Reputation in AlphaBay: the effect of forum discussions on the business success of cryptomarket sellers.

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Abstract

Since the discovery of cryptomarkets, scholars have marvelled at the success of these online marketplaces for illicit items (Norbutas, Ruiter & Corten, 2020a; Przepiorka, Norbutas, & Corten, 2017). Reputation is often quoted as the primary reason that trust and mutual cooperation can emerge, given the sublegal context (Ter Huurne, Ronteltap, Guo, Corten & Buskens, 2018). While the reputation system present within the cryptomarket itself has been trialled-and-tested as a facilitator of trust, discussion forums are scarcely examined, despite growing evidence that these threads fulfil a similar function (Bancroft & Reid, 2017). This paper uses a subset of data accumulated by Macanovic and Przepiorka (2021) to explore the effects of discussion forums on the market outcomes of vendors within the AlphaBay cryptomarket. This subset contains a sample of 1,655 drug items from 555 sellers. Combining several multivariate models, it is consistently found that (1) an integral component of almost every cryptomarket's reputation system, namely customer feedback, does not have a substantial effect on the business success of vendors active within the AlphaBay cryptomarket, whereas (2) discussion forums and (3) other indicators of seller reputation do. Limitations and recommendations for future research are discussed.

Keywords: AlphaBay, cryptomarkets, darknet marketplaces, reputation system, discussion forums, trust, cooperation, business success, economic sociology.

Introduction

In 2011, the launch of Silk Road heralded a black market eCommerce revolution (Chen, 2011). As the first cryptomarket or darknet marketplace operating outside of the purview of the surface web (Christin, 2012; Rhumorbarbe et al., 2018), Silk Road instantly became one of the most renowned cryptomarkets, also known as online darknet marketplaces, to date (Van Hout & Bingham, 2013; Mirea, Wang & Jung, 2018). Through a combination of anonymising browser technologies (i.e. Tor software) and Bitcoin as the currency for transactions (Horton-Eddison & Cristofaro, 2017), the site was able to gain traction and amass a never-before-seen amount of active customers (Christin, 2012; Kethineni, Cao, & Dodge, 2017; Mirea et al., 2018). With this, Silk Road paved the way for other cryptomarkets to emerge.

Since its closure in 2013, many other darknet marketplaces have attempted to take Silk Road's place, following a similar business model (Christin, 2012; Rhumorbarbe et al., 2018; Mirea et al., 2018). Websites, discussion forums, and even entire discovery services have been established in pursuit of the same success (Van Buskirk, Roxburgh, Farrell, & Burns, 2014). AlphaBay is perhaps the most notable successor. Established in 2014, the platform's popularity surged after another prominent darknet marketplace performed an exit scam (Cimpanu, 2017), wherein the administrators closed the entire marketplace and disappeared with the funds of investors, customers and vendors alike (Barratt & Aldridge, 2016). As users flocked to AlphaBay, the size of this marketplace became unprecedented (FBI, 2017).

Ever since the discovery of Silk Road in 2011, scholars have marvelled at the success of these cryptomarkets: though the anonymous character creates ample opportunities for opportunistic behaviour, most transactions occur in mutual cooperation (Norbutas, Ruiter & Corten, 2020a; Przepiorka, Norbutas, & Corten, 2017). In the existing body of literature, reputation has often been quoted as the primary source of this success (e.g. Przepiorka & Berger, 2017; Resnick & Zeckhauser, 2002; Norbutas, Przepiorka, & Corten, 2017). Reputation can be seen as a proxy of the vendor's trustworthiness, which is accumulated over time via a number of sources (Norbutas, 2020). According to Bancroft and Reid (2017), this reputation can be inferred from two sources, namely the reputation system present within the cryptomarket itself, as well as from discussion forums. In almost all instances, such forums operate as separate entities besides the cryptomarket, allowing buyers and sellers to establish a direct line of communication on various topics, ranging from products to politics (Norbutas, 2020).

Notably, most research on darknet marketplaces is limited to the reputation system inherent to the cryptomarket itself. This reputation system functions as a buyer rating system (Norbutas, 2020) that “collects, distributes, and aggregates feedback about participants’ past behaviour” (p. 2), thereby signalling the potential risk of an interaction with a particular vendor to interested buyers (Resnick, Kuwabara, Zeckhauser, & Friedman, 2000). Comparatively, other sources of information about the seller’s trustworthiness are scarcely examined, with the prime example being discussion forums. Nonetheless, research has found that such forums are often consulted by cryptomarket buyers to better estimate the seller’s reliability and make a more informed decision to either make the purchase or abstain (Bancroft & Reid, 2017; Munksgaard & Demant, 2016; Norbutas, 2020; Van Hout & Bingham, 2013). With this, forums appear to function as additional facilitators for cooperation, thereby potentially influencing market outcomes (Norbutas, 2020). By not considering their effect, a considerable gap of knowledge persists.

In addition, most research conducted on the reputation effect focusses on licit items, sold in surface marketplaces such as Amazon and eBay, i.e. marketplaces that are indexed on the so-called surface web and therefore searchable via web engines (Hoelscher, 2018). In comparison, far less is known about this mechanism within cryptomarkets, which do not operate within the same social and legal context and therefore offer no assurance that fraudulent practices will be punished by law enforcement (Przepiorka et al., 2017). What further sets cryptomarkets apart from surface marketplaces is the aforementioned use of discussion forums. Such active online communities are rarely observed in any surface marketplace (Norbutas, 2020).

This paper further explores the effect of discussion forums on the seller’s business success, aiming to contribute to a better understanding of cryptomarkets. All in all, darknet marketplaces provide an unique insight into the inner mechanisms of the online drug market. By providing extensive data on both vendors and customers, cryptomarkets may be used to identify emerging trends and inform subsequent policy (Bancroft & Reid, 2017). In this regard, AlphaBay sets itself apart with its unprecedented size, sporting over 250,000 listings for drugs and other narcotics in December of 2015 (FBI, 2017; US Department of Justice, 2017). Moreover, discussion forums offer a more thorough look into marketing strategies and evasion tactics (Norbutas, 2020), which can be used to understand the success of the online drug market and the response of sellers and buyers to law enforcement efforts.

With regard to forums, a differentiation is made between self-advertisement threads and scammer threads. On self-advertisement threads, sellers can promote their products, announce discounts and/or communicate any positive feedback they might have received. As previously mentioned, research by Norbutas (2020) has indicated that activity on such forum threads can positively affect sales. On scammer threads, buyers can disclose their experience with cryptomarket sellers and warn others of malpractices, which might negatively impact market outcomes. Hence, the research question that this paper aims to answer is: *How has the frequency with which a seller was mentioned or otherwise active on a particular type of forum thread impacted their business success within the AlphaBay cryptomarket?*

In the forthcoming section, the theoretical underpinning of the reputation mechanism is further explored. Within this section, the interaction between buyers and sellers within the AlphaBay cryptomarket is approached as a trust game with information asymmetries. What follows is a brief explanation of the applied methodologies and data, after which the results are considered. In this research, negative binomial regression as well as multivariate regression with clustered standard errors will be utilized, the results of which are interpreted in the discussion section. Finally, a conclusion is drawn about the effect of forum threads on the business success of sellers within the AlphaBay cryptomarket. Potential limitations and recommended paths for future research are discussed.

Theory

Cryptomarkets are peer-to-peer marketplaces that allow for transactions between sellers and buyers (Norbutas et al., 2020a). The typical transaction within a darknet marketplace takes the following shape. First, the seller lists their item, often complemented by a picture and a description of its characteristics, such as the weight and price. Any user that comes across the listing can simply select the item and contact the seller to set the trade into motion. After receiving the order, the seller ships the item, often concealing its illicit contents with a vacuum seal in order to prevent the package from being intercepted by law enforcement (Norbutas et al., 2020a). This exchange is almost completely confidential, thanks to anonymizing technologies (Christin, 2012; Horton-Eddison & Cristofaro, 2017). This means that if all goes well, the identities of both actors remain hidden during the transaction.

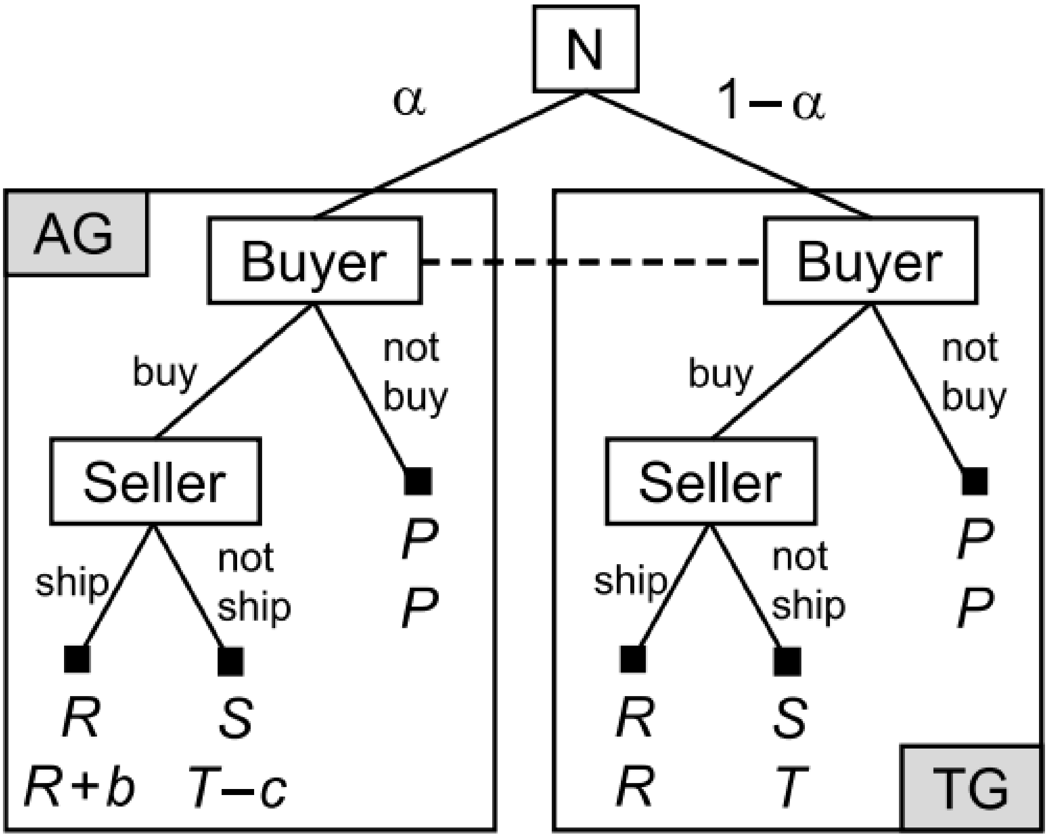
The anonymous character of the transactions within a cryptomarket creates a trust problem (Norbutas, Ruiter, & Corten, 2020b; Beckert & Wehinger, 2013), as the actors involved in the transaction are unsure of each other's intentions (Jiao et al., 2021). From the perspective of the buyer, there is no assurance that the seller will return their advance and ship the item as promised, after payment (Diekmann & Przepiorka, 2019). Furthermore, unlike in surface marketplaces, there is no guarantee that fraudulent practices will be punished by law enforcement (Barratt & Aldridge, 2016; Martin, 2014). Given this lack of deterrence, the good intentions of the seller remain highly uncertain at best (Przepiorka et al., 2017). As such, this situation produces a social dilemma (Kollock, 1999), which can be conceptualised as a trust game from game theory (Dasgupta, 1988; Jiao et al., 2021).

This paper borrows Diekmann's and Przepiorka's (2019) description of a standard trust game, summarizing it as follows: If the buyer does not trust the seller, they abstain from purchasing the item and both actors end up with payoff P. If the buyer transfers the money and the seller delivers the item, both actors receive payoff R. If the buyer places their trust in the seller, but the seller does not honour this trust, the buyer ends up with the sucker's payoff (S), while the seller receives the exploitation profit (T). Given the assumption of rational self-interest, all actors participating in this economic exchange will attempt to maximize their payoff, such that $T > R > P > S$ (Diekmann & Przepiorka, 2019). In a standard trust game, it is therefore inevitable that the seller chooses to exploit the trust of the buyer, as exploitation (T) yields a higher utility than cooperation (R). As a consequence, the buyer would always abstain from purchasing the item under these circumstances, in order to avoid the sucker's payoff.

What complicates this standard trust game is the asymmetry of information that exists between buyers and sellers in cryptomarkets. Economic exchanges that occur within a cryptomarket can either be an assurance game (AG) or a trust game (TG), as is modelled in Figure 1 (Jiao et al., 2021). Within an assurance game, the cost of not shipping the item (T-c) trumps the cost of shipping the item (R+b), so that sellers are incentivized to cooperate (Jiao et al., 2021). The problem of incomplete information is that the buyer does not know beforehand which type of game they will enter, but only knows the probability of entering the AG, as is denoted by α (Jiao et al., 2021). This information asymmetry has been identified as one of the largest impediments for actors looking to participate in online exchanges (Ter Huurne, Ronteltap, Guo, Corten & Buskens, 2018).

Figure 1.

Trust game with incomplete information (TGI)



Note. From "Reputation effects in peer-to-peer online markets: A meta-analysis" by Jiao, R., Przepiorka, W. and Buskens, V. (2021). In *Social Science Research, 95,* 102522.

In order to remain operative, darknet marketplaces therefore attempt to reduce transactional uncertainty and punish those users that have demonstrated opportunistic behaviour in the past, for example by banning them from the website (Beckert & Wehinger, 2013; Norbutas et al., 2020b). In addition, many cryptomarkets put an escrow system into place to sustain cooperation within the marketplace (Norbutas, 2020; Tzanetakis, Kamphausen, Werse, & Von Laufenberg, 2016). Simply put, an escrow is the financial agreement that the customer's payment will be withheld by a third party until the terms of contract have been met (Pritchard, 2020). In the case of cryptomarkets, the escrow system allows the cryptomarket administrators to function as conflict moderators and return the buyer's investment if the item is not delivered as promised (Tzanetakis et al., 2016). As such, the escrow system encourages the seller to uphold their end of the bargain, as the payment is only finalized once the customer confirms the item has been received (Przepiorka et al., 2017; Tzanetakis et al., 2016). With this, the seller's benefit of deviating from the contract is minimized (-c), while the utility of cooperating is increased (+b).

However, both cryptomarket sellers and buyers alike have been known to evade the escrow system. Though this might sound counterintuitive at first, it should not be forgotten that the system puts the cryptomarket into a position of undeniable power (Tzanetakis et al., 2016). Over the years, several administrators have disappeared with the funds in the escrow (see Gwern, 2015). What's more is that the system creates a situation in which the seller is at the mercy of the buyer's good intentions, as the customer could easily make a false claim to have never received the item (Norbutas, 2020). As such, the potential benefit of shipping the item is reduced. In addition, the system also economically burdens the seller, as the escrow inevitably hinders any direct cash flow (Horton-Eddison & Cristofaro, 2017). All of this combined, means that many will evade the escrow system if possible. Direct trades are preferred, wherein the item is only shipped after payment (Diekmann, Jann & Wyder, 2009).

Hence, the trust problem persists, with sellers having plenty of opportunity to scam their customers in a direct trade (Akerlof, 1970; Dasgupta, 1988; Diekmann et al., 2009). Given the limited information the buyer has about the seller, the question remains how the buyer decides whether to trust the vendor and, subsequently, engage in the economic exchange. Research has shown that reputation is one of the most important mechanisms for facilitating this trust (Ter Huurne et al., 2018). Herein, reputation can be seen as a proxy of the vendor's trustworthiness, which is accumulated over time (Norbutas, 2020). In this case, reputation can be inferred from two sources, namely the reputation system present within the cryptomarket itself and the discussion forums associated with that cryptomarket (Bancroft & Reid, 2017).

Reputation allows customers to make an informed decision on whether to trust the vendor, as it allows the customer to use the aggregate experience of the seller's entire clientele as a reference of the seller's trustworthiness, rather than merely their own lived experience (Norbutas et al., 2020a). With this, reputation casts a certain 'shadow of the past', which carries information about the seller's trustworthiness over to future customers (Diekmann & Przepiorka, 2019). This ability to share information shifts the seller's expected utility, insofar that cooperation becomes more beneficial than opportunistic behaviour (Norbutas et al., 2020b; Przepiorka, 2013; Resnick & Zeckhauser, 2002), even in instances where the chances of another interaction ever happening are low (Diekmann & Przepiorka, 2019). That being said, the chance that the exchange may be repeated in the future does cast a similar shadow, namely the 'shadow of the future' (Axelrod, 1984). This shadow can foster cooperation in expectancy of long-term benefit (Diekmann & Przepiorka, 2019). This is especially the case for actors that plan to remain active in the marketplace for a long time, as reputation is costly to build, but also costly to lose (Diekmann & Przepiorka, 2019; Friedmann & Resnick, 2001).

Reputation systems

While research on the reputation system within cryptomarkets has increased in recent years, most research has thus far primarily focussed on online surface marketplaces (Przepiorka et al., 2017). In many online marketplaces, the reputation system mainly comprises a rating system, in which customers can publicly share information about their experiences with certain sellers via customer feedback (Norbutas, 2020). This reputation system allows customers to differentiate between sellers in terms of the quality of products and their customer service provision (Resnick et al., 2000). Without the reputation system in place as a structural reassurance (Przepiorka et al., 2017), customers would be much more cautious in their decision to purchase at full price, as there is no a priori way of knowing whether the item they will receive is of high or poor quality (Resnick et al., 2000). Due to this asymmetry in information, customers will demand lower prices for all items, even from sellers that do offer high-quality products and excellent customer service (Akerlof, 1970; Resnick et al., 2000). High-quality sellers would be reluctant to accept such unwarranted reduction of their payoff (Resnick et al., 2000). As such, these sellers would abandon the marketplace in search of a replacement. The reputation system has been quoted as the primary resolution to this problem of economic exchange, which Akerlof (1970) dubbed as the “the market for lemons'' (Resnick et al., 2000).

If a reputation system is indeed present within a surface marketplace, it has been found to promote an economically healthy environment (Resnick et al., 2000). Though the market still offers “bitter lemons” (i.e. products of lower overall quality), Akerlof’s (1970) problem is negated with the help of such reputational markers (Resnick et al., 2000). Cryptomarkets form no exception. In most if not all online darknet marketplaces, a customer rating system is in place that forms an integral component of the market’s reputation system, which serves as a mark of the vendor’s reputation (Norbutas, 2020). With the help of such markers, an environment is created in which low-quality sellers receive lower prices for their items, while high-quality sellers are able to amass higher prices and even price premiums (Resnick et al., 2000). Price premiums have been observed in many online surface marketplaces, such as eBay and Amazon (e.g. Ba & Pavlou, 2002; Mohamed & Kamel, 2017).

Despite the overwhelming presence of buyer rating systems in cryptomarkets (Norbutas, 2020), many of the additional structural assurances that surface marketplaces provide are not present. Additionally, research outcomes on the complex relationship between the reputation system and vendor’s business success have been known to vary, seeming inherently intertwined in some studies and completely independent in the next. Hence, the question still remains whether the reputation system within cryptomarkets promotes cooperation to the same extent as in surface marketplaces. The most notable difference between surface marketplaces and cryptomarkets in this regard is that darknet marketplaces are not embedded in the same legal context. Within surface marketplaces, this legal system might promote trust and cooperation in and of itself due to the threat of punishment by law enforcement (Bakos & Dellarocas, 2011; Przepiorka et al., 2017). Additionally, in cryptomarkets, the uncertainty produced by the asymmetry of information is exacerbated, as this doubt is extended to not only encompass the item price and service provision of the vendor, but also whether the item will be delivered at all. Unlike in cryptomarkets, there are many safety mechanisms in place within surface marketplaces to avoid such losses of funds, e.g. buyer protection under credit card payment (Resnick et al., 2000).

Nevertheless, similar trends have been identified within cryptomarkets, with the price and number of sales increasing once a seller acquires the reputation of a reliable vendor (e.g. Diekmann & Przepiorka, 2019; Przepiorka et al., 2017). However, as there is no a priori way for the customer to discern between high-quality vendors that have only recently entered the market, and vendors that offer bitter lemons, many sellers with the ambition to remain in the market for a long time focus on developing a positive reputation upon their arrival in the cryptomarket (Diekmann & Przepiorka, 2019; Jiao et al., 2021). For this reason, many new sellers offer a substantial discount in the hopes of kick-starting their business (Jiao et al., 2021; Norbutas, 2020). With this, sellers hope to incentivize buyers to take the additional risk of trading with a vendor that does not yet have a reputation (Przepiorka et al., 2017). Once the positive reviews come in, their initial investment can be compensated for, as the reputation of being an honourable seller subsequently allows the vendor to charge higher prices for their items or even amass price premiums (Friedman & Resnick, 2001; Przepiorka, 2013; Przepiorka et al., 2017; Shapiro, 1983). Not only the price that the seller is able to obtain for their item increases, but also the chance that this item will sell (Jiao et al., 2021). Following this logic and building on what is known about online surface marketplaces and reflected here and there in research on cryptomarkets, this paper constructs the following hypotheses regarding the seller's business success and the market's internal reputation system:

H1. The better the seller's reputation within AlphaBay, the higher the number of items that will be sold.

H2. The better the seller's reputation within AlphaBay, the higher the price the seller is able to obtain for their item.

Discussion forums

While the reputation system might be an important source that customers infer a seller's trustworthiness from, it is not the only source. More often than not, forums are consulted for advice and information about the seller (Bancroft & Reid 2017; Van Hout & Bingham 2013; Munksgaard & Demant 2016). While these forums operate as separate identities from the cryptomarket, many sellers and buyers alike use it as an extension for additional information about the marketplace (Bancroft & Reid, 2017).

Research by Norbutas (2020) suggests that the predominant reason that discussion forums emerged was to combat the high level of uncertainty that characterises cryptomarkets, as an additional means to facilitate trust. The importance of these discussion forums is evident from Gwern's (2021) research on Silk Road, in which the author notes that "buyers take much more notice of info and feedback posted here [in the forum] than the feedback posted on their listings on SR".

Discussion forums support a wide array of topics, including but not limited to product reviews, philosophy, and political debates (Maddox, Barratt, Allen & Lenton, 2016; Munksgaard & Demant, 2016; Norbutas, 2020). In principle, the main categories are market and non-market related discussions (Norbutas, 2020). As there is virtually no evidence that non-market related discussions yield any considerable difference in terms of their effect on market outcomes (Norbutas, 2020), this paper limits itself to market-related discussions. The seller's behaviour as anything else than a rational market actor is thus beyond the scope of this paper. For market-related discussions, a differentiation is made between self-advertisement threads and scammer threads.

On self-advertisement threads, sellers are able to promote their items, offer insight into upcoming discounts or share any positive feedback they might have received (Norbutas, 2020). Seller's activity in such forums may serve as a relatively cheap signal to potential buyers about their trustworthiness (Norbutas, 2020). However, this activity does require a considerable investment in order to yield any benefit, whether it be time or sporadic price reductions (Norbutas, 2020). Additionally, vendors attempt to discern themselves from their unreliable counterparts by providing evidence of the quality of their goods, which exacerbates the cost of these strategic market-related signals and might thereby strengthen their effect (Lusthaus, 2012; Norbutas, 2020; Van Hout & Bingham, 2014). Exactly for this reason, buyers may interpret this activity as an indication of the seller's trustworthiness (Lusthaus, 2012; Norbutas, 2020). As such, activity in self-advertisement threads might positively contribute to the way the seller is perceived, thereby increasing their business success within the cryptomarket. From this, the following hypothesis is derived:

H3. The positive effect of the seller's reputation within AlphaBay on their business success increases the more the seller is active on a self-advertisement thread.

On the other hand, the forums also offer plenty of room to question the seller’s trustworthiness. Buyers can turn to so-called scammer threads to open threads about any negative experiences they might have had with the seller or read such accounts by other buyers. While not all problems discussed in this forum thread are necessarily a direct consequence of the seller’s actions, as packages might for example be intercepted by law enforcement with sellers consequently being wrongly accused of not having shipped the item instead (Norbutas, 2020), these claims might nevertheless damage a seller’s reputation. Once this damage has been done, the seller may no longer be able to signal their reliability via strategic market-related posts (Norbutas, 2020). In a similar vein, one might thus expect the business success of the seller to suffer if they are mentioned frequently in such a context:

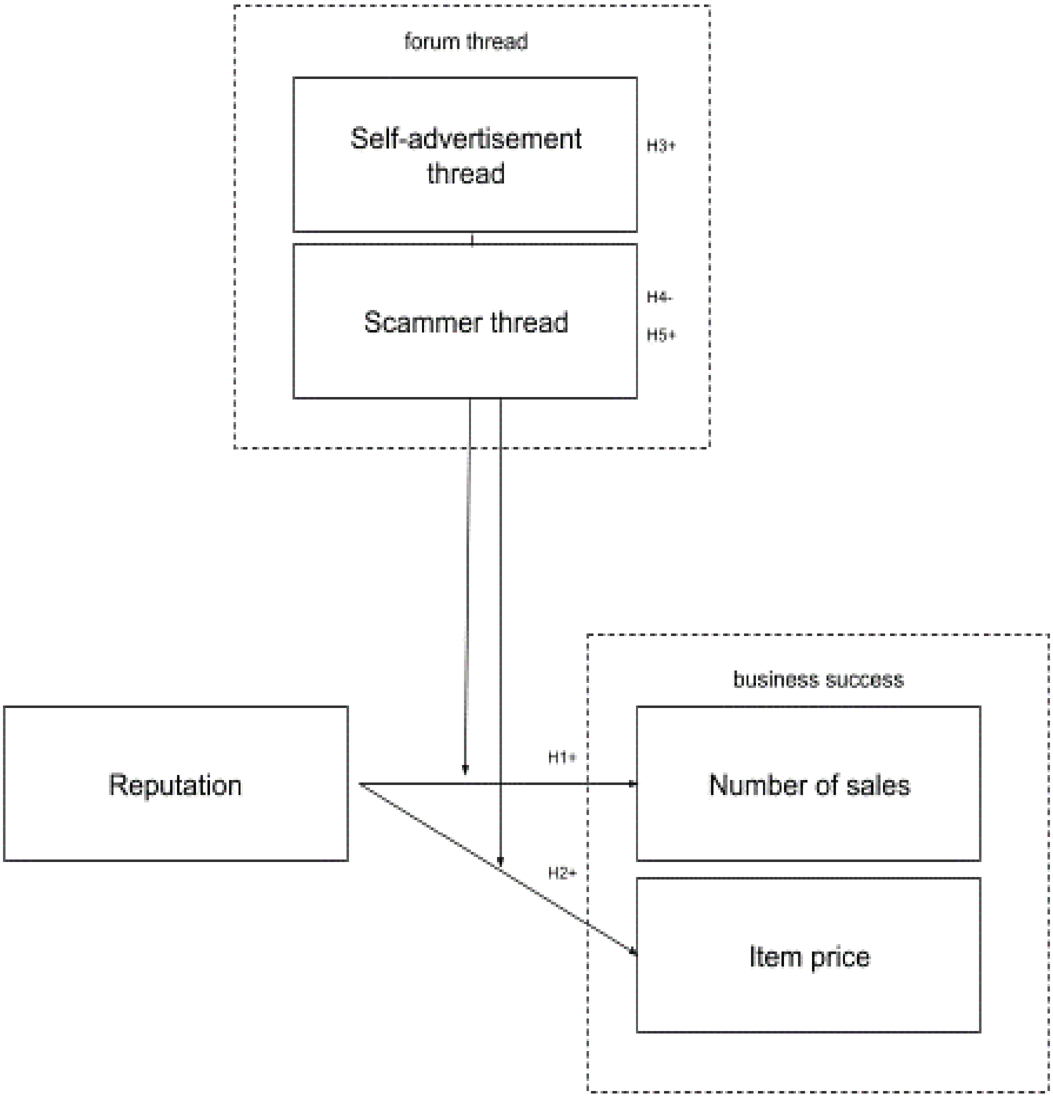
H4. The positive effect of the seller’s reputation within AlphaBay on their business success decreases the more the seller is mentioned on a scammer thread.

If the seller wants to repair their reputation, they must make costly investments to compensate for their loss of credibility. Such investments are so costly that the predominant course of action in this instance is to exit the market altogether, albeit to re-enter under a pseudonym (Norbutas, 2020). Following the logic that buyers might interpret strategic market-related communication with a higher cost as a stronger signal of good intention (Norbutas, 2020), it may be expected that any vendor that takes the time to reply to those accusations, either seeking to come to a solution or otherwise counter the claim, will be able to minimize the damage:

H5. The negative effect of being mentioned on a scammer thread decreases the more the seller replies to posts on a scammer thread.

Figure 2.

The research model.



Methodology

Data

Data is used from the AlphaBay cryptomarket and the AlphaBay Market Forum, which is the discussion forum that accompanies this darknet marketplace. AlphaBay launched in 2014 and was operational until 2017, when it was seized by the FBI (Europol, 2017). At its prime, it had accumulated over 40.000 users (FBI, 2017). Data on the AlphaBay marketplace and AlphaBay Market Forum was collected by Norbutas, Ruiter and Corten (2020b) and obtained between June and July of 2017. Information about the textual features of this data was subsequently gathered by Macanovic and Przepiorka (2021). Textual feedback derived from the cryptomarket's internal reputation system, as well as posts acquired from the discussion forums, were manually coded for sentiments, such as polarity. Coding was primarily conducted by students from Utrecht University. To avoid inaccuracies, an extensive tutorial was provided and coders had to complete a multiple-choice test in assessment of their proficiency in the English language, before being able to partake.

For this thesis, a subset of the complete dataset is used, which comprises several drug categories, specifically: “Weed”, “Hash”, “Heroin”, “Cocaine”, “MDMA”, and “Ketamine”. This subset covers transactions between May 1st and June 16th of 2017 and contains 1,655 items from 555 unique sellers. The main unit of analysis in this subset is an individual item listing of the seller. As the data contains relatively subjective assessments of polarity, a majority rule was applied: up to three participants coded the same text manually, and a decision was made based on their aggregate assessment. See Norbutas, Ruiter and Corten (2020b) for a more elaborate account of the data collection and Macanovic and Przepiorka (2021) for more details about the information acquisition of the textual features.

Methods

Four variables are constructed to serve as the main explanatory variables in the analyses. Each of these variables capture a different aspect of the seller's reputation within the AlphaBay cryptomarket. First and foremost, a distinction is made based on the type of customer feedback the seller received, with feedback either being quantitative (i.e. ratings) or qualitative (i.e. texts). Per type of feedback, two variables are constructed to reflect the feedback’s polarity. Herein, feedback that is positive is contrasted to feedback that is not. The total number of positive feedback of that type (i.e. quantitative or qualitative) signifies the seller’s positive reputation within the cryptomarket, whereas the sum of non-positive feedback - that is, neutral or negative feedback - represents the vendor’s non-positive reputation within the market.

The primary reason for the analytical distinction between quantitative and qualitative feedback comes forth from AlphaBay’s administrative approach to feedback moderation: positive ratings could not be removed as per the vendor’s request, whereas negative ratings could. Hence, some buyers would purposefully rate an item 5-stars, but simultaneously leave negative textual feedback as a means to express their discontent, without the fear of their criticism being removed (Macanovic & Przepiorka, 2021). Additionally, textual feedback has shown to oftentimes offer a much more nuanced view than their quantitative counterparts (Schoenmueller, Netzer, & Stahl, 2020). Hence, these different types of feedback might produce different effects.

Business success is operationalized via two target variables, specifically the vendor’s total number of sales and the price sellers were able to obtain for their item in grams. A Shapiro-Wilk test for normality was conducted, which showed a significant departure from normality for both the number of items sold, $W(1655) = 0.4$, $p < .001$, as well as for the price sellers were able to amass for their items in grams, $W(1655) = 0.42$, $p < .001$. All of the models with the number of items sold as the dependent variable account for this overdispersion via negative binomial regression. However, as price in grams is not a count variable, a different approach is taken there, namely that of log-transformation. This minimises the variable’s skewness.

As the assumption of independence is violated, observations are clustered in all analytical models to produce clustered standard errors (SEs), which allows for within-cluster correlation to exist between different observations from the same cluster. This produced 555 clusters of observations, one for each individual seller in the dataset, whose total of recorded items varied between 1 and 30. As there are numerous sellers in the dataset of which more than one item has been recorded, the observations can be seen as repeated measures. As such, a Generalized Estimating Equation (GEE) is used to test all hypotheses about the number of items sold, whereas a General Linear Model (GLM) is used to test all hypotheses involving the log-transformed price USD in grams. Both of these models allow for correlation to exist between repeated measures (Cui, 2007). With regard to the number of items sold, the model's robustness is checked for by comparing the outcomes of the GEE with the outcomes that are produced when this variable is modelled according to the GLM. While negative binomial regression is arguably the best approximation possible in SPSS, this is necessary because the model's QIC exceeds the preferred parameters (which is in smaller-is-better format) with a score of about 1700, thereby indicating that the data's structure does not fit the model perfectly.

Following Norbutas' (2020) example, skewed variables are log-transformed where possible to account for overdispersion. All relevant independent variables underwent this transformation. As such, the main reputation variables have been log-transformed. Table 1 shows their initial distribution and simultaneously exemplifies that such a transformation was necessary to satisfy the assumption of normality. In the GLM-model about the price sellers are able to amass for their items, the dependent variable of price in grams is also log-transformed to approximate a normal distribution. A transformation of the total number of items sold did not yield the desired effect, as the variable did not follow a near log-distribution. Hence, when checking for the GEE's robustness with the GLM-model, this variable has not undergone any transformation.

Table 1. Descriptive statistics of the main variables of analysis.

Name	N	Mean	SD	Median	Min	Max
# Number of items sold	1655	5.75	11.6	2	1	198
Price in USD per grams	1655	35	70.1	11.8	0.2	1500
# Number of positive quantitative ratings	1655	551.6	1369.3	75	0	16842
# Number of non-positive quantitative ratings	1655	6.8	17.6	1	0	287
# Number of positive qualitative texts	1655	380.1	974.5	46	0	10975
# Number of non-positive qualitative texts	1655	40.6	92.7	6	0	941
# Amount of activity in the self-advertisement thread	1655	4.1	18.1	0	0	339
# Number of mentions in the scammer thread	1655	0.9	4.5	0	0	85
# Number of replies in the scammer thread	1655	0.2	1.0	0	0	20

Multiple interaction variables are computed and incrementally introduced into the models (see Appendix A for all intermediary models) to represent the subforums of the AlphaBay Market Forum. Activity in the self-advertisement thread is signified by the total number of forum posts opened by the seller in the ‘Drug discussions’ subforum, combined with the number of seller replies in this subforum (i.e. the sum of the seller’s posts and replies in the self-advertisement thread). This way, the vendor’s entire activity in this section of the discussion forum can be captured. The subforum ‘Scam reports’ represents the scammer thread, with the number of times the seller’s username was mentioned in this particular subthread being the statistic of interest. Lastly, the replies of the seller in this ‘Scam reports’ subforum are considered to see if answering in such a scammer thread produces a soothing effect in the face of reputational damage. For all of these models, the seller’s total amount of posts, mentions, and replies in all other subforums is controlled for, to account for any effect produced by activity not in the “Drug discussion” or “Scam reports" subforums (e.g. in other, non-market related discussion subforums).

In models about the number of items sold, the time an item has been online for in days is included as a control variable. This approach is taken to avoid any differences arising from the mere duration the item was online for, as items that have been online for longer had more time to sell. To account for any variances simply produced by differences in price categories, all models are controlled for using a dummy variable of three price categories, namely low price (weed, hash), medium price (cocaine, MDMA, ketamine), and high price (heroin, meth). Herein, low price comprises the reference category, as most observations in the dataset are low-price items. For the models with the number of items sold, an increase is expected due to the increase in demand and decrease in supply for higher priced items. For all other instances, the seller’s obtainable price in grams is expected to be heavily influenced by the price category of the item, with items in the high price category (e.g. heroin and meth) inherently producing more revenue.

In addition, item weight (in grams) is introduced into all models as a control variable to account for bulk discounts and an overall lower demand for bulk offers (Aldridge & Décary-Hétu, 2016; Norbutas, 2020). As such, it is expected that both the number of sales and the price in grams decrease once the item weight increases. Furthermore, a dummy variable is constructed based on shipping location, with domestic shipping as the reference, as postage from any other location may lead to additional risks and thereby influence item price and sales negatively (Norbutas, 2020), while not necessarily being related to a seller's reputation.

The seller's Vendor Level and Trust Level in the market at the time of the data collection are also included as control variables. Of particular interest is the seller's Vendor Level, which was displayed next to the seller's profile on the item listing page as a representation of the vendor's trustworthiness (Kalberg, 2017). This variable was calculated via the number of sales, the revenue for those sales, and a percentual threshold that maintained that the seller's feedback had to be at least 90% positive (Kalberg, 2017). The Vendor Level was theorized by Kalberg (2017) to visibly attribute to the seller's reputation in a number of ways, thereby influencing market outcomes. While not necessarily the main explanatory variable, it is therefore nonetheless included alongside Trust Level to investigate its effects and control for any unobserved influence on the primary reputation measures.

Results

Table 2 shows the model estimations with the clustered SEs. In Appendix A, all intermediary models can be found. Notably, Model 1a (M1a) is inconclusive about the main effect of reputation on the vendor's total number of sales. The results contradict the initial expectation that the seller's reputation within the cryptomarket considerably influences their market outcomes in terms of their number of sales, as none of the predetermined main measures of reputation (i.e. the variables capturing customer feedback per type and polarity, denoted as 'Reputation variables' in Table 2) yield a statistically significant effect. Nevertheless, although their effect on the seller's total number of sales is statistically insignificant, the direction of these main reputation variables should be mentioned. Especially the effect of positive ratings is notable. The results indicate that the seller's total number of item sales decreases with each increase of positive ratings. This deviates from the expectations of the first hypothesis, which stated that the number of items sold would increase, the better the seller's reputation within the AlphaBay cryptomarket. For textual feedback, however, all effects are in the anticipated direction, such that an increase in positive textual feedback is accompanied by an increase in the number of sales, whereas an increase in non-positive textual feedback decreases this number. While no firm conclusions can be drawn regarding these reputation variables due to their statistically insignificant effect on the number of items sold, the results are nevertheless remarkable.

Table 2. Models with clustered SEs (N^1 = 1655, N^2 = 555).

	Total number of items sold		Total number of items sold		LOG(price in g)	
	Model 1a: GEE		**Model 1b: GLM**		**Model 2: GLM**	
	B	*SE*	*B*	*SE*	*B*	*SE*
Const.	**2.775*** **	0.288	**12.610*** **	1.978	**1.193*** **	0.051
R^2	-		0.109		0.754	
Reputation variables						
LOG(#positive ratings+1)	-0.191	0.406	-2.101	2.255	-0.069	0.071
LOG(#non-positive ratings+1)	-0.365	0.215	-1.280	1.322	-0.031	0.042
LOG(#positive texts+1)	0.080	0.469	1.853	2.598	0.170	0.091
LOG(#non-positive texts+1)	-0.218	0.258	-2.335	1.616	**-0.191*** **	0.057

Interaction variables						
LOG(#Activity in the self-advertisement thread+1)	0.025	0.332	-0.062	2.294	0.026	0.062
LOG(#Activity in the self-advertisement thread * positive ratings+1)	-0.224	0.672	-3.788	3.915	0.318	0.164
LOG(#Activity in the self-advertisement thread * non-positive ratings+1)	-0.039	0.189	-0.968	1.415	-0.025	0.045
LOG(#Activity in the self-advertisement thread * positive texts+1)	0.361	0.749	3.956	4.419	**-0.388***	0.172
LOG(#Activity in the self-advertisement thread * non-positive texts+1)	-0.092	0.270	1.092	1.769	0.085	0.067
LOG(#Mentions in the scammer thread+1)	-0.202	0.267	4.078	3.074	-0.009	0.086
LOG(#Mentions in the scammer thread * positive ratings+1)	**5.653***	2.704	35.931	24.510	0.578	0.637
LOG(#Mentions in the scammer thread * non-positive ratings+1)	0.428	0.280	3.860	1.996	-0.003	0.070
LOG(#Mentions in the scammer thread * positive texts+1)	**-5.929***	2.830	-39.275	25.108	-0.620	0.640
LOG(#Mentions in the scammer thread * non-positive texts+1)	-0.028	0.472	-0.771	3.690	0.062	0.108
LOG(#Replies in the scammer thread+1)	-1.578	0.969	-15.109	10.943	0.156	0.225
LOG(#Replies in the scammer thread * positive ratings+1)	-3.127	3.731	-38.408	40.306	-0.626	1.043
LOG(#Replies in the scammer thread * non-positive ratings+1)	-0.523	0.751	-2.965	9.221	0.323	0.175
LOG(#Replies in the scammer thread * positive texts+1)	2.011	3.787	32.842	40.686	1.130	1.065
LOG(#Replies in the scammer thread * non-positive texts+1)	**2.551***	1.277	16.159	14.828	**-0.849***	0.362
Item variables						
LOG(price in grams)	**-1.058*****	0.144	**-6.418*****	1.246	-	-
#Number of items sold	-	-	-	-	**-0.003*****	0.001
LOG(weight in grams)	**-0.724*****	0.062	**-4.038*****	0.596	**-0.290*****	0.013
Days online	**0.026*****	0.004	**0.142*****	0.028	-	-

Control variables						
International shipping	-0.155	0.150	-0.387	1.072	**-0.117*****	0.031
Regional shipping	-0.105	0.156	-0.259	1.190	**-0.082*****	0.026
Unknown shipping	**-0.664****	0.127	**-3.473****	0.793	**-0.110*****	0.034
Medium price	**0.464*****	0.140	**3.409****	1.154	**0.554*****	0.029
High price	**0.738*****	0.190	**5.637*****	1.683	**0.717*****	0.041
Vendor Level	**0.277*****	0.053	**1.618*****	0.483	**0.038*****	0.011
Trust Level	**-0.127***	0.057	-0.716	0.386	0.002	0.013
LOG(#Total of seller replies+1)	-0.020	0.197	-0.318	1.358	0.006	0.048
LOG(#Total of seller posts+1)	-0.044	0.151	-0.109	1.118	0.027	0.042
LOG(#Total of seller mentions+1)	0.090	0.156	0.853	1.077	-0.032	0.039

*** p < .001, ** p < .01, * p < .05

The coefficients of the control variables in M1 are in the expected direction and yield significant effects in some instances. Especially prominent is the influence of Vendor Level. With each increase in Vendor Level, the total number of items sold increases with 0.277. This result is in line with Kalberg's (2017) expectation that Vendor Level substantially influences market outcomes, the implications of which are further discussed in the next discussion and conclusion section. Also notable is the decrease in the seller's total number of sales once the seller's shipping location is not disclosed or otherwise 'unknown', as compared to the domestic reference. This implies that customers prefer domestic vendors and at the very least want to know the location of the seller, which might be explained by the increased risk and additional cost (whether in shipment fees or arrival time) for the vendor and customer when making long-distance shipments. As for price categories, the effect is as theorized, with medium priced items and higher priced items yielding more sales than those in the lowest tier.

A careful conclusion can be drawn about the second hypothesis, which maintained that a more positive reputation would allow sellers to charge higher prices and even price premiums for their items. While no evidence has been found to support the notion that a positive reputation leads to an increase in item price, the opposite effect has been identified: non-positive textual feedback results in a significant decrease in the item price that is achieved. Specifically, the seller's price in grams decreases by about $(1.10^{-0.191}-1) * 100 = -1.8\%$ for every 10% increase in non-positive texts. For all other effects of the reputation variables, however, no evidence is found. While non-positive textual feedback thus appears to significantly decrease the seller's obtainable price in grams, all other coefficients do not produce a conclusive effect.

Note again that Vendor Level significantly increases the price in grams sellers were able to amass for their items. With every increase in Vendor Level, the obtainable price in grams increases with ($exp^{0.038}$-1) * 100 = 3.9%. For both M1s and M2 the relationship of the 'item variables' (i.e. the variables that capture the characteristics of the item listing, as denoted in Table 2) is mostly as expected, with the price in grams negatively influencing the total number of items sold and the weight in grams reducing both the number of sales as well as the item price. This can be explained by the lower demand for bulk orders and the price discounts that accompany orders of higher volumes. That being said, the seller's number of items sold does not lead to higher prices in M2, but rather lower. However, while statistically significant, this effect is rather small, namely only a ($exp^{-0.003}$-1) * 100 = -0.30% decrease per item sold.

All control variables in M2 follow the anticipated direction. The additional risk of shipping further distances is translated to a steady decrease in the obtainable price in grams with the more distance that has to be abridged. Similarly, the achievable price in grams steadily increases per price category, with about an ($exp^{0.554}$-1) * 100 = 74% increase for items out of the medium price tier (such as MDMA and ketamine) and a ($exp^{0.717}$-1) * 100 = 104.8% difference to the highest tier (e.g. heroin and meth). This is in line with the expectations that the seller's obtainable price in grams is heavily influenced by the price category of the item, because items in the high price category (e.g. heroin and meth) usually sport higher market prices by default.

Based on several theories, it was hypothesized that the positive effect of the seller's reputation on their business success would increase the more the seller was active on a self-advertisement thread of the AlphaBay Market Forum. First and foremost, it should be noted that activity in self-advertisement threads did not produce any considerable effect in models with the number of items sold, as all such interaction variables proved to be statistically insignificant in M1s. Furthermore, in almost all instances, the direction of these variables differs from what was expected. Whereas activity in the self-advertisement thread was hypothesized to contribute positively to the number of items sold, the effect is not only statistically negligible, but also the opposite: for the interaction with positive ratings, non-positive ratings, and non-positive texts, the effect of their respective main reputational variable counterpart appears to further decrease, the more the seller is active in the self-advertisement thread. Only the effect of positive feedback texts is as anticipated, aside from its statistically insignificant effect on the number of items sold. All in all, however, this paper thus does not find support for the notion that activity in the self-advertisement thread substantially influences sales.

In M2, evidence is found that – holding all other variables constant - the main effect of positive textual feedback on the obtainable item price in grams is weakened, the more the seller is active in the self-advertisement thread. With each 10% increase of activity in this the self-advertisement thread, there is a $(1.10^{-0.388}-1) * 100 = -3.6\%$ decrease of the main effect of positive texts, which by itself only increases the obtainable item price per gram with 1.6% per every 10% increase in positive texts. The results thus indicate that the seller's post and replies in the self-advertisement thread substantially diminish the otherwise positive main effect of positive feedback texts. This deviates from the expectation that activity in this particular forum thread would result in more business success. Although the results suggest that activity in the self-advertisement thread can, at least to some extent, negate the negative main effects of positive ratings and non-positive textual feedback, the respective effects of these interaction variables on the obtainable price in grams is statistically insignificant. Hence, while some of the identified directions are in line with the previously established expectations, the evidence remains inconclusive.

The fourth hypothesis was constructed as a test of signalling theory. It was argued that once sellers are mentioned frequently in the context of scammer threads, they are no longer able to signal their reliability via strategic market-related posts. As a result, the positive effect of having a positive reputation on the seller's business success was thought to decrease. While no evidence has been found that such a positive main effect exists at all, being mentioned on a scammer thread does have consequences for the seller's business success. Specifically, in M1, the negative but overall statistically insignificant effect of positive ratings on the total number of items sold is dependent on the number of times the seller is mentioned on a scammer thread, but significantly increases the more the seller is mentioned in such a context. This effect is sizable, with a $5.653 * \ln(1.10) = 0.53$ increase per each 10% increment of being mentioned in the scammer subthread. This deviates from the initial expectation that the total number of items sold would further decrease. On the other hand, the interaction of being mentioned in the scammer thread with positive texts is as anticipated, yielding a considerable decrease of -5.929 * ln(1.10) = -0.57 of the main effect of positive textual feedback, per each 10% increase of mentions. With regard to the obtainable price in grams in M2, the aforementioned variables follow the same trend, although their effects on the item price prove to be statistically insignificant.

To test the last hypothesis, the seller's replies in the scammer subforum are considered. This fifth hypothesis proposed that the negative effect of being mentioned on a scammer thread would decrease the more the seller replied to posts in the scammer thread. Notable is that for M1, the interaction of seller replies in the scammer subforum with non-positive textual feedback compensates for the negative main effect of non-positive textual feedback, whereas in M2 this same interaction exacerbates the negative main of non-positive textual feedback effect even further. For M1, each 10% increment in seller replies in the scammer threads results in a 2.551 * ln(1.10) = 0.24 increase in the direct effect of non-positive textual feedback on the vendor's total number of sales. Thus, replying in the scammer subthread minimizes the negative effect of this main reputation variable. On the other hand, for M2 of price in grams, there is an even further decrease of $(1.10^{-0.849}-1) * 100 = -7.8\%$ of the negative main effect of non-positive textual feedback, per every 10% increase of replies in the scammer thread. Hence, only partial support is found for the fifth hypothesis, namely that replies can flip the negative effect of non-positive textual feedback on sales at higher values of replies, but a considerable investment is required from the seller.

Discussion and conclusion

This paper examined the influence of discussion forums on the business success of cryptomarket sellers. Data on the AlphaBay darknet marketplace and AlphaBay Market Forum was used to explore the discussion forums as a complementary facilitator of trust, that operate alongside the cryptomarket's own reputation system. This reputation system is often quoted as the solution to the trust problem and heralded as the primary reason that interactions can take place in mutual cooperation within darknet marketplaces, given the sublegal context (e.g. Resnick et al., 2000). While the reputation system within cryptomarkets has been trialled and tested, discussion forums have been scarcely examined, despite growing evidence that its threads provide an additional source of trust (Bancroft & Reid, 2017). This paper aimed to fill this considerable gap in knowledge by exploring the AlphaBay Market Forum, specifically investigating the impact that activity on the self-advertisement thread, being mentioned in the scammer thread, and replying in the scammer thread had on the business success of vendors active in the AlphaBay cryptomarket.

Combining several multivariate models with clustered standard errors, it is consistently found that customer feedback does not influence the business success of AlphaBay vendors substantially, despite being the pinnacle of most other cryptomarket's reputation system. Almost all measures of quantitative and qualitative feedback are statistically insignificant in their effect on sales and item price. Within AlphaBay, customer feedback thus does not appear to be the main driver behind the reputation mechanism, nor the predominant facilitator for trust. However, here and there some traces of the reputation effect can be identified. For example, evidence is found that non-positive textual feedback leads to a substantial decrease in the obtainable item price in grams. When taking a closer look at this reputation variable, the mean-descriptives in Table 1 reveal that comparatively, customers leave non-positive textual feedback far more frequently than non-positive quantitative ratings. This suggests that customers indeed use textual feedback as a means to express their discontent more so than quantitative ratings, as was proposed by Macanovic and Przepiorka (2021). In combination with the more nuanced view that textual feedback offers (Schoenmueller et al., 2020), this might mean that this type of feedback is also interpreted as more meaningful by customers looking for information about the seller's trustworthiness than, for example, positive ratings, which every customer seems to leave by default. If future customers infer from the non-positive textual feedback that the product is of lower quality, they are likely to demand lower prices, which urges vendors to offer price reductions until their reputation is restored.

The lack of evidence in support of customer feedback suggests that there are other factors at play that influence the business success of vendors within AlphaBay. Vendor Level might be one such factor. Based on the current research, it can be theorized that customers within the specific cryptomarket of AlphaBay base their purchase decisions first and foremost on more visible markers of reputation, rather than the buyer rating system. Additional analyses illustrated that upon the inclusion of Vendor Level, the effect of positive textual feedback on the vendor's obtainable item price became statistically insignificant, whereas the significance of non-positive feedback lowered considerably. This indicates that Vendor Level indeed explains some of the variance in item price. Within AlphaBay, the seller's Vendor Level was displayed at the top of the item listing page, as part of the seller's profile overview. The convenience and visibility of this reputational marker might mean that customers would use the Vendor Level as a pointer of the seller's trustworthiness, rather than making the time-investment to delve through the feedback themselves. Additionally, as Vendor Level was attributed by administrators of the cryptomarket itself, it may be interpreted by the customers as a more unbiased and trustworthy marker of reputation than customer feedback. Hence, within AlphaBay, Vendor Level appears to be the solution to Akerlof's (1970) problem of bitter lemons and Jiao's et al.'s (2021) trust game, more so than any other type of reputational marker.

As for the AlphaBay Market Forum, the analyses continually find that each of the discussion forum threads moderate at least one of the effects of customer feedback on vendor's market outcomes. This is in line with the expectation that the discussion forums are often consulted to acquire advice and additional information regarding the seller (Bancroft & Reid 2017; Van Hout & Bingham 2013; Munksgaard & Demant 2016) and that buyers take more notice of the information posted there than the customer feedback posted in cryptomarkets (Gwern, 2021). However, not all of the effects are in the expected direction, nor are all of them statistically significant. For example, it was expected that vendors that were active in the self-advertisement thread would be more successful in the marketplace. While no evidence is found that activity in this particular type of forum thread influences the vendor's total number sales, the results reveal that activity in the self-advertisement thread effectively diminishes the positive effect of positive textual feedback on the seller's obtainable price in grams. In other words, activity in this particular type of forum thread lowers the obtainable item price in grams at higher values of activity. This contradicts the notion of price premiums. An explanation for this unexpected result may be found in Jiao et al.'s (2021) and Norbutas' (2020), who maintain that sellers often invest into discounts with the hopes of attracting new customers or kick-starting their business. The self-advertisement thread might be the most suitable place in the forum for vendors to announce such discounts, and those with a positive reputation may be able to make this monetary investment much more frequently due to their already established business success and the possession of higher volumes of drug items. This is partially reflected by the results, insofar that more sales lead to a slight decrease in item price.

The results are inconclusive about Norbutas' (2020) notion that sellers, accused of fraud, are no longer able to signal their reliability via strategic market-related posts. First and foremost, the analytical models reveal that the more the seller is mentioned in the scammer thread, the more the originally negative main effect of positive ratings is subdued. Positive ratings might thus start to exude a positive effect on the seller's total number of sales, but only if the seller is mentioned frequently in such a context. This contradicts the initial expectation that the business success of sellers would suffer the more their name is mentioned in the scammer thread. This paper is not alone in finding such counterintuitive results (see, for example, Cui, Lui & Guo, 2007, who find that negative reviews lead to positive market outcomes). In this case, the result might stem from the nature of these mentions. For the sake of argument, it was assumed that most mentions in the scammer thread were inherently negative about the experience with the seller. This does not factor in that users of the AlphaBay Market Forum might have also flocked to the scammer thread to come to the seller's aid and defend their reputation or otherwise dispute the claim.

An alternative explanation for this phenomenon is offered by De Maeyer (2012), who argues that negative reviews might prompt potential customers to examine reviews of all types more thoroughly. As a result, the customer's knowledge about the product increases, which boosts their confidence and trust in the product, thereby stimulating them to make the purchase. The scammer thread might serve a similar function to Cui et al.'s (2007) negative review in this regard, as it provides potential customers with a more complete image of the seller – flaws and all. It does not seem improbable to assume that those active in the forum threads, would indeed examine the customer feedback within the cryptomarket more thoroughly when making a purchase, by virtue of their use of the market forum. These customers would thus not necessarily be deterred from purchasing if the seller was mentioned in such a context.

However, evidence has also been found in support of Norbutas' claim. The results show that the frequency with which an AlphaBay seller is mentioned in the scammer thread influences the effect of positive textual feedback on the number of items sold, insofar that being mentioned in this context leads to a substantial decrease of this otherwise positive main effect. Each mention in the scammer thread thus effectively diminishes the effect of positive texts, even potentially flipping it at higher values of mentions. Thus, partial support has been found for the claim that the positive effect of reputation on the seller's business success within AlphaBay decreases the more the seller is mentioned on a scammer thread. Together, these findings unveil a complex puzzle, which above all underline the need for more research.

Lastly, the seller replies in the scammer subforum should be discussed. On the one hand, the negative main effect of non-positive ratings on the number of sales diminishes the more the seller replies to the scammer thread. This indicates that continuing to participate in the market after sustaining damage to one's reputation is a costly investment for vendors, but one that bears fruit. For item price in grams, on the other hand, the negative and significant main effect of non-positive textual feedback is exacerbated, the more the seller replies in the scammer thread. In other words, the main effect of non-positive textual feedback becomes even more negative, the more the seller replies in this particular subforum. In terms of the obtainable item price in grams, sellers are thus not able to negate the effect of being mentioned in a scammer thread by replying to said subthread. A possible reason is that one of the investments that vendors have to make to protect their business' future interest after being mentioned in the scammer thread, is monetary, such as discounts. This would explain the further reduction in obtainable item price. That being said, it should be emphasized that not many sellers replied in this subforum, suggesting that sellers either do not like to invest energy into rebutting the claims, or that instead the strategy of a complete market exit is preferred.

The limitations of this research should be acknowledged. First and foremost, the distribution of the data should be mentioned. There were some cases in which the seller had a limited amount of feedback, a limited amount of sold items, a limited amount of items captured by the dataset, and/or a limited amount of presence in the discussion forums (i.e. zero inflation). This is especially true for replies in the scammer thread, a finding that indicates that Norbutas' (2020) proposed strategy of complete market exit is indeed more prevalent. While log-transformation was performed and a

Generalized Linear Model (GLM) was used to account for this, not all of these factors could be perfectly adjusted for due to limitations within the analytical software. What this research offers is thus not a set-in-stone conclusion about the discussion forums or the inner workings of AlphaBay's reputation system, but rather an indication that these topics are worthwhile to pursue alongside some preliminary conclusions.

The GEE-model (M1b) does appear to be robust when compared to the GLM-model: the outcome is similar in both models, albeit with differences in effect size. However, negative binomial regression was definitely not a perfect fit for modelling the data as the QIC exceeded the preferred parameters, despite being the best approximation attainable in SPSS. Therefore, while the robustness check does provide some evidence that the model is sturdy, further research using different statistical software with less limitations could prove to be useful. Furthermore, a lot of factors appear to remain unobserved at the sales-level, with the coefficient of determination never exceeding 10.9%. This could for example be information about the preferences of the customer, about purchasing habits, and so on. Insight into these factors could help solve the puzzle that the number of items sold remains.

To conclude: AlphaBay was one of the largest darknet marketplaces to date, with over 40.000 active users at its prime (FBI, 2017). Though the marketplace was seized in 2017, researchers and policymakers alike may learn from its history. Above all, the results of this paper exemplify that cryptomarket discussion forums should no longer escape the purview of academic scholars and policymakers. The current research illustrates the importance of these forums: although their precise effect is yet to be explained, their influence on vendors' business success is substantial. Future research should focus on unveiling this complex relationship between the reputation system and the discussion forums. Herein, special attention should be paid to Vendor Level, which has proven to be an important reputational marker within AlphaBay. With this, the results of this study have several implications for drug control policies. Most importantly, it signals that law enforcement efforts should not only focus on dismantling cryptomarkets, but also discussion forums. After all, the forums are a valuable source of information and trust, that allows for direct communication between sellers and customers. If law enforcement wants to keep up with the emerging drug trends and law evasion tactics of customers and vendors alike, this tool of communication should not be ignored. While it is thus true that, as of now, the discussion forums raise a lot of questions, its many forum threads may also lead to many answers.

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Appendix A: Intermediary tables

Table 3. Models to test H1+H2 with clustered SEs (N^1 = 1655, N^2 = 555).

	Total number of items sold		Total number of items sold		LOG(price in g)	
	Model 2a: GEE		**Model 2b: GLM**		**Model 3: GLM**	
	B	*SE*	*B*	*SE*	*B*	*SE*
Const.	**2.611*****	0.297	**11.518*****	1.941	**1.158*****	0.055
R^2	-		0.093		0.745	
Seller variables						
LOG(#positive ratings+1)	-0.324	0.340	-2.786	1.981	-0.012	0.067
LOG(#non-positive ratings+1)	-0.190	0.207	-0.910	1.403	-0.023	0.043
LOG(#positive texts+1)	0.151	0.395	2.071	2.247	0.091	0.083
LOG(#non-positive texts+1)	-0.136	0.239	-1.466	1.477	**-0.176****	0.057
Item variables						
LOG(price in grams)	**-1.083*****	0.157	**-6.320*****	1.288	-	-
Number of items sold	-	-	-	-	**-0.003*****	0.001
LOG(weight in grams)	**-0.730*****	0.066	**-3.990*****	0.613	**-0.286*****	0.014
Days online	**0.028*****	0.004	**0.152*****	0.029	-	-
Control variables						
International shipping	-0.125	0.137	-0.082	0.981	**-0.114****	0.032
Regional shipping	-0.049	0.149	0.175	1.126	**-0.075****	0.025
Unknown shipping	**-0.431****	0.159	**-2.417****	0.811	**-0.089***	0.039
Medium price	**0.475*****	0.147	**3.378****	1.143	**0.555*****	0.030
High price	**0.731*****	0.194	**5.577*****	1.705	**0.719*****	0.041
Vendor Level	**0.288*****	0.049	**1.706*****	0.439	**0.043*****	0.012
Trust Level	-0.098	0.067	-0.588	0.414	0.008	0.014

*** p < .001, ** p < .01, * p < .05

Table 4. Models to test H3 with clustered SEs (N^1 = 1655, N^2 = 555).

	Total number of items sold		Total number of items sold		LOG(price in g)	
	Model 4a: GEE		**Model 4b: GLM**		**Model 5: GLM**	
	B	*SE*	*B*	*SE*	*B*	*SE*
Const.	**2.657*****	0.308	**11.761*****	2.019	**1.162*****	0.057
R^2	-		0.096		0.746	
Seller variables						
LOG(#positive ratings+1)	-0.214	0.381	-1.947	2.202	-0.076	0.072
LOG(#non-positive ratings+1)	-0.186	0.232	-0.567	1.433	-0.008	0.043
LOG(#positive texts+1)	0.008	0.448	1.084	2.526	**0.172***	0.092
LOG(#non-positive texts+1)	-0.146	0.264	-1.844	1.604	**-0.212*****	0.059
Interaction variables						
LOG(activity_self+1)	-0.124	0.331	-0.925	2.260	0.033	0.060
LOG(activity_self*pos_qr+1)	-0.174	0.601	-3.176	3.576	0.277	0.162
LOG(activity_self*nonpos_qr+1)	0.051	0.172	-0.312	1.270	-0.027	0.039
LOG(activity_self*pos_qt+1)	0.306	0.698	3.711	4.274	-0.346	0.174
LOG(activity_self*nonpos_qt+1)	-0.124	0.266	0.390	1.747	0.082	0.058
Item variables						
LOG(price in grams)	**-1.075*****	0.157	**-6.284*****	1.268	-	-
Number of items sold	-	-	-	-	**-0.003*****	0.001
LOG(weight in grams)	**-0.729*****	0.066	**-3.976*****	0.601	**-0.287*****	0.014
Days online	**0.027*****	0.004	**0.148*****	0.029	-	-
Control variables						
International shipping	-0.170	0.147	-0.409	1.058	**-0.114*****	0.031
Regional shipping	-0.076	0.150	-0.084	1.147	**-0.080****	0.026
Unknown shipping	**-0.476****	0.158	**-2.670****	0.850	**-0.092***	0.038

Medium price	**0.474***	0.153	**3.245**	1.164	**0.551***	0.030
High price	**0.734***	0.198	**5.494***	1.704	**0.718***	0.041
Vendor Level	**0.286***	0.050	**1.704***	0.441	**0.045***	0.012
Trust Level	-0.098	0.065	-0.583	0.425	0.008	0.014
LOG(# total of seller replies+1)	0.228	0.191	1.217	1.403	-0.002	0.037
LOG(# total of seller posts+1)	-0.104	0.154	-0.514	1.112	0.016	0.043

*** p < .001, ** p < .01, * p < .05

Table 5. Models to test H4 with clustered SEs ($N^1 = 1655$, $N^2 = 555$).

	Total number of items sold		Total number of items sold		LOG(price in g)	
	Model 6a: GEE		**Model 6b: GLM**		**Model 7: GLM**	
	B	*SE*	*B*	*SE*	*B*	*SE*
Const.	**2.720*** **	0.298	**12.511*** **	2.064	**1.176*** **	0.052
R^2	-		0.104		0.751	
Seller variables						
LOG(#positive ratings+1)	-0.200	0.401	-2.073	2.245	-0.071	0.072
LOG(#non-positive ratings+1)	-0.340	0.212	-1.212	1.335	-0.034	0.043
LOG(#positive texts+1)	0.053	0.463	1.586	2.577	0.172	0.092
LOG(#non-positive texts+1)	-0.190	0.259	-2.067	1.612	**-0.203*** **	0.058
Interaction variables						
LOG(activity_self+1)	-0.096	0.318	-0.879	2.292	0.026	0.059
LOG(activity_self*pos_qr+1)	-0.173	0.642	-3.467	3.854	0.292	0.160
LOG(activity_self*nonpos_qr+1)	0.065	0.180	-0.448	1.502	-0.015	0.038
LOG(activity_self*pos_qt+1)	0.284	0.731	3.817	4.470	**-0.355***	0.171
LOG(activity_self*nonpos_qt+1)	-0.083	0.270	0.849	1.887	0.072	0.060
LOG(mention_scam+1)	-0.094	0.259	4.090	2.784	0.023	0.095
LOG(mention_scam*pos_qr+1)	3.996	2.421	24.491	23.230	0.278	0.660
LOG(mention_scam*nonpos_qr+1)	**0.326***	0.291	**3.303***	2.073	0.042	0.077
LOG(mention_scam*pos_qt+1)	-4.531	2.499	-28.465	23.085	-0.293	0.669
LOG(mention_scam*nonpos_qt+1)	0.463	0.514	1.121	4.220	0.020	0.121
Item variables						
LOG(price in grams)	**-1.083*** **	0.144	**-6.546*** **	1.265	-	-
Number of items sold	-	-	-	-	**-0.003*** **	0.001
LOG(weight in grams)	**-0.729*** **	0.063	**-4.063*** **	0.602	**-0.288*** **	0.014
Days online	**0.026*** **	0.004	**0.142*** **	0.029	-	-

Control variables						
International shipping	-0.194	0.150	-0.583	1.069	**-0.115*****	0.031
Regional shipping	-0.109	0.153	-0.249	1.190	**-0.080*****	0.026
Unknown shipping	**-0.654****	0.128	**-3.402****	0.819	**-0.107*****	0.034
Medium price	**0.490*****	0.139	**3.507****	1.161	**0.553*****	0.029
High price	**0.742*****	0.188	**5.640*****	1.690	**0.720*****	0.040
Vendor Level	**0.274*****	0.048	**1.615*****	0.453	**0.041*****	0.011
Trust Level	-0.099	0.064	-0.623	0.420	0.006	0.013
LOG(# total of seller replies+1)	0.068	0.189	-0.103	1.347	0.032	0.048
LOG(# total of seller posts+1)	-0.067	0.153	-0.311	1.114	0.028	0.041
LOG(# total of seller mentions+1)	0.097	0.148	1.076	1.057	-0.044	0.041

*** $p < .001$, ** $p < .01$, * $p < .05$

Table 6. Models to test H5 with clustered SEs ($N^1 = 1655$, $N^2 = 555$).

	Total number of items sold		Total number of items sold		LOG(price in g)	
	Model 8a: GEE		**Model 8b: GLM**		**Model 9: GLM**	
	B	*SE*	*B*	*SE*	*B*	*SE*
Const.	**2.775*****	0.288	**12.610*****	1.978	**1.193*****	0.051
R^2	-		0.109		0.754	
Seller variables						
LOG(#positive ratings+1)	-0.191	0.406	-2.101	2.255	-0.069	0.071
LOG(#non-positive ratings+1)	-0.365	0.215	-1.280	1.322	-0.031	0.042
LOG(#positive texts+1)	0.080	0.469	1.853	2.598	0.170	0.091
LOG(#non-positive texts+1)	-0.218	0.258	-2.335	1.616	**-0.191*****	0.057
Interaction variables						
LOG(activity_self+1)	-0.025	0.332	-0.062	2.294	0.026	0.062
LOG(activity_self*pos_qr+1)	-0.224	0.672	-3.788	3.915	0.318	0.164
LOG(activity_self*nonpos_qr+1)	-0.039	0.189	-0.968	1.415	-0.025	0.045
LOG(activity_self*pos_qt+1)	0.361	0.749	3.956	4.419	**-0.388***	0.172
LOG(activity_self*nonpos_qt+1)	-0.092	0.270	1.092	1.769	0.085	0.067
LOG(mention_scam+1)	-0.202	0.267	4.078	3.074	-0.009	0.086
LOG(mention_scam*pos_qr+1)	**5.653***	2.704	35.931	24.510	0.578	0.637
LOG(mention_scam*nonpos_qr+1)	0.428	0.280	3.860	1.996	-0.003	0.070
LOG(mention_scam*pos_qt+1)	**-5.929***	2.830	-39.275	25.108	-0.620	0.640
LOG(mention_scam*nonpos_qt+1)	-0.028	0.472	-0.771	3.690	0.062	0.108
LOG(replies_scam+1)	-1.578	0.969	-15.109	10.943	0.156	0.225
LOG(replies_scam*pos_qr+1)	-3.127	3.731	-38.408	40.306	-0.626	1.043
LOG(replies_scam*nonpos_qr+1)	-0.523	0.751	-2.965	9.221	0.323	0.175
LOG(replies_scam*pos_qt+1)	2.011	3.787	32.842	40.686	1.130	1.065
LOG(replies_scam*nonpos_qt+1)	**2.551***	1.277	16.159	14.828	**-0.849***	0.362

Item variables						
LOG(price in grams)	**-1.058*****	0.144	**-6.418*****	1.246	-	-
Number of items sold	-	-	-	-	**-0.003*****	0.001
LOG(weight in grams)	**-0.724*****	0.062	**-4.038*****	0.596	**-0.290*****	0.013
Days online	**0.026*****	0.004	**0.142*****	0.028	-	-
Control variables						
International shipping	-0.155	0.150	-0.387	1.072	**-0.117*****	0.031
Regional shipping	-0.105	0.156	-0.259	1.190	**-0.082*****	0.026
Unknown shipping	**-0.664****	0.127	**-3.473****	0.793	**-0.110*****	0.034
Medium price	**0.464*****	0.140	**3.409****	1.154	**0.554*****	0.029
High price	**0.738*****	0.190	**5.637*****	1.683	**0.717*****	0.041
Vendor Level	**0.277*****	0.053	**1.618*****	0.483	**0.038*****	0.011
Trust Level	**-0.127***	0.057	-0.716	0.386	0.002	0.013
LOG(# total of seller replies+1)	-0.020	0.197	-0.318	1.358	0.006	0.048
LOG(# total of seller posts+1)	-0.044	0.151	-0.109	1.118	0.027	0.042
LOG(# total of seller mentions+1)	0.090	0.156	0.853	1.077	-0.032	0.039

*** $p < .001$, ** $p < .01$, * $p < .05$