cryptomarkets (Abraxas, Agora and AlphaBay) and follow their reputation history by linking user accounts between marketplaces using the Grams database. We use longitudinal multi-level regression models to compare market success of migrant and non-migrant sellers. In total, the data contains more than 7,500 seller account and 2.5 million buyers' reputational feedback messages over a period of 3 years.

Findings: It is predominantly the successful sellers with a large number of sales and high reputation who choose to migrate and maintain their identity using cryptographic methods after market closures. We find that reputation history from previous markets creates a competitive advantage to migrant sellers compared to market entrants.

Conclusion: Reputation transferability embeds cryptomarket users beyond a single market platform, which incentivizes cooperative behavior. The results also suggest that reputation transferability might contribute to a quick recovery of online drug trade after shutdowns and accumulation of market share in the hands of a small fraction of successful sellers.

Introduction

Recent years have seen rapid growth of online user-to-user drug marketplaces, or cryptomarkets (Barratt & Aldridge, 2016; Martin, 2014). Individual buyers and sellers of illegal drugs have been able to successfully conduct business online due to technical innovations employed by cryptomarkets, which ensure online anonymity (Martin, 2014). One such innovation is hosting the marketplace websites in the TOR network, which ensures that all personally identifying information of each user, such as an IP address or geographic location, are securely hidden. Coordinated international law enforcement operations have been conducted over the last few years aimed at closing these cryptomarkets. Numerous cryptomarkets and servers have been seized, and administrators arrested as a result of several large operations, including Operation Onymous (Décary-Hétu & Giommoni, 2017; Europol, 2014; van Buskirk et al., 2017) or Operation Bayonet (Afilipoaie & Shortis, 2018; van Wegberg & Verburgh, 2018).

Despite these operations, the cryptomarket ecosystem remains a viable space for drug trade, with multiple new cryptomarkets starting operations after each shock (Soska & Christin, 2015; van Buskirk et al., 2017). Previous research has found that drug sellers operate in multiple cryptomarkets (Broséus et al., 2016; Soska & Christin, 2015) and tend to migrate to new marketplaces once their current cryptomarkets get shut down (Ladegaard, 2019). Evidence from the Grams database, a

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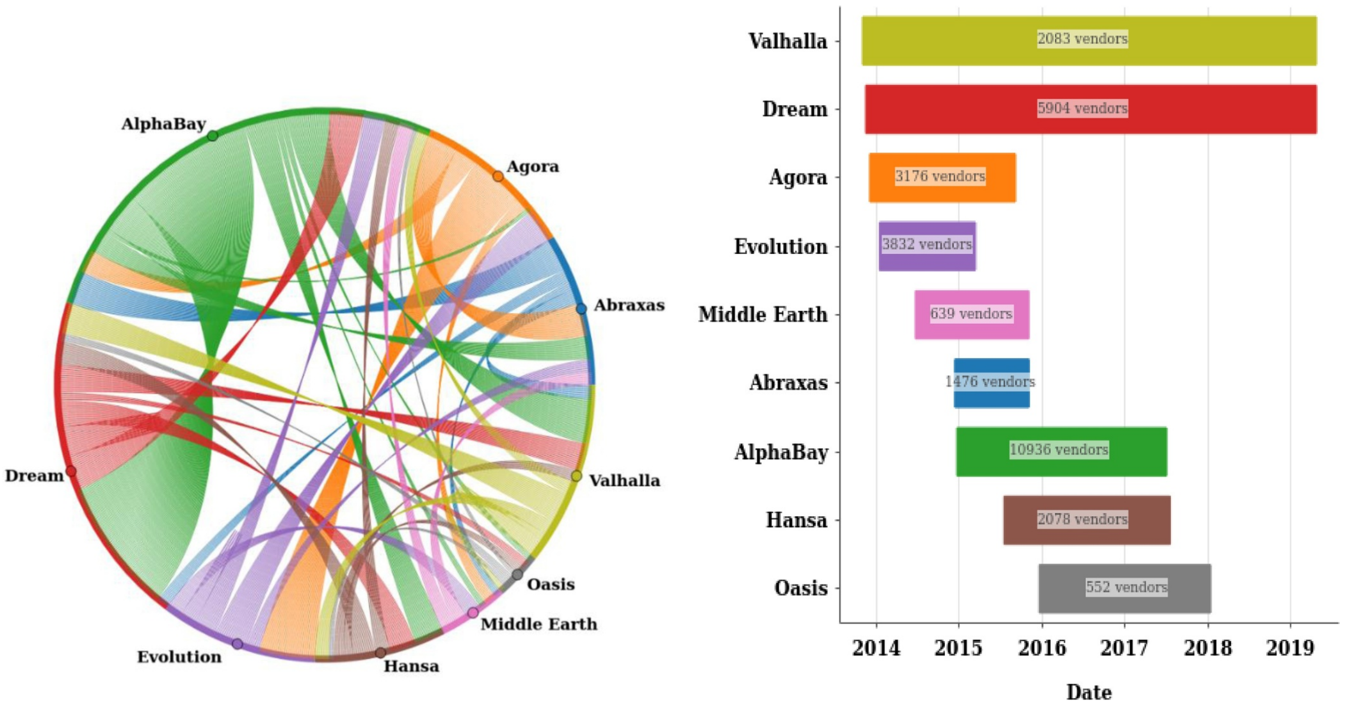

Fig. 1. A, B. Seller migration patterns between cryptomarkets (left; direction is indicated by color, e.g., Agora sellers moving to AlphaBay are depicted by an orange flow towards green circle border area). Cryptomarket lifetimes and seller account statistics (right).

website that registered sellers' accounts in the largest cryptomarkets until 2017, shows that more than 20% of all observed sellers moved between and operated in multiple cryptomarkets (see Fig. 1; Masson & Bancroft, 2018). This number is likely a conservative estimate, since it does not take into account sellers that operated in multiple marketplaces with different online identities.

A key aspect of understanding such resilience is to analyze how market actors – buyers and sellers – maintain trust in each other over time in an environment where every user is fully anonymous, and marketplaces are likely to disappear due to takedown operations, website administrator scams or voluntary exits (Aldridge & Décary-Hétu, 2016; Barratt & Aldridge, 2016). Anonymity of online identities in the TOR network, despite its effectiveness in enabling illegal online trade, also creates a trust problem (Buskens, 2002; Buskens & Raub, 2013). Buyers of drugs cannot be certain about the quality of goods and true intentions of an anonymous seller, while sellers may have incentive to run away with buyers' money without distributing the product. Even if buyers place their trust in trustworthy sellers, research has not yet investigated what happens when these anonymous buyers and sellers move to a new marketplace following the closure of an existing market.

Illegal online marketplaces, in order to remain operative, have to reduce the uncertainty and provide additional incentives for users to cooperate or increase costs of opportunistic behavior, for example, by introducing fees for opening a seller account, monitoring and banning untrustworthy sellers or by other means of making fraudulent behavior less beneficial for sellers (Beckert & Wehinger, 2013; Reuter, 1983). It has been found that one of the key aspects in creating and maintaining trust between cryptomarket users is the reputation system (Hardy & Norgaard, 2016; Przepiorka, Norbutas & Corten, 2017; Nurmi et al., 2017; Bakken, Moeller & Sandberg, 2018). Reputation systems disseminate buyers' feedback on trustworthiness of sellers and their product quality to all users on the marketplace. Public availability of information about past deeds provides sellers additional benefits for being cooperative via attracting new buyers and increases the cost of fraudulent behavior (e.g. false advertising, not shipping the product) by warning potential buyers and damaging future business opportunities. It has also been found that repeated exchanges between the same dyads of buyers and sellers play a crucial role in maintaining trust over time (Décary-Hétu & Quessy-Doré, 2017).

Reputation effects on cooperation in cryptomarkets have been analyzed under stable conditions, namely, by analyzing market exchanges within a single cryptomarket, assuming that buyers have no prior information about sellers (Hardy & Norgaard, 2016; Przepiorka et al., 2017). To the best of our knowledge, there are no studies that analyze reputation effects in a larger ecosystem of marketplaces that have overlapping userbases of buyers and sellers. This problem is important for cryptomarket research, since it could at least partially explain why cryptomarkets recover so quickly after takedowns – a phenomenon that has mostly been analyzed descriptively so far (Décary-Hétu & Giommoni, 2017; van Buskirk et al., 2017). If a seller's history of reputation in one market can affect the trust of buyers in other markets, trust relations between users cannot be fully interrupted by shutting down specific markets. Perhaps more importantly for cryptomarket research, this would imply that cryptomarkets cannot be accurately analyzed by focusing on specific markets in isolation and a broader context has to be considered.

Reputation effects on cooperation have a long history of research in interdisciplinary game-theoretic experiments (see Buskens & Raub, 2013; Raub, Buskens & Corten, 2015 for reviews). While reputation transferability across contexts, to our knowledge, has not been tested directly, experimental studies have examined related effects of imperfect information about partner's reputation (e.g. Bolton, Katok and Ockenfels, 2005) and unstable user identities (e.g. Wibral, 2015). The results show that users with more information about partner's reputation and stable identities tend to trust each other more in uncertain exchange situations, similar to those in cryptomarkets. We argue that cryptomarkets are a perfect environment to test external validity of these experiments and analyze whether reputation affects trust between users in a natural setting where both, imperfect reputation information and unstable user identities are present.

We propose that reputation transferability in cryptomarkets should be tested by analyzing two related processes, largely neglected in previous research. First, conditions under which sellers choose to maintain their online identity when migrating between cryptomarkets should be analyzed. Since reputation is tied to a seller's online identity, reputation transferability cannot be adequately tested without understanding why users choose to maintain their identities. In other words, to understand whether reputation is transferable, we first need to study whether highly reputed sellers migrate, or tend to disappear with the profit they had earned. Second, we should analyze the extent to which buyers take incomplete or noisy reputation information[1] from previous markets into account, when complete reputation information is available in the present market.

The first research problem is related to the anonymity of cryptomarket users. Buyers cannot be certain that they are dealing with the same seller in a new environment, even if they observe a user with the same nickname. To solve this problem, cryptomarket users employ a text encryption method (PGP), which allows them to encrypt textual messages and verify the author (Afilipoaie & Shortis, 2018; Christin, 2013). While the TOR network ensures that a user cannot be traced to his or her physical location, PGP encryption enables unique online identities and allows users to identify specific individuals, even if anonymous, in different contexts. This technology also allows buyers to attribute reputation histories of sellers from one market to sellers in another.

The use of PGP encryption is optional and not all cryptomarket sellers choose to use it (Soska & Christin, 2015). Reputation is a strong signal of trustworthiness which is costly to build, and it can be expected that sellers with a good reputation will choose to maintain their identity and display their accumulated reputation in a new environment (Przepiorka & Berger, 2017). On the other hand, law enforcement operations create non-trivial risks for sellers, such as leaked information on their identity, and they might weigh this risk against the cost of reputational loss when choosing whether to continue using the same online identity. To our knowledge, there are no previous findings on the extent to which sellers choose to maintain their identity and specific conditions under which they do so. In this study, we will answer this question by analyzing the extent to which sellers' history of transactions and reputation increase the odds of a seller to maintain the same PGP-verified identity in a new environment.

The second research problem relates to buyers' response to sellers' reputational information from previous cryptomarkets. Buyers might be aware of trustworthiness of sellers who migrate to a new cryptomarket with the same identity due to having observed them in the past or having had bought goods from them. In both cases, the transferred reputation information is imperfect in the sense that buyers might not perfectly recall seller's reputation from the previous marketplace, or have perfect information about few but not all sellers (Bolton, Katok and Ockenfels, 2005). It is unclear to what extent buyers actually take such noisy information into account when choosing a seller, especially when complete information about sellers' trustworthiness is available from the reputation system in the current market. We will compare market success of sellers who entered a cryptomarket already having a history of reputation in previous markets, to those that register with a new identity.

Theory

Trust problems in online drug sales

Trust between anonymous actors has been studied in many branches of social sciences, which has resulted in a wide variety of definitions. Coleman (1990) argued that trust implies an actor putting resources at the disposal of another actor, in expectation that trust will be returned and the trustor will be better off. In online marketplaces, a buyer sending money to a seller prior to receiving goods would be an example of a trust situation. The underlying problem lies in the incentive structure of a typical trust dilemma - the seller often has an incentive not to honor buyer's trust and maximize profit by keeping the good to himself, or sending a good of lower quality than promised (Dasgupta, 1988; Kreps, 1990). Although both actors would be collectively better off by cooperating, the most individually beneficial option for the trustee after being trusted is to abuse the first actor. Without additional mechanisms that keep sellers' behavior in check, trusting anyone might be too risky for any buyer in a trust dilemma situation (Beckert, 2009; Beckert & Wehinger, 2013; Przepiorka et al., 2017).

The trust problem is especially relevant in online marketplaces (Diekmann, Jann, Przepiorka & Wehrli, 2014). Information about the true quality of products on the market is unequally distributed between buyers and sellers. Buyers cannot be certain about the quality of the product before making a purchase. Additionally, in cryptomarkets, market actors need to remain fully anonymous in order to avoid getting arrested. It is not only important for users to conceal their physical location, but also to avoid sharing any other self-disclosing social cues, that otherwise help to increase perceived trustworthiness in the eyes of potential customers (Bente, Baptist & Leuschner, 2012; Ert, Fleischer & Magen, 2016; Ma, Hancock, Lim Mingjie & Naaman, 2017; ter Huurne, Ronteltap, Corten & Buskens, 2017). Finally, even if a buyer decides to trust an anonymous seller and place an order, the contract is not secured legally, which exposes buyers and sellers to additional risks of being defrauded. As a result, exchanges on cryptomarkets take place without the state, against the state and among users who cannot easily trust one another (Beckert & Wehinger, 2013).

Reputation systems can reduce the trust problem by facilitating information exchange among buyers and incentivizing cooperation in online markets (Hardy & Norgaard, 2016; Przepiorka et al., 2017; Tzanetakis, Kamphausen, Werse & von Laufenberg, 2016). Buyers' ability to share information publicly shifts the incentive structure, making cooperation more beneficial for sellers, and opportunistic behavior more costly (Przepiorka, 2013; Resnick & Zeckhauser, 2002). Good reputation attracts new buyers and allows sellers to charge a higher price for their goods, since buyers are willing to pay more for a lower risk. Bad reputation deters future buyers from trusting the seller and make him or her lower the price to compensate for it. Reputation effects on cooperative behavior have been supported empirically in both legal and illegal online marketplaces (Diekmann et al., 2014; Przepiorka et al., 2017).

On the other hand, there are several underlying conditions for reputation effects to work in online environments. Reputation is tied to an actor's online identity, not the actual person behind it (Wibral, 2015). Actors with an accumulated reputation history must therefore have stable online identities. Sellers theoretically have an incentive to maintain their identity, since reputation is costly to build (Friedman & Resnick, 2001).

Empirical evidence from cryptomarkets show that even though the majority of sellers are active for 7 months or less, about 10% of analyzed drug sellers have been active for multiple years (Soska & Christin, 2015). The short length of seller careers might be partially related to the volatility of cryptomarket platforms themselves. Around 100 cryptomarkets have been opened and closed or are still active since 2013, with an average lifespan of less than 2 years, making users migrate frequently (Branwen, 2019).

Movement across contexts presents additional risks. Sellers, in cases where their identity cannot be verified, face the risk of losing their reputation. Buyers, exchanging with non-verified sellers, risk getting exposed to deceptive mimicry (Bacharach & Gambetta, 2001; Gambetta, 2005). Reputation of cryptomarket sellers can be exploited

[1] Noisy reputation scores might contain accidentally or purposefully posted feedback messages that do not reflect the trustworthiness . For example, buyers blaming sellers for having their orders intercepted at border checks; competing sellers posting low ratings to increase their own market position; buyers accidentally posting lower-than-perfect ratings without textual comments (see Utz, 2009; Martin, 2014, Xu et al., 2015)

by untrustworthy pretenders who could mimic successful sellers' online identities and defraud convinced buyers. Although no quantitative research exists on the scope of sellers' identity theft in cryptomarkets, sellers' discussion forum posts used in related literature provide examples of sellers changing their online identities and publicly distancing themselves from actors with similar or identical nicknames in other cryptomarkets (Broséus et al., 2016; see also Ladegaard, 2019).

Identity verification and market migration

A technical solution for the problem of online identity verification across contexts is a cryptographic encryption protocol, called PGP (Pretty Good Privacy; Zimmerman, 1995). This tool allows users to encrypt their text messages using a person-specific private key. The encrypted text can then be decrypted using that person's public key, which is shared publicly. PGP encrypted messages can be used to verify that the same author is sending messages using different pseudonyms, or the same pseudonym in different cryptomarkets (Bancroft & Reid, 2017; Broséus et al., 2016). After the closure of Silk Road, cryptomarket users created vendor encryption key databases that enabled buyers to match vendors and their public keys before and after market shutdowns (Ladegaard, 2017).

PGP encryption provides a proof of identity which is virtually impossible to fake for potential opportunistic actors. However, the conditions under which market actors choose to maintain their identities between contexts are unclear. On the one hand, the ability to change one's identity without cost often results in less trust placed in market newcomers (Friedman & Resnick, 2001; Resnick & Zeckhauser, 2002), who would then have to turn to alternative measures, such as lowering prices or making additional time investments in communicating with buyers. Sellers therefore have a clear incentive to maintain their identities.

On the other hand, these benefits might be outweighed by associated risks. Previous research shows that a large portion of sellers who migrate between marketplaces change their aliases and PGP keys (Broséus et al., 2016; Soska & Christin, 2015; van Wegberg & Verburgh, 2018). It is unlikely that sellers do this in order to shed bad reputation (Wibral, 2015), since sellers could as easily change their identity before market shutdown. A possible explanation for the utility of identity change is that sellers might aim to decrease the risk of getting deanonymized. Publicly known cases of cryptomarket users' arrests show that they can take place after multiple years of evidence collection, in some cases long after a seller decides to no longer appear online (Branwen, 2019). In cases where sellers get de-anonymized, a stable identity would link him or her to a longer history of operation in previous cryptomarkets and potentially lead to more severe sentences.

We therefore hypothesize that a seller's decision to migrate to a new marketplace using the same identity may in part depend on the reputation accumulated in a previous marketplace. We expect a trade-off, where sellers with a higher number of sales or a better reputation will be more likely to maintain their identity in a new marketplace, since reputational benefits will be more likely to outweigh perceived risk of getting exposed.

H1: *Sellers who migrated to a new marketplace will be more likely to maintain identity of the old marketplace, the higher reputation or the more sales they had in the old market place.*

Reputation transferability

Sellers who choose to maintain their identity when migrating might benefit from transferring their reputation history and become more likely to be trusted by buyers in a new context. In order for these effects to take place, buyers must be aware of the reputation a verified seller had in the previous marketplace. This might happen if buyers themselves migrate between marketplaces and observe seller's reputation scores before the prior gets shut down. Empirical evidence from cryptomarkets show that the total number of new users and generated feedback messages typically grow rapidly after marketplace shutdowns (Décary-Hétu, Paquet-Clouston & Aldridge, 2016; van Wegberg & Verburgh, 2018). This suggests that at least some buyers are able to observe sellers' reputation in multiple cryptomarkets.

Alternatively, buyers could rely on a now closed third-party vendor search engine Grams, which was created to aggregate sellers' reputations from different cryptomarkets and match accounts using their PGP public encryption keys (Masson & Bancroft, 2018). Buyers could search a vendor by their nickname and observe all feedback messages with textual comments, posted items and other properties that the aggregator had collected since the beginning of its operation.

As a result, buyers who had observed reputation history in cryptomarkets that got shut down, could evaluate seller's trustworthiness in a new market based on that information. It can be expected, however, that transferred reputation history does not have the same effect on a buyer's trust as it did in the previous context. Buyers might perfectly recall reputation information about few actors they exchanged with, or partially recall reputation of sellers they observed. In such cases, buyers' willingness to cooperate might not be as strongly affected by transferred reputation as it is by perfectly observable reputation in the current context (Bolton, Katok and Ockenfels, 2005).

The degree to which buyers are able to observe sellers' reputation in previous cryptomarkets depends on sellers' visibility (Bockstedt, Goh & Ng, 2012; Paquet-Clouston, Décary-Hétu & Morselli, 2018). Since many cryptomarkets contain hundreds or thousands of sellers, buyers could be more likely to remember sellers that have been active in multiple cryptomarkets. Opening accounts in multiple cryptomarkets simultaneously might not be an unexpected strategy from online drug sellers, since this might help them hedge against closures, downtimes and other unexpected events (Soska & Christin, 2015). This might also be a possible strategy to maximize the potential pool of possible clients. Empirical evidence shows that a significant fraction of sellers operates in multiple cryptomarkets, although some choose to focus on specific platforms (Broséus et al., 2016; Ladegaard, 2019; Soska & Christin, 2015).

It is unclear to what extent buyers observe sellers' past reputation and to what extent it is discounted against reputation that sellers have in the current context. However, if reputation is indeed transferable between contexts, we can expect that market entrants who have a history of sales in previous markets will be trusted more often than market entrants with no history or a changed identity and therefore get more sales on average. We can also expect that this effect will be moderated by the migrating seller's visibility – the more cryptomarkets a seller was active in, the stronger should the effect be of past reputation on the number of sales be in the current context. A comparison of migrating market entrants to market entrants with no history should provide a conservative test of reputation transferability – since market entrants do not have a reputation in the new context, the result should not be biased by possible discounting effects of sellers' exchange history.

H2: *The more sales/higher reputation a market entering seller had in previous cryptomarkets, the higher sales in the current market compared to those with no previous accounts*

H3: *The positive effect of market entrant's history of sales/reputation on the number of sales in the current market, compared to those with no previous accounts, is stronger the more cryptomarkets a seller had been active in the past*

Data and methods

Four data sources were used in our study to test the hypotheses. We analyzed drug vendor movements from two cryptomarkets, Abraxas and Agora, to a third marketplace, AlphaBay. AlphaBay was one of the largest cryptomarket to date, which started its operation in late December 2014 and was seized during a law enforcement operation in

July 2017. Agora opened a year earlier, while Abraxas opened at the same time. Both marketplaces were closed in 2015, almost a year after AlphaBay opened – Agora closed down voluntarily, while Abraxas allegedly closed down after an exit scam (Branwen, 2019). This resulted in a spike in the number of new sellers and feedback messages in AlphaBay shortly after (Paquet-Clouston et al., 2018) and a good environment to test which sellers maintained their identity in AlphaBay after migration, and how their history in Agora and Abraxas affected subsequent sales in the new market.

We collected data from AlphaBay in June and July 2017, shortly before the cryptomarket was seized. The data contain a copy of the website, including item and user profile pages. Item listings in AlphaBay can be deleted by sellers over time, which introduces a large number of unobserved items. Each item listing in AlphaBay was numbered with a unique identifier - starting from ID1 and ending with ID381593 for the most recent item. We tried to retrieve every item page in this ID range, which returned 145,724 listings out of 381,593 that ever existed in AlphaBay (38.2%), the coverage being more complete for more recent items (65.1% for items posted in 2017). Collected items were sold by 7593 sellers, who received a total of 2419,628 feedback messages from buyers. Since sellers' feedback messages for both deleted and existing item listings were stored in their profiles, feedback data can be considered highly complete for the sellers that we were able to observe during our data collection.

The data for Abraxas and Agora markets were collected by Branwen et al. (2015; see also data description in Norbutas, 2018) and Soska and Christin (2015) respectively. Abraxas data set contains daily copies of the website, including item and user profile pages since the marketplace's opening until July 2015. The aggregated data contain information on 463 sellers, 11,814 unique item listings and 10,898 buyer feedback messages. Agora data by Soska and Christin (2015) contains data on 27,974 item listings posted by 1960 sellers, and a total of 234,372 feedback messages. The data contained 161 snapshots of the Agora website collected between December 2013 and December 2015.

We used the three cryptomarkets to aggregate information about all available sellers, specifically the type of goods they sold, their reputation, the number of sales based on buyers' feedback messages, and shipping destinations. To link vendor accounts between marketplaces, we used the final data source, a database from the Grams website, which operated between 2014 and 2017. The website was hosted on TOR and provided information on 38,415 accounts of 22,356 unique sellers in more than 15 largest cryptomarkets at the time. The service used vendor PGP keys to link accounts between marketplaces. The database was published by the website administrator shortly before the website went offline.

After cleaning the missing information in item and user pages, we derived two data sets used for testing our hypothesis. The first data set contains aggregated information on Abraxas and Agora sellers and was used to test the association between their reputation in the respective markets and whether they opened accounts with the same PGP key in other markets after Agora/Abraxas were shut down. The data contain 1960 sellers from Agora and 432 out of 463 sellers in Abraxas. 31 sellers were removed due to missing information on sellers' item listings.

The second data set contains information on AlphaBay sellers' weekly reputation and sales. We grouped sellers' market data into weekly windows since each sellers' date of registration on the website. We measured whether each seller migrated from another market, and whether their history of sales before AlphaBay affects their subsequent market sales in comparison to non-migrant sellers who had spent a similar amount of time on AlphaBay. The data contain 341,223 weekly timepoints of all 7593 sellers.

Variables used in the analyses

We used several dependent variables to test the hypotheses (see Table 1). In the first set of models we tested whether *sellers from Abraxas and Agora cryptomarkets registered in any other cryptomarket* after the shutdown of each website. The dummy variable was constructed using the Grams database by looking for accounts of each Abraxas and Agora seller available in our data and their accounts registered after the shutdown dates.

In the second set of models the dependent variable is the *weekly number of sales*, calculated by summing up all buyers' feedback messages left for the seller each week. This measure has been used in previous research (Décary-Hétu et al., 2016; Przepiorka et al., 2017; Soska & Christin, 2015) and can be considered a conservative proxy for the number of sales – feedback can only be left after a purchase, but not all purchases receive a feedback message.

The main independent variables in the first set of models measure the *total number of sales* of each seller, and the *average reputation*, calculated as the mean of ratings received in all feedback messages in the corresponding cryptomarket. The total number of sales was constructed by summing up all feedback messages for each seller account in their respective markets. Ratings in both markets range between 0 and 5.

The main independent variables in the second set of models are the *number of sales, average reputation* in feedback messages each seller had before joining AlphaBay, and the *number of cryptomarkets* a seller had been active in before AlphaBay. The number of sales and average reputation were calculated by linking AlphaBay seller accounts to accounts in Agora and Abraxas using the Grams database. As in previous cases, the number of sales contains the sum of feedback messages each seller had received in either one of Agora or Abraxas, or both if a seller had accounts in both markets. Average reputation was calculated by taking the mean of all available ratings. The number of cryptomarkets for each AlphaBay seller was constructed by using the Grams database, and counting the number of accounts in different marketplaces, registered before AlphaBay's registration date.

We used several types of control variables. *Percentage of listings in 2nd-4th category price quartiles* were constructed by calculating price quartiles for all items in every item category (see below), and counting what percentage of the total number of seller's listings belong to each price quartile. The reference category, 1st quartile, contains the cheapest items in each category. Percentages are calculated for each seller separately (i.e. these 4 variables sum up to 100% for each seller), which leads the means across all sellers to slightly deviate from 25% in Table 1.

We classified items in *8 drug categories*, including Cannabis & Hashish, Stimulant, Ecstasy and Opioids. Most categories in this scheme were originally used in the 3 analyzed cryptomarkets. This categorization was used in previous research (Soska & Christin, 2015) in ordere to harmonize varying categories used in different marketplaces. The baseline category is non-drug and mixed-drug items. We use this variable to control for differences in the popularity of categories that might affect sellers' market outcomes and their willingness to maintain identity.

We also controlled for the *destination of shipping* locations that sellers provided in their listings. We used a set of dummy variables that reflect the 5 most frequent shipping destinations: USA, United Kingdom, Australia, EU, and Worldwide shipping. Note that the categories are not mutually exclusive – sellers might offer shipping only to the UK, only to the EU, or both. The baseline category contains the remaining shipping countries.

The second set of models uses the *number of months since market opened* as a control for calendar time, to account for the trend of user growth in cryptomarkets over time. Buyers or sellers who enter the market at different time-points might face different market conditions (e.g. competition, item diversity) which might affect their sales. We also control for the *number of weeks since seller's market entry*, which is individual for each seller. The variable counts how many weeks passed since seller's registration in AlphaBay, to control for seller-specific time differences (e.g., experience, accumulated visibility of posted items, etc.).

Table 1
Descriptive statistics of variables used in the analyses.

Variable name		Model set 1 Mean (SD)	Range	Model set 2 Mean (SD)	Range
Dependent variables	Seller migrated	0.53	0/1		
	Seller's weekly # of sales			6.56 (22.38)	0–1039
Main predictors	Total # of sales	102.37 (209.57)	0–2729		
	Average reputation	4.76 (0.69)	0–5		
	Total # of sales (Abrx. + Agr.)			17.72 (115.71)	0–2310
	Avg. reputation (Abrx. + Agr.)			0.40 (1.34)	0–5
	# Markets before AlphaBay			0.77 (1.37)	0–14
Control variables	Total # of listings	16.63 (33.99)	1–937		
	% of listings in Q2 price	0.24 (0.23)	0–1	0.22 (0.24)	0–1
	% of listings in Q3 price	0.24 (0.23)	0–1	0.24 (0.23)	0–1
	% of listings in Q4 price	0.23 (0.28)	0–1	0.23 (0.29)	0–1
	Number of items in:				
	Cannabis	4.58 (12.23)	0–161	4.79 (17.98)	0–344
	Stimulant	2.14 (4.44)	0–48	2.28 (6.85)	0–181
	Ecstasy	1.91 (6.04)	0–109	1.72 (6.99)	0–148
	Opioid	1.04 (3.15)	0–36	1.30 (5.79)	0–165
	Psychedelic	1.25 (4.90)	0–101	1.17 (6.10)	0–126
	Benzo	0.79 (3.38)	0–52	1.07 (5.85)	0–109
	Prescription	0.98 (7.00)	0–214	0.88 (6.11)	0–190
	Dissociative	0.24 (1.16)	0–16	0.30 (1.65)	0–26
	Ships to:				
	Worldwide	0.33	0/1	0.64 (0.47)	0/1
	U.S. only	0.28	0/1	0.26 (0.44)	0/1
	Europe only	0.10	0/1	0.14 (0.35)	0/1
	U.K. only	0.05	0/1	0.09 (0.29)	0/1
	Australia only	0.08	0/1	0.07 (0.25)	0/1
	Cryptomarket (= Abraxas)	0.18	0/1		
	Average reputation (AlphaBay)			0.63 (0.46)	−1 - 1
	No sales before AlphaBay			0.68 (0.46)	0–1
	No accounts before AlphaBay			0.65 (0.47)	0–1
	Weeks since market entry			36.63 (28.19)	1–133
	Months since market opened			20.10 (7.70)	1–32
		N(sellers)	2392	N(sellers)	7593
				N(sellers*weeks)	341,223

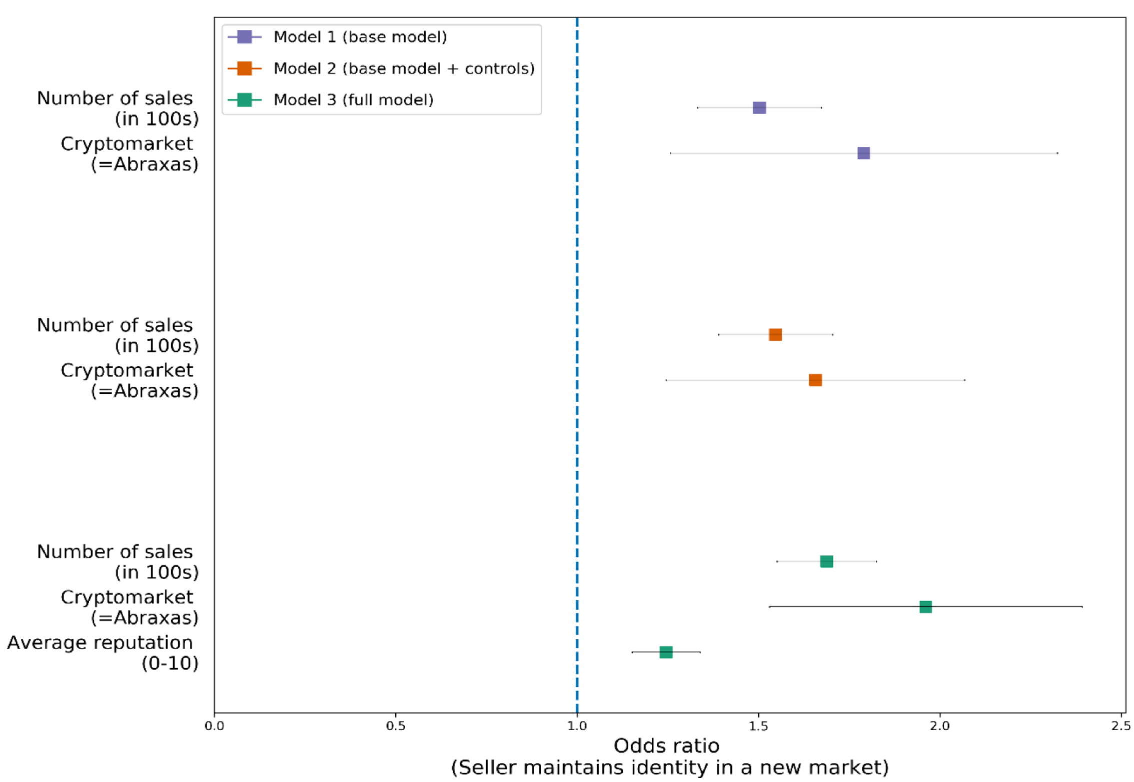

Fig. 2. The main results of logistic regression models of seller properties on odds of migrating to a new market with the same identity (for full results, see Appendix 1A).

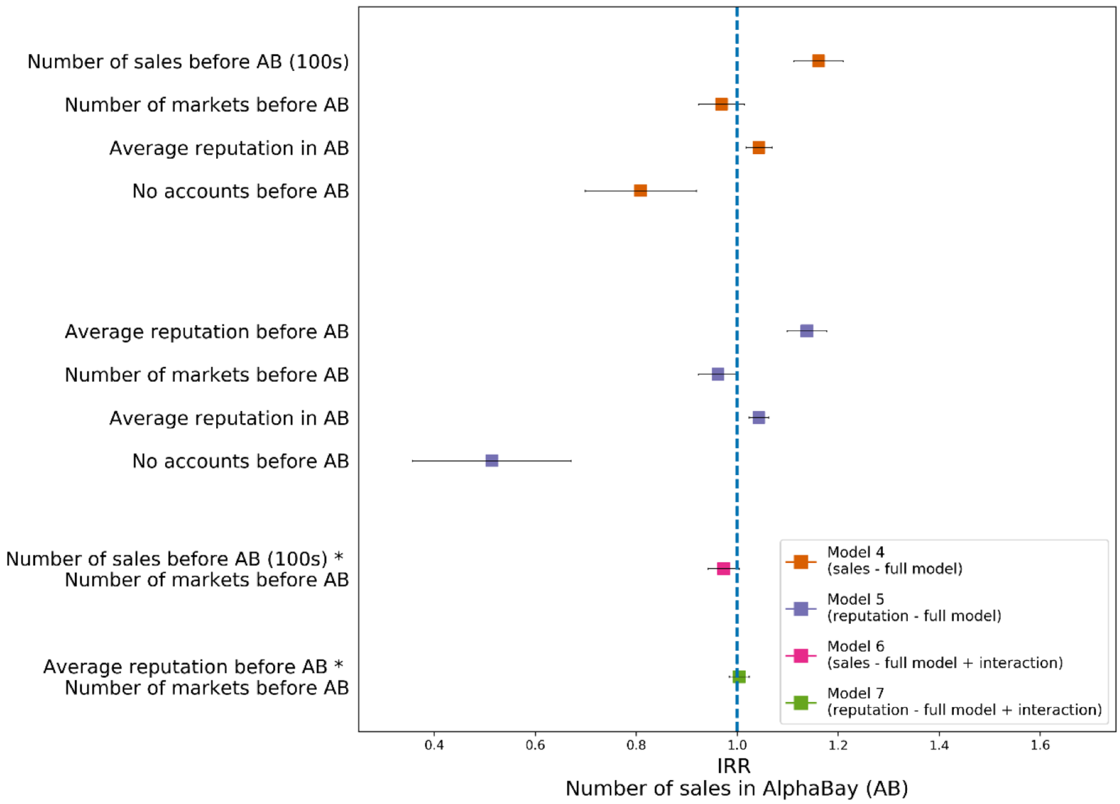

Fig. 3. The main results of multi-level negative binomial regression models on weekly number of sales (for full results, see Appendix 1B).

In the first set of models, a dummy variable *Abraxas cryptomarket* marks seller accounts that were observed in Abraxas, with Agora accounts as the reference. In the second set of models *no sales before AlphaBay* is a dummy variable that controls for sellers that had no sales before AlphaBay. This is necessary, since such sellers have an average pre-AlphaBay reputation equal to zero, but this does not mean they belong to the same group as those sellers who had low reputation before AlphaBay, but had sold many items. *No markets before AlphaBay* is equal to 1 for AlphaBay sellers that had no accounts before registering there, to differentiate between sellers who are new, and those who are not but might have made no sales in previous cryptomarkets.

Results

Sellers' identity maintenance

The first set of models (see Fig. 2) test hypothesis 1 and uses data on sellers from Agora and Abraxas. The three logistic regression models test whether sellers' sales and reputation had a positive impact on their likelihood to maintain the same identity and move to a different cryptomarket after the shutdown of their respective marketplaces. Each case represents a seller in either Abraxas or Agora. Fig. 2 depicts results of the models (odds ratios and standard errors). Only the effects of the main independent variables are shown in the figure (for the complete table of results including control variables, see Appendix 1A).

In the first model, to observe the effect without control variables, we only included the variable with sellers' aggregate sales count and a dummy for the marketplace an account was observed in. In Model 2 we added sellers' total number of listings, their prices and categories, and the shipping destinations each seller offered. In the final model, we added the reputation effect. We kept this variable for the final model, since sellers with 0 sales had no information on reputation ($N = 127$), therefore dropped out, which decreased the sample size in the final model.

Logistic regression Model 1 shows that sellers' accumulated total number of sales increases the odds that the seller migrates to a new cryptomarket with the same identity ($OR = 1.005$, $p < .001$). Every 10 sales increase the odds of a seller to migrate by about 5%. We also observed the expected positive effect of the seller being registered in Abraxas, since a relatively larger proportion of all sellers did so, as discussed in the descriptive results section.

The hypothesized effect of the number of sales remained statistically significant in Model 2, once sellers' listing- and shipping controls were taken into account. Based on the results, a seller's decision to move to a new market is not associated with the type or price of goods they sell, or the market they ship their products to. Sellers who ship items to Australia only are the only exception - these sellers are more likely to migrate than others ($OR = 1.568$, $p < .01$).

Model 3 shows that on top of the positive effect of sales, high reputation is also strongly positively related to the odds of a seller migrating with the same identity ($OR = 1.689$, $p < .001$). Both of these effects show that it is primarily the successful and well-reputed sellers who migrated maintaining their identity after cryptomarket shutdowns and maintained their identity. These results are in line with Hypothesis 1.[2]

Reputation transferability and market outcomes

The second set of models (Fig. 3; for full results see Appendix 1B) are multi-level random intercept negative binomial models, with weekly observations of sellers nested in seller IDs. Here we test whether sellers' history of sales and reputation in previous cryptomarkets (if

[2] We also tested a quadratic and cubic effects of sales on the probability of migration, adding them to Model 2. The results show a non-linear (inverse u-shape) effect – sellers with no sales have the lowest probability to migrate, which increases rapidly for those with 100-600 sales and somewhat decreases for those with > 600 sales.

any) had an effect on their market success in AlphaBay. These models test hypotheses 2 and 3. The dependent variable, number of sales, is at the weekly level. The main independent variables, reputation and sales in Abraxas and Agora are constant at the seller-level (level 2 effects). Reputation effects in Abraxas vary at the seller*week level (lagged level 1 effects). The remaining controls for item categories and shipping locations are measured at the seller level (level 2).

In these models we only used data on sellers that migrated from Abraxas and Agora, since we only had sales data available for these 2 markets. We used data on sellers who were new in AlphaBay (or had changed their identity) as the comparison group. In models 4 and 5, we added the main effects of the number of markets a seller had been active in before AlphaBay, the number of sales and average reputation in Abraxas and Agora and analyzed whether it had an impact on sellers' subsequent weekly number of sales in AlphaBay (hypothesis 2). In the third and fourth models we added control variables to check the robustness of these effects. In the models 6 and 7 we tested the interaction effect between the main variables (hypothesis 3).

The results of Models 4 and 5 show that both the pre-AlphaBay accumulated number of sales (IRR = 1.001, $p < .001$) and reputation (IRR = 1.198, $p < .001$) of seller migrants with maintained identity are positively associated with weekly number of sales in AlphaBay. In this model we also observe that the number of markets migrating sellers had been active in have a positive effect on weekly sales (M4: IRR = 1.310, $p < .001$; M5: $b = 1.256$, $p < .001$).

Models 6 and 7 show that the effects of pre-AlphaBay number of sales and reputation remain statistically significant once control variables are accounted for. The effect of the history of number of sales and positive reputation score are both in line with hypothesis 2. We therefore find substantial evidence in favor of this hypothesis.

The control variables in Models 4 and 5 show similar results to those observed in previous studies on cryptomarket vendors (Hardy & Norgaard, 2016; Przepiorka et al., 2017). We find that sellers' lagged reputation in AlphaBay positively affects the number of sales in the current week (IRR = 1.043, $p < .001$). Interestingly, the effect size of reputation from previous marketplaces, and the current marketplace are similar, the latter being slightly weaker, even though the range of the latter is much smaller – ratings in AlphaBay ranging from -1 to 1, while those in Agora and Abraxas from 0 to 5. We also find a similar effect of time to that found in previous studies – sellers tend to gradually make fewer weekly sales over time (IRR = 0.994, $p < .001$), and those, who joined or were active later in terms of calendar time, had on average more weekly sales (IRR = 0.031, $p < .001$). We also found that sellers who ship specifically to the United States, United Kingdom, Australia and the EU get more weekly sales than sellers who ship to fewer specific locations or other countries (IRRs between 1.226 and 1.749 in Models 4 and 5, $p < .001$). We also find that seller with a higher number of items within the highest price quartile in respective item categories have fewer weekly sales, compared to those with more items in the first price quartile (IRR = 0.605, $p < .001$).

Models 6 and 7 include the interaction effects and test hypothesis 3. We expected that the effects of the number of marketplaces a seller had been active in before AlphaBay, would significantly increase the effects of the history of sales and reputation on current weekly sales due to increased visibility. We found no statistically significant interaction effect in either Model 6 (IRR = 0.999, $p = .11$) or Model 7 (IRR = 1.004, $p = .71$). In other words, the results suggest that it does not matter how many markets a seller had been active in. What matters is the seller's reputation and sales in those markets - this leads us to reject hypothesis 3.

Discussion

In this study, we analyzed cryptomarket sellers' reputation transferability by answering two related research questions: under what conditions do sellers choose to maintain their online identities in new environments, and, for those who do, to what extant does reputation from previous marketplaces increase market outcomes in a new one.

Regarding the first research question, the results show that sellers with higher reputation and a longer history of sales are more likely to keep their online identity when migrating to new marketplaces. With the exception of Australia, there is virtually no difference between sellers in different geographic locations, sellers specializing in different types of items and price brackets. Australia is known to be a relatively isolated niche in cryptomarkets, in terms of having mostly domestic shipments and high prices, primarily due to geographic location, strict border controls and high offline drug prices (Cunliffe, Martin, Décary-Hétu & Aldridge, 2017; Norbutas, 2018). We conclude that at a certain point the potential future market benefits of having a good reputation might outweigh risks related to maintaining identity for a long time, such as getting exposed to the law enforcement.

In contrast to previous findings showing that some cryptomarket vendors choose to "throw away" their reputation and change their identity upon migration (van Wegberg & Verburgh, 2018), our findings suggest that these sellers might not have much to throw away in the first place. It is the more successful sellers that choose to maintain their "brand" or identity, while the less successful ones, having less to lose, might choose to start with a clean slate and avoid any additional risks.

Our second finding relates to whether reputation from previous contexts yields market benefits in new cryptomarkets for sellers who choose to maintain their online identities. We find strong support for reputation transferability effects – history of sales and a good reputation significantly increased sellers' sales in a new marketplace - AlphaBay, compared to other sellers with previously unverified identity. The positive effects of "transferred" reputation are of comparable size to those of reputation that sellers accumulated in the new market. These findings suggest that while sellers' reputation in previous markets might no longer be perfectly observable for buyers in the current context, it is still relevant in shaping their decisions when choosing a seller in new contexts, which eventually triggers further reputation benefits for migrating sellers.

The findings have important implications when considering the distribution of market success across cryptomarket sellers. Although we focused on only three cryptomarkets (AlphaBay, Abraxas and Agora), descriptive results from the Grams database show that around 20% of sellers with cryptographically verified identities migrate and have multiple accounts in different markets under the same identity. This tendency, along with our findings, suggests that law enforcement operations aimed at closing down specific cryptomarkets might have unintended consequences and contribute to accumulation of profit in the hands of a relatively small number of successful sellers, as suggested in previous empirical findings (Soska & Christin, 2015). If it is the top sellers that choose to maintain their identity, over time this might lead to an increased competitive advantage over market entrants, also known as reputation cascading (Frey & van de Rijt, 2016). This might be further strengthened by reputation transferability effect found in this study and further consolidate the market advantage of already successful drug sellers.

Our findings also stress the importance of reputation systems as a mechanism that sustains trust across contexts. Previous experimental findings show that the ability for actors to change their identities easily (e.g. by re-registering a new seller's account) and imperfect information about each actor's reputation might harm cooperation (Bolton et al., 2005; Wibral, 2015). Our results show that PGP encryption is sufficient to validate sellers' identities across contexts. Reputational benefits create incentives for sellers to maintain their identity after migration. Reputation transferability therefore embeds trust relations between buyers and sellers beyond a single cryptomarket's boundaries, and allows buyers to punish opportunistic sellers by damaging their business even in future markets via feedback messages (Buskens & Raub, 2013). This aspect further increases cooperative behavior of drug sellers and pushes out untrustworthy sellers out of the market, making reputation systems and identity verification a vital duo for maintaining trust in cryptomarkets (Hardy & Norgaard, 2016; Przepiorka et al., 2017).

Another consequence of reputation transferability might be its impact on cryptomarkets' resilience to disruptions. Since well reputed sellers are more likely to migrate and maintain identity, and buyers take sellers' history of reputation into account, exchanges in cryptomarkets after disruptions do not start from scratch. Established trust and cooperation between market actors can simply transfer to new venues, limiting the uncertainty that would otherwise increase drastically after market closures.

Conclusion

In summary, we found that reputation effects in cryptomarkets are transferable across marketplaces – more highly reputed online drug sellers choose to maintain their online identity in different contexts, while buyers take their past reputation into account when considering exchange partners in current contexts. We observed an interesting tension between anonymity and embeddedness when it comes to sellers' success. Trust in cryptomarkets is consolidated by reputation and repeated exchanges. Market closures and the risk of getting arrested, however, make sellers balance the trade-off between remaining fully anonymous on the one hand, and maintaining their identity and reputation across contexts on the other.

Limitations

There are several limitations in this study that could be improved in future research. Firstly, we have limited information on identity maintenance. Specifically, we defined "maintaining identity" as users having the same PGP key in multiple cryptomarkets. There might be cases when sellers change the key or drop the encryption and use non-technical/informal alternatives to prove their identities to other users (e.g., private messages to buyers, vouching of trusted third-parties). While these identity signals are weaker than PGP encryption and we do not expect them to take place often, especially when the number of migrating sellers is so high, this might mean that some of the sellers we analyzed as "new" were actually those that maintained identity by different means.

Secondly, we used buyers' feedback scores to operationalize sellers' reputation. Although this is by now the standard way of measuring sellers' sales in empirical studies of cryptomarkets (Décary-Hétu et al., 2016; Przepiorka et al., 2017; Soska & Christin, 2015), this measure has its limitations. We could not account for the cases where buyers did not leave any feedback after the transaction. We expect, however, that such cases are more or less equally distributed across different sellers and not being able to account for such transactions should not have significant impact on our results.

Finally, we did not make use of buyers' comments left with the feedback messages. Aggregated 0–5-star reputation scores might reflect multiple dimensions of seller's trustworthiness, such as good operational security practices, high product quality, good communication or others. Future studies could use the textual information to model the complexity of trust relations between buyers and sellers in more detail.

Conflict of Interest

None.

Appendix 1A. Full results of logistic regression models for Hypothesis 1

Table A1.

Table A1
Logistic regression model of seller properties on odds of migrating to a new market with the same identity.

	M1 (Sales) Odds ratio (SE)	**M2 (M2 + controls)** Odds ratio (SE)	**M3 (M2 + reputation)** Odds ratio (SE)
Number of sales	1.005*** (0.000)	1.004*** (0.000)	1.004*** (0.000)
Average reputation			1.689*** (0.163)
Cryptomarket (= Abraxas)	1.961*** (0.220)	1.642*** (0.210)	1.786*** (0.272)
Total # of listings		1.012* (0.006)	1.014* (0.006)
% of listings in Q2 price		1.352 (0.279)	1.383 (0.301)
% of listings in Q3 price		0.959 (0.186)	0.993 (0.205)
% of listings in Q4 price		0.877 (0.152)	0.964 (0.175)
Number of items in:			
Cannabis		0.989 (0.007)	0.985 (0.007)
Stimulant		0.984 (0.012)	0.982 (0.012)
Ecstasy		1.008 (0.012)	1.004 (0.012)
Opioid		1.001 (0.016)	0.996 (0.017)
Psychedelic		1.002 (0.014)	0.996 (0.014)
Benzo		1.014 (0.018)	1.008 (0.019)
Prescription		0.980* (0.009)	0.977* (0.010)
Dissociative		0.972 (0.040)	0.978 (0.042)
Ships to:			
Worldwide		1.152 (0.117)	1.167 (0.124)

(*continued on next page*)

Table A1 (*continued*)

	M1 (Sales) Odds ratio (SE)	**M2 (M2 + controls)** Odds ratio (SE)	**M3 (M2 + reputation)** Odds ratio (SE)
U.S. only		1.217 (0.131)	1.232 (0.138)
Europe only		1.099 (0.164)	1.063 (0.165)
U.K. only		1.011 (0.200)	0.951 (0.194)
Australia only		1.568** (0.250)	1.404* (0.234)
Constant	0.662 (0.038)	0.550 (0.068)	0.042 (0.027)
N(sellers)	2392	2392	2265
Pseudo R^2	0.068	0.077	0.095

* -$p < .05$;.
** -$p < .01$;.
*** -$p < .001$. Odds ratios are reported with standard errors in parentheses.

Appendix 1B Full results of multi-level random intercept negative binomial regression models for Hypotheses 2 and 3

Table A2.

Table A2
Multi-level random intercept negative binomial regression model of seller pre-AlphaBay history of sales and AlphaBay activity on weekly number of sales.

	M4 (pre-Alpha sales + controls)	M5 (pre-Alpha rep. + controls)	M6 (M4 + interaction)	M7 (M5 + interaction)
Number of sales (Abraxas + Agora)	1.001*** (0.00)		1.002*** (0.00)	
Average reputation (Abraxas + Agora)		1.138*** (0.02)		1.123** (0.04)
# Markets before Alphabay	0.989 (0.02)	0.962 (0.02)	0.999 (0.02)	0.957 (0.03)
Number of sales (Abr. + Ago.) * # Market bef. Alphabay			0.999 (0.00)	
# Average rep. (Abr. + Ago.)* # Market bef. Alphabay				1.004 (0.01)
# Average reputation (Alphabay, cumulative)	1.043*** (0.01)	1.043*** (0.01)	1.043*** (0.01)	1.043*** (0.01)
No sales before Alphabay		1.625*** (0.23)		1.631*** (0.23)
No accounts before Alphabay	0.809*** (0.05)	0.514*** (0.08)	0.828*** (0.05)	0.507*** (0.08)
Weeks since market entry	0.994*** (0.00)	0.994*** (0.00)	0.994*** (0.00)	0.994*** (0.00)
Months since market opened	1.005*** (0.00)	1.005*** (0.00)	1.005*** (0.00)	1.005*** (0.00)
Number of items in:				
Cannabis	1.019*** (0.00)	1.019*** (0.00)	1.019*** (0.00)	1.019*** (0.00)
Stimulants	1.013*** (0.00)	1.013*** (0.00)	1.012*** (0.00)	1.013*** (0.00)
Ecstasy	1.014*** (0.00)	1.014*** (0.00)	1.014*** (0.00)	1.014*** (0.00)
Opioids	1.021*** (0.00)	1.021*** (0.00)	1.021*** (0.00)	1.021*** (0.00)
Psychedelics	1.020*** (0.00)	1.020*** (0.00)	1.021*** (0.00)	1.021*** (0.00)
Benzodiazepines	1.015*** (0.00)	1.015*** (0.00)	1.014*** (0.00)	1.015*** (0.00)
Prescription items	1.006 (0.00)	1.006 (0.00)	1.006 (0.00)	1.006 (0.00)
Dissociatives	1.039*** (0.01)	1.039** (0.01)	1.037* (0.01)	1.039** (0.01)
Seller ships to:				
Worldwide	1.024 (0.05)	1.024 (0.05)	1.034 (0.05)	1.027 (0.05)
United States	1.571*** (0.08)	1.571*** (0.08)	1.552*** (0.08)	1.576*** (0.08)
Europe	1.226*** (0.07)	1.226*** (0.07)	1.230*** (0.07)	1.226*** (0.07)
United Kingdom	1.720*** (0.12)	1.720*** (0.12)	1.701*** (0.12)	1.726*** (0.12)
Australia	1.749*** (0.14)	1.749*** (0.14)	1.723*** (0.14)	1.755*** (0.14)
% of listings in Q2 price	0.906 (0.08)	0.901 (0.08)	0.903 (0.08)	0.901 (0.08)
% of listings in Q3 price	0.855 (0.07)	0.847 (0.07)	0.855 (0.07)	0.848 (0.07)
% of listings in Q4 price	0.605*** (0.04)	0.600*** (0.04)	0.605*** (0.04)	0.600*** (0.04)
Constant	1.963 (0.19)	1.909 (0.18)	1.914 (0.19)	1.928 (0.19)
N(sellers)	7593	7593	7593	7593
N(seller*week)	341,223	341,223	341,223	341,223
Variance (intercept)	2.279 (0.04)	2.281 (0.04)	2.278 (0.04)	2.281 (0.04)

* - $p < .05$;.
** - $p < .01$;.
*** - $p < .001$. IRR values reported. Standard errors in parentheses.
Seller*week cases clustered in seller ids.

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