



Utrecht University

The Effect of Feedback Polarity on the Sales and Prices on Cryptomarket AlphaBay

Khiedo van Deursen (5641497)

Faculty of Social Sciences, Utrecht University

201100018: Bachelorproject Sociologie

Ana Macanovic

June 14th, 2021



Introduction

This January, Darkmarket got taken offline (Europol, 2021). This was the world's largest illegal market, situated on the dark web. On this market, users traded all kinds of drugs, sold counterfeit money, as well as counterfeit credit card details, anonymous sim cards and malware. It is estimated by Europol that this so called 'cryptomarket' has facilitated exchanges worth over €140.000.000, between over 500.000 users and 2.400 sellers worldwide. This is an indication of the scale and prevalence of these illegal marketplaces. The term 'cryptomarkets' was initially used by hackers in forums to describe anonymous online marketplaces. When defining the term 'cryptomarkets', this thesis will utilize the definition provided by Barratt & Aldridge (2016). Here, cryptomarkets are defined as: "a marketplace that hosts multiple sellers or 'vendors', provides participants with anonymity via its location on the hidden web and use of cryptocurrencies for payment, and aggregates and displays customer feedback ratings and comments." These illegal marketplaces exist on the dark web, which entails they are only accessible through use of an encrypted browser (hence the name 'cryptomarkets').

In recent years, the popularity of these cryptomarkets has seen a sharp increase. The first cryptomarket, 'Silk Road' was founded in early 2011 (Norbutas, 2020). After 'Silk Road' was taken down by the FBI in 2013, multiple new cryptomarkets took its place. Between the years 2013 and 2016, over 60 cryptomarkets appeared on the dark web (Branwen, 2019), one of which was AlphaBay . Seeing as these cryptomarkets are a relatively new phenomenon, academic attention has only recently shifted towards these anonymous, online marketplaces. A large body of this scientific literature concerns the success these cryptomarkets often have. The anonymous nature of these cryptomarkets creates a myriad of possibilities for opportunistic, self-serving behaviors, which creates a cooperation problem. (Przepiorka, Norbutas, & Corten, 2017; Norbutas, 2020). Yet, cryptomarkets have flourished over the last few years, which reveals limited occurrences of this opportunistic, self-serving behavior. In most of the literature, this lack of opportunistic, self-serving behavior in cryptomarkets is attributed to the reputation systems (Diekmann & Przepiorka, 2019; Przepiorka, Norbutas, & Corten, 2017). These reputation systems frequently consist of quantitative measures (i.e. a rating from 1 to 10, or a one-to-five star rating), in combination with qualitative text messages (Jiao, Przepiorka, & Buskens, 2020). Research on these reputation systems, has been mostly limited to the legal markets as opposed to the cryptomarkets. Existing literature has also been

mostly concerned with the quantitative ratings (Hu, Koh, & Reddy, 2014; Lee, Im, & Jun Lee, 2009; Pavlou & Dimoka, 2006). In legal spheres, the legal system maintains the threat that fraudulent businesses will be persecuted and punished. In this legal sphere, the online market platforms can be held accountable for sellers' misconduct by the community of buyers simply choosing to do business elsewhere. This creates an incentive for the providers of these platforms to protect buyers from fraud (Przepiorka, Norbutas, & Corten, 2017). The anonymous nature of cryptomarkets entails they do not experience any legal threat of punishment and persecution (Armstrong & Forde, 2003). It remains to be seen if the incentive of taking one's business elsewhere is as present in cryptomarkets as is it in legal markets, considering cryptomarkets operate in a somewhat different context.

Previous research pertaining to cryptomarkets has focused more on the quantitative measures than the qualitative measures of reputation (Przepiorka & Berger, 2017). Their research on reputation, which is seen as a quantitative form of feedback, reveals that, in cryptomarkets, the quantitative feedback, or reputation, works in a linear fashion. Positive reputation had a positive influence on their sales, just as negative feedback has had a negative influence on the sales on AlphaBay. The effect of qualitative measures of feedback, though, has not been as investigated as often. Qualitative feedback consists of comparisons and descriptions of characteristics in a non-numerical manner, as opposed to quantitative measures of feedback. Potential sources of the qualitative measures of feedback can be the feedback texts received in addition to the quantitative feedback ratings, yet, this is not the only possible source from which qualitative feedback on vendors on AlphaBay can be retrieved. Community forums on AlphaBay provide another source for this qualitative feedback, this will be further explained in the paragraph below.

According to the Global Drug Policy Observatory (Global Drug Policy Observatory, 2015), community forums are an important medium for cryptomarkets, where vendors can market their product, make offers, and where URL's can be exchanged. The community forums are also used for reviews, and for sharing experiences (Van Hout & Bingham, 2013). Users can post reviews about products and vendors they have encountered on the cryptomarket. Moreover, these discussion forums also contain so called scammer threads. In these threads, users can 'call out' buyers or sellers, with which they have had negative experiences, and so, warn other users about these scammers. These community forums lie outside the reputation system of the cryptomarket, and provide a qualitative rating, as opposed to the more

quantitative rating measures of the feedback system. An in-depth look into the feedback texts and forum posts left by users could provide both the scientific community and law-enforcement with a better understanding of cryptomarkets as a whole, as well as potentially help discern new criminal trends. Finally, maintaining a qualitative perspective might further elucidate underlying reasons for the differential effects of texts polarity of these feedback texts and forum posts on AlphaBay, instead of monitoring macro-level trends, as often can be case with quantitative research. Researching these forums thus provides a qualitative source of information from the studied cryptomarket, which could prove to be more insightful, and will at the very least be a useful addition to the current body of knowledge.

The community forum posts have various characteristics, but because of the limited scope of this research, the decision has been made to put the focus on the polarity of the feedback and forum posts. Polarity refers to the message the post is conveying, which can be either a positive message, a negative message, or a neutral message about various aspects of the transaction. This thesis will assess whether the ‘polarity’ of the feedback texts and forum has a beneficial or detrimental effect on the market performance of vendors on AlphaBay. Thus, in order to further explore cryptomarkets by assessing the influence of polarity of feedback and discussion forums, the following research question is devised: “How does the polarity of forum posts on a vendor on cryptomarket AlphaBay affect their sales and prices?”

To provide an answer to this research question, first cryptomarkets as a whole have to be considered. Cryptomarkets are a relatively new concept. The first cryptomarket “SilkRoad” has been taken down by the FBI in 2013 (Newsroom, 2016), yet multiple alternatives have originated in its place. AlphaBay is one of these alternatives, and for some time was considered the largest cryptomarket on the Dark Web, but has been shut down in 2017, by an international investigation of the United States, Canada and Thailand (Statt, 2017). Unlike AlphaBay, not all of these markets, have acted honorably with regards to its users. Some of these markets performed a so called ‘exit scam’, in which the administrators of the site suddenly close it down and take off with all money still deposited in the accounts or in the escrow service (Vice News, 2021). Furthermore, a survey done by Global Drug Survey (Winstock, 2019) found that in the last 6 years, there has been a year on year increase in the participants reporting to have obtained drugs on the Dark Web. Accordingly, Interpol views these markets as a growing threat

Barratt & Aldridge (2016) pose several reasons why attention should be paid to cryptomarkets. Cryptomarkets provide a unique opportunity to analyze the supply side of the

illegal market in its entirety, instead of relying on small and incomplete samples. When analyzing cryptomarkets, it is possible to analyze the entire population within the market. Secondly, cryptomarkets are not isolated from the conventional (offline) illegal market, as for instance, drugs flow in and out of cryptomarkets into the broader commercial drug supply chains. Cryptomarkets thus, following Barratt & Aldridge (2016) provide a new way of monitoring criminal trends, and is an example of the way criminals innovate, in order to evade law-enforcement.

This thesis will aim to better understand how people cooperate in these illegal cryptomarkets, by analyzing what effect qualitative and quantitative ratings have in an environment which does not have the conventional, legal 'safeguards' for cooperation. In order to better understand the cryptomarkets, and understand how people cooperate within them, this thesis will first introduce some fundamental information about the Dark Web, in which these cryptomarkets are embedded. Then, this thesis will discuss previous research regarding cryptomarkets, based on which several hypotheses are constructed. Subsequently, in order to investigate these hypotheses, a dataset collected in June 2017 by scraping the entirety of the AlphaBay marketplace will be used. By means of regression-analysis, the dataset will be analyzed in order to assess the effects of qualitative and quantitative feedback and forum posts. Finally, based on the results of the analyses, conclusions regarding the hypotheses will be drawn.

Theoretic framework

First, before diving into the theoretical framework for this research, some background information concerning the Dark Web is required. According to Chertoff (2017), the internet can be divided into two segments: the Surface Web, and the Deep Web. The Dark Web is a very small, hard to access part of the Deep Web. It accounts for less than 0,01% of the sites on the internet, and requires using a special, encrypted browser in order to be able to visit. The encrypted browsers provide users with anonymity, usually by means of relaying, or encrypting (converting information into code, in order to prevent unauthorized access) data. By downloading an encrypted web browser (i.e. The Onion Router or more commonly known as TOR) users have access to these illegal online marketplaces like 'SilkRoad' and 'AlphaBay'. As discussed in the introduction, since the shutdown of 'SilkRoad' in 2013 numerous cryptomarkets have tried to take its place. AlphaBay was officially launched in

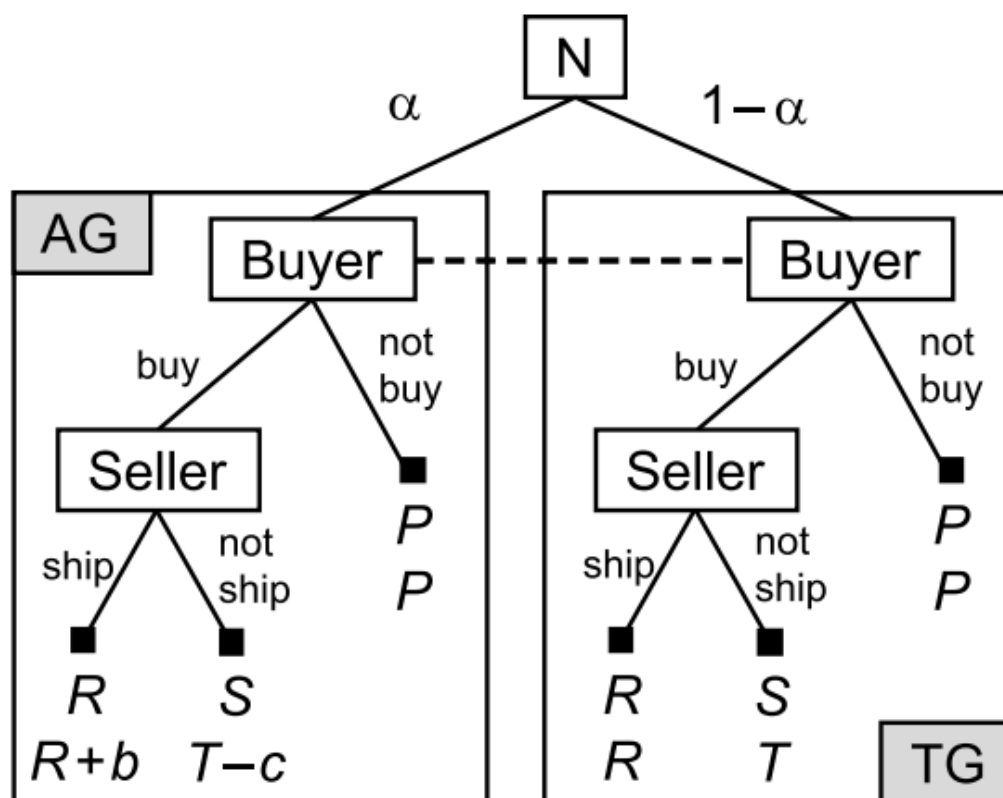
December 2014, and since its launch, has seen a steady grow of users, with around 14.000 new users within its first 90 days of operation. This grow continued, as AlphaBay, at the time of its demise, had over 400.000 users and was regarded as one of the largest cryptomarkets on the Dark-Web(Cimpanu, 2017), therefore the decision has been made to utilize AlphaBay as a context for this research.

In order for any marketplace to facilitate effective exchanges, all users must be able to benefit from exchanges on this market. This process is made more difficult because of the asymmetry of information between the traders (Beckert, 2009). In legal markets, there are several legal, organizational, social and moral assurances to promote cooperation between the parties. A cryptomarket, however, does not necessarily possess these same assurances. As these cryptomarkets are embedded in the Dark Web, which can be accessed anonymously by users all over the world, these markets have the potential to overstep national legal systems. This extrajudicial context could also further amplify the trust problems following the anonymity between buyers and sellers on this marketplace, as well as create a trust problem between traders and the market platform itself (Macanovic & Przepiorka, 2021).

In online marketplaces, buyers are able to browse through items listed online by vendors, who come to an interaction when the buyer agrees with the price set by the vendor. This interaction between a buyer and a seller in an online environment, when viewed in terms of Game Theory, can be conceptualized as a trust game with incomplete information (Jiao, Przepiorka, & Buskens, 2020). This serves as a model for an interaction between rational players, both trying to receive the maximum possible payoff. ‘Payoff’, in this framework, is seen as the individual reward a ‘player’ receives for arriving at a particular outcome. In a conventional trust game, the first-moving agent (the buyer) decides whether to trust the second-moving agent (the seller) and send the money to buy an item. When having received the money, the seller has to decide either to ship the product the buyer paid for, or to pocket the money, and retain the item as well. The payoffs in the Trust Game are ordered in such a way that the payoff for not shipping the product is higher than the payoff for shipping the items, The Trust Game then predicts the seller will decide not to ship the item. The seller will achieve a higher payoff by retaining the product, while also collecting the money from the buyer. When the buyer is aware of this, he/she will expect the seller not to ship his product in reciprocation to the payment, and thus, will not buy the product.

However, as mentioned before, an online interaction between a buyer and a seller is conceptualized as a Trust Game with Incomplete information (TGI). For the sake of simplicity, masculine pronouns are used when referring to both buyers and sellers, however, naturally, these can be female as well. The TGI accounts for the fact that the buyer is uncertain about the seller's incentive and ability to be trustworthy. The seller has information about his preferences and constraints, which are unknown to the buyer. The buyer, then, knows he is 'playing' one of two games. Either the buyer 'plays' an Assurance Game (AG) or the buyer 'plays' a Trust Game. The two games differ only in the order of seller payoffs. In the Trust Game, the seller does not gain an additional benefit when shipping the product. Also, the seller would not suffer a cost to their payoff for not shipping the product. A vendor in the Assurance Game will gain a benefit to his payoff when shipping his product, and will suffer a cost to his payoff when deciding not to ship his products. These benefits and costs can be translated into benefits and costs to one's reputation. This way, shipping the product (thanks to the beneficial effect to one's reputation) leads to a higher payoff for the vendor when compared with not shipping the product, and pocketing the received money (which will prove detrimental to the reputation of the vendor). This way, the order of payoffs is such that the seller has an incentive to ship if the buyer buys. Whereas the seller knows whether he is in the AG or the TG, the buyer only knows the possibility of being in the AG. Knowing this possibility, and the TGI-payoffs, the buyer assesses the possible payoffs from either buying or not buying; and will thus choose to maximize his payoff. If they think they are entering a Trust Game, they will consider that the maximum payoff for the seller is to pocket his sent money, and not send the product in return. On the other hand, if the buyer believes he is entering an Assurance Game, he will consider that the maximum payoff for the seller is achieved when shipping the product in response to the made payment. Following this, a rational buyer will choose to buy from a seller when he believes he is entering an Assurance Game, and will choose not to buy when under the impression he is entering a Trust Game. Figure 1, displayed below, gives a visual representation of the choices available to both buyers and sellers in a TGI.

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.

Most sellers want to make money from doing business online. They, thus, have an interest in remaining in the market, as well as expanding their business (Jiao, Przepiorka, & Buskens, 2020). Fraudulent sellers also have an incentive to stay in the market, however, this reputation system would not allow them to stay when they have acted untrustworthy in the past. If a seller once fails to reciprocate a buyer’s trust, the seller will be perceived as dishonest, which entails that no buyer in the future will buy from him. The seller then would have to exit the market, and re-enter the market using a different pseudonym (Friedman & Resnick, 2001). Sellers who value the future gains from trading with buyers more than they value the gains of cheating a buyer once and then having to start from scratch will enter the market and build up their good reputation through honest business conduct.

A good reputation is thus a reliable signal of trustworthiness because it is costly to produce and can distinguish sellers who are able to produce the reputation from those who cannot (Przepiorka & Macanovic, 2021). Buyers, then, could use this reputation as an indication whether they are entering a Trust Game, or an Assurance Game, and decide on their further actions on the associated payoffs. Building reputation is not only costly because sellers have

to consistently behave cooperatively, but also because new entrants in the market (without a track record of reputation) have to sell their products at lower prices (Friedman & Resnick, 2001). When a seller is a new entrant into the market, he/she would have to lower his/her price to make the buyer indifferent about their offer (with lack of a good reputation) and an offer by a seller who does have a good reputation.

On AlphaBay, the reputation of a seller was captured in their statistic ‘% positive feedback’. When transacting on this cryptomarket, buyers had the option of leaving feedback regarding the seller, which could then be found on the seller’s pages. The feedback amounted to two elements. The first element was the quantitative feedback. This consisted of the buyer rating his experience either positive, neutral or negative, which was then further accumulated into the measure ‘% positive rating’. The second element of feedback was the qualitative feedback. The qualitative feedback consisted of textual feedback which could be written in support of the quantitative feedback; however, this was not compulsory. Leaving feedback text accompanying a rating is, however, not the only way of leaving textual feedback on AlphaBay. Another source for textual feedback can be found in the forum posts on AlphaBay. The AlphaBay forum was run next to the marketplace and served as a place where market participants and other interested users could exchange experiences with products and sellers encountered in the market (Afilipoaie & Shortis, 2015). The AlphaBay forum consisted of several sections. These sections all served a different purpose. Some provided room for discussing the various drugs, some sections were dedicated to review listed items on AlphaBay. Finally, the forum had subsections for general discussion, as well as covering topics relating to a myriad of different criminal activities. This textual information in the forum posts is another source of qualitative data, written voluntary, and separate from the quantitative ratings given within the transactional feedback system of AlphaBay. This qualitative information is similar in the sense that it provides textual feedback to a seller, yet it does not require any transaction to be completed.

Research by Jiao, Przepiorka & Buskens (2020) on quantitative reputation effects, shows that the reputation of a seller affects their performance in a linear fashion. Positive ratings had, overall, a positive effect on the selling performance, and negative ratings had a negative effect on the selling performance. A similar effect was found when investigating reputation effects in an online auction website in China (Ye, Li, Kiang, & Wu, 2009). They found positive

ratings to have a significant, positive effect on seller performance. Negative ratings were found to negatively impact the seller performance. This relationship between negative ratings and negative seller performance was found as well by Lee, Im & Jun Lee (2009). In their research on reputation effects in the context of internet auction markets as well, the number of negative evaluations were shown to have a significant, negative effect on the final auction price, and thus, were a significant indicator for price discounts. Following these findings, one's selling performance on AlphaBay would be expected to increase when rated more positively and decrease when rated more negatively.

Pavlou & Dimoka (2006) have investigated the role of feedback text comments in online marketplaces. In this research, feedback texts of over 420 sellers on the online marketplace eBay.com are analyzed using content analysis. They found that the vast majority of buyers in this study reported having assessed both quantitative and qualitative information about the seller's reputation before transacting. Furthermore, when assessing the differential effects of qualitative and quantitative feedback., they found textual feedback comments to have a larger influence on the credibility of a seller than crude, numerical ratings did. We then, would, following this research, expect qualitative feedback to have a greater influence on the sale and the prices of the items being sold when compared to the influence of the quantitative ratings on their sale and prices.

To be able to utilize the feedback texts and forum posts in the analyses, their content was described in terms of polarity. Text polarity describes whether a text is a positive, a neutral, or a negative statement. In order to further determine whether or not the polarity of the forum posts have any influence on the sales and prices on AlphaBay, further attention has to be given to previous research regarding sentiments in texts. Using sentiment analysis, positive, neutral and negative emotions within a text can be identified (Wilson, Wiebe, & Hoffmann, 2005). Previous research regarding the effect of sentiments on prices have established the relationship between text sentiments and selling prices. Hu, Koh & Reddy (2014) investigated the relationship between ratings, sentiments and sales on books on Amazon.com. They find that ratings do not have a significant direct impact on sales, however, they find that ratings do have a significant indirect effect on sales through sentiment, while they also found that the impact of sentiment on sales was mostly direct. This research further establishes the relation between online sentiment and the sale of a product. Shin, Hanssens & Gajula (2008), investigated the effect of online 'buzz', or electronic word-of-mouth, on the price of digital music players. They found that positive online sentiment towards a product is

a leading indicator of price increases, and negative online sentiment is a leading indicator of price decreasing.

Following previous research the following is hypothesized regarding the differential impact of qualitative feedback and forum posts, and quantitative feedback (Pavlou & Dimoka, 2006; Ye, Li, Kiang, & Wu, 2009)

- *Hypothesis 1: “Qualitative ratings have a greater influence on the number of sales than quantitative ratings have”*
- *Hypothesis 2: “Qualitative ratings have a greater influence on the prices per gram of the sold items than quantitative ratings have.”*

The research regarding text polarity, and its effects on sales performance (Hu, Koh, & Reddy, 2014; Shin, Hanssens, & Gajula, 2008) would predict linear effects of text polarity on sales and prices. Therefore, the following is hypothesized in relation to these effects.

- *Hypothesis 3: “Positive polarity of feedback texts and forum posts will increase the number of sales.”*
- *Hypothesis 4: “Forum posts and feedback with a positive polarity will lead to an increase in the price per gram of the sold items.”*

Furthermore, other research (Chevalier & Mayzlin, 2006) regarding online book sales on Amazon.com, shows that one-star reviews have a greater effect on sales than five-star reviews did. This research would predict that forum posts with negative sentiment have a larger influence on the sales than forum posts with positive sentiments would have. Research touched upon earlier has also found asymmetrical effects of positive versus negative feedback (Shin, Hanssens, & Gajula, 2008). Remarkably, they found negative online ‘buzz’ to significantly decrease prices, while, in this research, positive online buzz did not significantly increase the prices of the music players. Similarly, Standifirt (2000), in researching the reputational impact on eBay sales, also found this asymmetrical effect. Here, positive

reputational ratings were seen to have only a mildly significant effect on the final bidding price, whereas negative reputational ratings were found to have a highly significant impact on the final bidding price. Nonetheless, this again concerns the legal market. If the same effect occurs on the cryptomarkets is yet to be seen. Following previous groundwork, it is thus expected that this asymmetrical effect of negative ratings will appear in the ensuing analyses. Therefore, it is hypothesized that:

- *Hypothesis 5: “Forum posts and feedback with a negative polarity have a greater influence on the number of sales than posts with a positive sentiment.”*
- *Hypothesis 6: “Forum posts and feedback with a negative polarity have a greater influence on the prices per gram of the sold items than posts with a positive sentiment.”*

Data & Methods

The dataset used was accumulated from the cryptomarket AlphaBay, and the AlphaBay Market Forum. This dataset consisted of information on 1655 items posted by sellers on cryptomarket AlphaBay. For each of the items in the dataset, the accumulated number of feedbacks, feedback texts, and forum posts was accessed. This data was collected in June and July of 2017, not long before the market was seized by authorities, by scraping the entire marketplace. This dataset has been used in other research on cryptomarkets (Macanovic & Przepiorka, 2021; Norbutas, Ruiter, & Corten, 2020). The dataset used in this thesis was a subset of items, collected between May 1st, 2017 and June 16th, 2017. This subset includes data from several ‘drug categories’, namely: “Weed”, “Hashish”, “Heroin”, “Cocaine”, “MDMA” and “Ketamine”.

The total obtained dataset was deemed to contain too many observations for manually coding for text sentiments (polarity, emotionality and, where applicable, subjectivity). Therefore, the decision has been made to initially, manually code a sample of the observations for text sentiments. Then, this coding was further expanded onto the remainder of the dataset using text mining methods. With the use of the Random Forest algorithm, the dataset was then used to train a Machine Learning model to ‘replicate’ manual coding (Macanovic & Przepiorka, 2021). This model was then trained and validated on the same dataset. The main unit of observation in this dataset is an individual item listing of a seller.

In order to determine the effect of the forum posts on the sales of the items, the decision has been made to utilize the number of items sales¹ as a dependent variable in the analyses regarding the different effects on the number of sales. In order to be able to determine the different effects of the forum posts on the prices, the item price in grams² is used as a dependent variable in the analyses regarding the prices of the items.

The dataset used contained information on quantitative feedback received by a vendor, as well as qualitative feedback and forum posts pertaining to a seller. The quantitative feedback ratings rated buyers' experiences with sellers, by rating them either positive, neutral, or negative. To be able to assess the hypotheses regarding differential effects of quantitative and qualitative feedback and forum post polarity, the cumulative number of quantitative seller feedback ratings have been subdivided into ratings with a positive polarity, ratings with neutral polarity, and ratings with negative polarity. The same subdivision has been made with regards to the variables encompassing qualitative feedback and forum posts. These qualitative have also been subdivided on the basis of their polarity, creating variables for feedback texts and forum posts respectively, covering positive, neutral, and negative polarity of these qualitative measures.

In order to limit the effect of unobserved variables, to avoid omitted variable bias, these analyses will make use of several control variables. As discussed before, drug prices vary by type of drug. As is the case with almost all products sold, some types of drugs are more expensive than others. This is why dummy variables of the variable representing the different price categories will be computed, after which they will be added as a control variable. This categorical variable has thus divided the cases based on the price category of the listed items in low price (weed, hash), medium price (cocaine, MDMA, ketamine) and high price (heroin, meth)³. Controlling for these price range, will prevent the results from displaying significant price differences based solely on the price-category of the drug.

To account for variance in sales and prices based on the reputation of the sellers, Vendor Level and Trust Level will be added as control variables to the models. AlphaBay used two separate systems in order to assist its users in determining the trustworthiness of their trading partners (Kalberg, 2017). Vendor Levels were a mechanism which ensured the safety of the users when trading with a seller on AlphaBay. The 'Vendor Level' indicated the trustworthiness of a vendor by calculating how many sales have been made, how much

¹ "n_sold"

² "priceg"

³ "low_price"; "med_price"; "high_price"

money has been made, and the percentage of positive feedback the vendor had received. The procedures for calculating ‘Trust Level’ have not officially been publicized. The ‘Trust Levels’ ranged from 1 to 10, and applied to both vendors and buyers on the marketplace. The ‘Trust Levels’ were assigned based on how active a member was, how many actions a member performed, as well as voted on by other members situated in the same ‘Trust Level’. ‘Trust Level’ was introduced to replace the ‘buyer reputation’ system, in order to provide vendors on the market with an indication of the trustworthiness of the buyers. ‘Trust Levels’, therefore, is the visualization of the trustworthiness of the buyers on AlphaBay.

Product prices on AlphaBay are, as most products purchasable in bulk are, dependent on the total quantity purchased. Products bought in large quantities usually have a lower price per gram when compared with the same product bought per individual gram, and by incorporating the control variable for the total weight in gram of the listed item⁴, the results of the analyses are controlled for variance in pricing based on the quantity bought. Another variable potentially influencing the sales and prices of the items listed on AlphaBay is the shipping distance. When vendors only ship domestically for instance, this can potentially influence their sales as well, and so, by adding dummy variables of the different shipping categories (domestic, regional, international or unknown)⁵ this price premium or difference in sales based on the shipping categories can be controlled for. The final control variable that will be added is a variable controlling for the number of days the item was online for⁶. Naturally, a product which is listed online for only two days, is expected to have fewer sales than a product which has been listed online for over a month, and by controlling for the days the items have been listed online, a difference in sales exclusively based on the days the items were online is being controlled for.

To be able to, for Hypothesis 1 and 2, test for differential effects of qualitative and quantitative feedback and forum posts on the sales and prices of the items, two analyses have to be performed. Qualitative ratings are operationalized as the forum posts and feedback texts that somehow mention the seller⁷, whereas quantitative ratings have been operationalized as the total number of feedbacks received by the seller⁸. Then, a multiple linear regression was performed using both the qualitative and quantitative variables as independent variables,

⁴ “weight_gram”

⁵ “ship_dom”; “ship_regio”; “ship_inter”; “ship_unknow”

⁶ “item_days”

⁷ “s_t_cml”; “n_f_men_cml”

⁸ “s_r_cml”

where the analysis of Hypothesis 1 will use the number of sales per item listing as a dependent variable, whereas the analysis of Hypothesis 2 will use prices in gram as a dependent variable. Finally, the control variables are added into the model as well.

Hypotheses 3 and 4 are tested by way of multiple linear regression. Here, forum posts and feedback with positive polarity are predicted to increase the sales, as well as the prices of the items listed on AlphaBay. These variables are operationalized as “the total number of feedbacks with positive quantitative rating”, “the total number of feedback texts coded as positive” and “the total number of forum posts that somehow mention the seller (positive)”⁹. To assess Hypothesis 3, the independent variables and the control variables will subsequently be added in a regression model which uses the number of sales per item listing as an independent variable, after which the control variables will be entered into the model. The testing of Hypothesis 4 will have the same design as the testing of Hypothesis 3; however, this will utilize the price in grams as a dependent variable. These two models will incorporate an extra control variable, controlling for nonpositive feedback texts and forum posts.

In order to test Hypothesis 5 and 6, several new variables have been created. First, all the variables that account for positive polarity of the qualitative forum posts and feedback texts have been aggregated into an overarching variable¹⁰. The same has been done for all the qualitative feedback texts and forum posts regarded as nonpositive (here: neutral and negative)¹¹. These have been added in the analyses, with subsequent addition of the control variables. The analysis for hypothesis 5 will use the number of items sold as a dependent variable, whereas the analysis for hypothesis 6 will again use the prices per gram as the dependent variable.

The analyses will be performed using SPSS Statistics 26. Descriptive statistics of the main variables used in these analyses have been displayed in Table 1 below.

⁹ “*s_r_pos_cml*”; “*s_pos_t_cml*”; “*n_f_men_pos_cml*”

¹⁰ “*positive_quali*”

¹¹ “*nonpositive_quali*”

Table 1: Descriptive statistics of the main variables

<i>Independent Variables</i>	N	SD	Mean	Min	Max
<i>'number of items sold'</i>	1655	11,598	5,75	1	198
<i>'item's price per gram'</i>	1655	70,120	34,914	0,23	1500
<i>Dependent Variables</i>	-	-	-	-	-
<i>'cml # seller feedback ratings'</i>	1655	1379,473	558,36	0	16927
<i>'cml # seller feedback texts'</i>	1655	1058,245	420,70	0	11884
<i>'cml # of forum mentions'</i>	1655	37,730	9,78	0	532
<i>'cml # of positive forum mentions'</i>	1655	9,813	2,57	0	145
<i>'cml # of positive feedback ratings'</i>	1655	1369,280	551,55	0	16842
<i>'cml # of positive feedback texts'</i>	1655	974,450	380,11	0	10975
<i>'positive qualitative texts'</i>	1655	975,497	382,685	0	10995
<i>'nonpositive qualitative texts'</i>	1655	101,159	47,799	0	999,00
<i>Control Variables</i>	-	-	-	-	-
<i>'item's weight in grams'</i>	1655	234,756	56,480	0,05	4535,92
<i>'sellers vendor level'</i>	1655	2,580	3,34	1	10
<i>'sellers trust level'</i>	1655	1,389	4,45	3	10
<i>'days item was online'</i>	1655	11,413	26,58	0	47
<i>'price category "low"'</i>	1655	0,489	0,607	0	1,00
<i>'price category "medium"'</i>	1655	0,450	0,280	0	1,00
<i>'price category "high"'</i>	1655	0,317	0,113	0	1,00
<i>'shipping category "domestic"'</i>	1655	0,500	0,510	0	1,00
<i>'shipping category "international"'</i>	1655	0,420	0,228	0	1,00
<i>'shipping category "regional"'</i>	1655	0,353	0,146	0	1,00
<i>'shipping category "unknown"'</i>	1655	0,320	0,115	0	1,00

Results

Firstly, an initial inspection of Tables 2, 3 and 4 revealed that for all models using sales as a dependent variable, the R^2 has not been exceptionally high, with a maximum of 6,1% explained variance. The models utilizing prices per gram as dependent variable, however, do have a significantly higher R^2 , with a maximum R^2 of 28,1%.

Table 2 in Appendix A contains the results of the regression analysis performed to assess Hypothesis 1, with the dependent variable being the sales of the items. In total, the model indicated that there was a collective significant effect of the incorporated variables on the sales of the items ($R^2=0,056$; $F=(9, 1642)=8,068$; $p<0,001$) Hypothesis 1 expected the

qualitative feedback and forum posts to have a larger effect on the sales of the items than quantitative feedback would have. Following this, we would expect the variables encompassing qualitative feedback and forum posts to have the largest effect size. Indeed, looking at Table 2 reveals that the only significant effect on the items being sold derived from '*cumulative number of forum mentions*'. The effect size of this variable is the largest of all dependent variables in this analysis, and is also positive ($b=0,022$). These results provide support Hypothesis 1. However, the effect of the other qualitative variable (*cumulative number of seller feedback texts*), as well as the quantitative variable (*cumulative number of seller feedback ratings*) are not significant in this model. These findings provide support for Hypothesis 1. The fact that only '*cumulative number of forum mentions*' has a significant effect reveals that at least the qualitative forum posts have a significant effect on the sales of the items. The fact that the other qualitative and quantitative variables in this analysis do not carry a significant effect, reveals the confirmation of Hypothesis 1.

All control variables incorporated follow the expected direction, with the exception of '*seller Trust Level*' which seems to negatively impact the number of sales on AlphaBay.

Table 2 also displays the results of the regression-analysis for Hypothesis 2. The incorporated variables seem to have a significant effect on the prices per gram of the items ($R^2=0,281$; $F=(9, 1642)=53,475$; $p<0,001$). Assessing the effect of qualitative and quantitative feedback on the prices per gram of the items, all three independent variables are seen to have a significant effect on these prices. The largest effect size again stemmed from '*cumulative number of forum mentions*' ($b=-0,085$). This is a negative effect and so, this model predicts having more forum mentions on AlphaBay will lead to a decreasing price per gram. The effect sizes of '*cumulative number of seller feedback texts*' and '*cumulative number of seller feedback ratings*' (respectively $b=-0,035$ and $b=0,024$) are both smaller, however, still have significant effects. Remarkable is that both the qualitative measures of feedback have a negative effect on the prices of the items. When comparing these effect sizes, the variables considering qualitative feedback and forum posts ('*cumulative number of forum mentions*' and '*cumulative number of seller feedback texts*') both have a larger, significant effect size than the variable considering quantitative feedback ('*cumulative number of seller feedback ratings*'). These statistics, thus, provide support for Hypothesis 2; qualitative feedback and forum posts appear to have a larger influence on the prices of the items listed than quantitative feedback has. All control variables in this analysis follow the expected direction.

The output of the regression analysis regarding Hypothesis 3 are presented in Table 3 in Appendix A. Firstly, again a significant collective effect is found on the number of items sold ($R^2=0,059$; $F=(9, 1642)=8,619$; $p<0,001$). Here, the number of sales is again used as dependent variable of the analysis, of which positive polarity of forum posts and feedback was expected to have a positive effect on the sales of the items on AlphaBay. Assessing whether or not this effect occurred, reveals some interesting statistics. Firstly, in concordance with expectation, the effect size of '*cumulative number of positive forum mentions*' had the largest positive effect size ($b=0,070$; $p<0,051$) but was at the verge of significance. The variable '*cumulative number of positive feedback ratings*' in this analysis was also significant, however, had a smaller effect size ($b=0,004$; $p=0,041$). The cumulative number of forum posts and positive feedback ratings lead thus, as expected, to an increase in the items sold. Interestingly, converse to the expectation, the '*cumulative number of positive feedback texts*' was shown to have a negative, significant effect on the number of items sold ($b=-0,006$; $p=0,034$). This would entail that apparently, amassing positive feedback texts will lead to a reduction in the items sold in AlphaBay. These conflicting findings do not provide enough information to confirm Hypothesis 3. Almost all control variables follow the anticipated direction, however, '*seller trust level*' again seems to negatively impact the number of sales.

When analyzing Hypothesis 4, the same variables are used as when analyzing Hypothesis 3, however, the dependent variable in this analysis is '*price per gram*'. Again, a collective, significant effect is found influencing the dependent variable ($R^2=0,281$; $F=(9, 1642)=53,350$; $p<0,001$). Hypothesis 4 expected the prices per gram of the sold items to increase when vendors have received more positive feedback and forum posts. The results of this regression analysis are displayed in Table 3, in Appendix A. Table 3 reveals that the negative effect of '*the cumulative number of positive feedback texts*' on the prices per gram of the sold products is the largest, however is not significant ($b=-0,029$; $p=0,060$). This finding contradicts Hypothesis 3, which predicted a price increase to follow from having more positive feedback and forum posts. Other findings in this model do follow the expectation set by Hypothesis 3. The '*cumulative number of positive feedback ratings*' is found to have a positive, significant effect on the prices per gram ($b=0,021$; $p=0,055/2=0,0275$). The variable '*cumulative number of positive forum mentions*' was found to have a negative effect on the prices per gram of the items, however, this was not significant ($b=-0,218$; $p=1-0,250/2=0,875$). Therefore, following

the conflicting findings in this model, Hypothesis 4 cannot be confirmed. All control variables incorporated in the analysis of Hypothesis 4 again follow the anticipated direction.

Finally, the results of the regression analysis performed to weigh Hypothesis 5 and 6 are displayed in Table 4. Following Hypothesis 5, one would expect the nonpositive feedback and forum posts to have a larger, significant effect size than positive feedback and forum posts would have on the sales of a vendor on AlphaBay. Again, a significant collective effect is found on the number of items sold ($R^2=0,057$; $F=(9, 1642)=9,002$; $p<0,001$). Visible in Table 4 in Appendix A, only one independent variable is seen to have a significant effect. This variable is, as Hypothesis 4 would predict, the '*nonpositive qualitative texts*' ($b=0,020$; $p=0,001$). This would entail that nonpositive feedback texts and forum posts have a larger positive effect on the sales of the items, when compared with positive feedback texts and forum posts, which may seem counterintuitive. Positive feedback texts and forum posts did not have a significant effect on the sales of the items on AlphaBay ($p=0,130$), and thus, following these statistics, Hypothesis 5 can be confirmed. Again, all control variables follow the expected direction, with the exception of '*seller vendor level*', which again is seen to negatively affect the number of sales.

Hypothesis 6 predicted nonpositive feedback and forum posts to also have a greater effect on the prices of the items sold on AlphaBay. A significant collective effect of the model is again found ($R^2=0,279$; $F=(11, 1643)=57,806$; $p<0,001$). As was the case with the results of Hypothesis 4, the results of Hypothesis 5, displayed in Table 4 reveals a single significant variable. Again, '*nonpositive qualitative texts*' ($b=-0, 078$; $p=0,011$) is the only independent variable carrying a significant effect on the item price per gram, which is also negative. This would entail that nonpositive feedback texts and forum posts would have a detrimental effect on the prices per gram of the items listed on AlphaBay. Positive feedback and forum posts were not seen to carry any significant influence on the prices per gram, and so, Hypothesis 6 can be confirmed as well. All control variables in the model analyzing Hypothesis 6 follow the anticipated direction as well.

Conclusion & Discussion

Better understanding the effects of both qualitative and quantitative feedback and forum posts on the sales and prices of items sold on cryptomarkets is a relevant question, with implications for both the scientific community, as well as law-enforcement. The aim of this

thesis was to identify in which way the polarity of the forum posts and feedback left on cryptomarket AlphaBay affected the selling performance of the vendors there. Previous research regarding the effect of quantitative feedback on the sales and prices items sold online argues for a linear effect on online sales, where positive feedback was seen to positively affect the number of online sales, and negative feedback was seen to negatively influence the sales (Jiao, Przepiorka, & Buskens, 2020; Ye, Li, Kiang, & Wu, 2009; Lee, Im, & Jun Lee, 2009). Qualitative feedback texts were found to have a greater influence on the credibility of a seller, and in turn, his market performance, than numerical ratings were found to have (Pavlou & Dimoka, 2006). Past research has also established the relation between feedback text sentiments and selling prices. Positive polarity of feedback texts was seen to have a linear effect on the sales and prices of items sold (Hu, Koh, & Reddy, 2014; Shin, Hanssens, & Gajula, 2008). This thesis assessed whether these effects which have been observed for the most part in conventional legal markets, are also observed in the more unregulated cryptomarkets.

Finally, preceding research predicted the effect of nonpositive, qualitative feedback on online sales and prices to be greater than the effect of positive, qualitative feedback (Chevalier & Mayzlin, 2006; Shin, Hanssens, & Gajula, 2008; Standifirt, 2000). By performing several Linear Multiple Regressions, the effect of both quantitative, as well as qualitative feedback on the sales and prices on cryptomarket AlphaBay were assessed. The dataset used consisted of information on items posted by sellers on cryptomarket AlphaBay, scraped from the website in June and July of 2017. The findings mostly support past research. As predicted, qualitative feedback had a greater influence on the number of sales and prices of the items, when compared with quantitative feedback. The linear effect of positive feedback and forum posts on the sales and prices predicted by past research was not observed. Nonetheless, the differential effects of positive and nonpositive qualitative feedback predicted by earlier research, were observed in the results. Nonpositive feedback was shown to have a significant effect on the number of sales, as well as the prices, whereas this significant effect of positive feedback was not observed.

The results obtained mostly support previous research. Qualitative feedback is seen to have a greater influence than quantitative feedback has, likewise, the effect nonpositive feedback on the number of sales and prices is seen to be greater than that of positive feedback. However, this effect of nonpositive feedback texts and forum posts is in the opposite direction of what preceding research would expect. Nonpositive feedback is seen to have a positive

effect on the number of sales, which would entail that having received more nonpositive feedback and forum mentions would lead to an increased seller performance. The, by previous research predicted, linear effect of positive feedback and forum posts on sales and prices was also not observed.

Some remarkable results have been obtained. When assessing Hypothesis 1, it was expected that both the qualitative feedback as well as the qualitative forum posts would have a significantly larger effect on the dependent variable. However, only a significant effect was found for qualitative forum posts, whereas a significant effect of the qualitative feedback did not arise. This entails that, apparently, not all qualitative sources of information have the same effect on the sales of the items on AlphaBay. This could be due to the (more) voluntary nature of forum posts. When completing a transaction on AlphaBay, users are presented with the option of leaving a rating (quantitative feedback), after which an optional text message could be written in support of this rating (qualitative feedback). A forum post, however, is posted on the forum of the cryptomarket, and does not require a completed transaction. These forum posts are posted as a result of the initiative of the users themselves. This initiative might be the reason the qualitative forum posts do carry a significant positive effect on the number of sold items, as opposed to the qualitative feedback. Users might place more value on this initiative, as compared to feedback given only when presented with the option to.

In analyzing Hypothesis 2, both of the variables for qualitative feedback were seen to have had a negative effect on the prices per gram of the items, whereas quantitative feedback is found to positively affect the prices per gram of the sold items. The effect sizes (displayed in Table 2) of these variables were as expected, as qualitative feedback texts and forum posts were both seen to have a larger, significant effect size than the quantitative ratings had. Why then, does receiving quantitative feedback lead to a price per gram increase in the sold products, while receiving qualitative feedback would lead to price decreasing? This could be explained by the way AlphaBay monitors feedback left on its sellers. On AlphaBay, positive ratings could not be removed per the sellers' request, whereas negative ratings could (Macanovic & Przepiorka, 2021). Accordingly, some users, in order to express their dissatisfaction, would rate an item 5-stars, however, would leave negative textual feedback, so that this negative textual feedback could not be removed. To better chart these different effects of qualitative and quantitative information on the prices of items sold on cryptomarkets, further research is needed.

The analysis of Hypothesis 3 has revealed another noteworthy effect. Positive forum posts were found to have a significant, negative effect on the number of sales on AlphaBay. This would entail that a seller is expected to have fewer sales once he is more often positively mentioned in a forum post. Before exploring explanations for this counterintuitive effect, it must be noted again that the low R^2 of the models covering the number of sales of the items on AlphaBay might play a role here. It remains to be seen if this effect also occurs in future research, using a regression model with more explanatory power.

Another remarkable finding is that of the unexpected effect of the control variable covering the sellers Trust Level. In the models concerning the number of sales of the items, (Hypotheses 1, 3 & 5) '*sellers Trust level*' is consistently found to negatively impact the number of sales. Trust Level is supposed to indicate the trustworthiness of a seller. Having a higher Trust Level would entail a seller was more trustworthy, which would, in turn, translate into more sales (Kalberg, 2017). In these analyses however, the opposite effect is observed. Having a higher Trust Level, thus, following the models covering the number of sales on AlphaBay, leads to having a smaller number of sales. Again, the models concerning the number of sales of items on AlphaBay had a relatively low R^2 , so drawn conclusions on the basis of the found effects in these models might be premature.

It is important to note that the findings of this thesis might not be immediately applicable to other illegal online markets. The dataset used in this research consisted of information collected only on the cryptomarket AlphaBay. Therefore, it might be possible that the effects observed here are unique to AlphaBay. This could seem unlikely, as many of the results seem to support preceding research, however, not all results provide support. Text sentiments in this thesis are only gaged on the basis of text polarity, whereas preceding work has measured text sentiment on the basis of text polarity, in combination with emotionality, and subjectivity. In the dataset obtained, all variables were, at the least, coded for text polarity, therefore, in order to 'weigh' all text equally, the decision has been made to utilize text polarity as an indicator for text sentiment. Another possible limitation of this research is the relatively low explained variance found in the models with regard to the number of sales of the sellers (Hypotheses 1,3 & 5). The maximum R^2 achieved in these models was 6.1%, which indicates that other, unforeseen variables might have a larger effect on the number of sales than initially expected. The explained variance of the models covering the prices per gram of the items was found to be substantially higher, with a maximum of 28,1%. These

models thus encompass more of the variables affecting the prices per gram of the sold items, yet, these models can still be improved upon.

When evaluating the research question “How does the polarity of forum posts on a vendor on cryptomarket AlphaBay affect their sales and prices?” this thesis has partly provided answers, yet, has revealed some others. Why the models concerning the number of sales have a relatively low R^2 is one of these questions. What other unforeseen variables carry substantially more explaining power with regard to the number of sales? Seeing as the R^2 of the models covering the prices per gram is not exceptionally high as well, the same question could be asked with regard to the prices per gram of the items sold. What other unforeseen variables would better explain the prices per gram of the items sold on AlphaBay? The absence of the expected linear effects of positive feedback and forum posts on the number of sales and the prices of the items sold on AlphaBay provides another challenge. Is this absence a result of the illegal nature of the cryptomarkets? Or is this a result of other, unobserved variables or mechanisms affecting the prices on cryptomarket AlphaBay? Finally, why is the Trust Level of a seller negatively correlated with his number of sales, when Trust Level is supposed to be an indicator of the trustworthiness of this seller (Kalberg, 2017)?

Answering these questions could equip the scientific community and law-enforcement alike, with knowledge needed to better understand the cryptomarkets, and the mechanisms prevalent within illegal online markets. This research reveals that not all factors and mechanisms that influence seller performance present in conventional, legal markets, are equally present in online, illegal cryptomarkets. Qualitative feedback is seen to be of significantly more effect on the sales and prices of the items sold on AlphaBay, when compared with quantitative feedback. The, in the legal markets observed, linear effect of positive feedback on sales and prices remained absent when assessed on AlphaBay. Nonpositive feedback, however, was seen to affect the sales and prices in AlphaBay significantly more than positive feedback did. Future research should consider the differential effects of qualitative feedback texts and qualitative form posts, to assess whether or not users do in fact place more value on the forum posts due to their voluntary nature. Following the explained variance in the models covering the number of sales, future research should further explore what variables carry more explanatory power with regards to the number of sales. The counterintuitive effects of the seller Trust Level, which has been used as a control variable in this thesis, might prove to be another legitimate area for future research.

Literature:

- Afilipoaie, A., & Shortis, P. (2015, January). *GDPO Situation Analysis*. Global Drug Policy Observatory. <https://www.swansea.ac.uk/gdpo>
- Armstrong, H., & Forde, P. (2003). Internet anonymity practices in computer crime. *Information Management & Computer Security*, 11(5), 209–215. <https://doi.org/10.1108/09685220310500117>
- Barratt, M., & Aldridge, J. (2016, September 2). *Explainer: what are drug cryptomarkets?* UNSW Newsroom. <https://newsroom.unsw.edu.au/news/health/explainer-what-are-drug-cryptomarkets#:~:text=Silk%20Road%20was%20the%20first,single%2Dvendor%20markets%20are%20included>
- Barratt, M. J., & Aldridge, J. (2016). Everything you always wanted to know about drug cryptomarkets* (*but were afraid to ask). *International Journal of Drug Policy*, 35, 1–6. <https://doi.org/10.1016/j.drugpo.2016.07.005>
- Beckert, J. (2009). The social order of markets. *Theory and Society*, 38(3), 245-269. Retrieved June 13, 2021, from <http://www.jstor.org/stable/40587527>
- Branwen, G. (2013, October 30). *Darknet Market mortality risks*. GWERN. <https://www.gwern.net/DNM-survival>
- Butler, G. (2021, January 19). *2 Sentences and an Exit Scam: It's Been a Big Week on the Dark Web*. VICE. <https://www.vice.com/en/article/z3vgbj/big-week-on-the-dark-web-yellow-brick-market>
- Chertoff, M. (2017). A public policy perspective of the Dark Web. *Journal of Cyber Policy*, 2(1), 26–38. <https://doi.org/10.1080/23738871.2017.1298643>
- Chevalier, J. A., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*, 43(3), 345–354. <https://doi.org/10.1509/jmkr.43.3.345>
- Cimpanu, C. (2017, July 14). AlphaBay Dark Web Market Taken Down After Law Enforcement Raids. BleepingComputer. <https://www.bleepingcomputer.com/news/security/alphabay-dark-web-market-taken-down-after-law-enforcement-raids/>
- Décary-Héту, D., Paquet-Clouston, M., & Aldridge, J. (2016). Going international? Risk taking by cryptomarket drug vendors. *International Journal of Drug Policy*, 35, 69–76. <https://doi.org/10.1016/j.drugpo.2016.06.003>

- Diekmann, A., & Przepiorka, W. (2019). Trust and Reputation in Markets. *The Oxford Handbook of Gossip and Reputation*, 381–400.
<https://doi.org/10.1093/oxfordhb/9780190494087.013.20>
- Europol. (2021, January 12). *DarkMarket: world's largest illegal dark web marketplace taken down*. <https://www.europol.europa.eu/newsroom/news/darkmarket-worlds-largest-illegal-dark-web-marketplace-taken-down>
- Friedman, E. J., & Resnick, P. (2001). The Social Cost of Cheap Pseudonyms. *Journal of Economics Management Strategy*, 10(2), 173–199. <https://doi.org/10.1111/j.1430-9134.2001.00173.x>
- Hout, M. C. V., & Bingham, T. (2013). ‘Surfing the Silk Road’: A study of users’ experiences. *International Journal of Drug Policy*, 24(6), 524–529.
<https://doi.org/10.1016/j.drugpo.2013.08.011>
- Hu, N., Koh, N. S., & Reddy, S. K. (2014). Ratings lead you to the product, reviews help you clinch it? The mediating role of online review sentiments on product sales. *Decision Support Systems*, 57, 42–53. <https://doi.org/10.1016/j.dss.2013.07.009>
- Jiao, R., Przepiorka, W., & Buskens, V. (2021). Reputation effects in peer-to-peer online markets: A meta-analysis*. *Social Science Research*, 95,
<https://doi.org/10.1016/j.ssresearch.2020.102522>
- Kalberg, A. H. (2017, September). *An Endeavour in the Domain of Cybercrime: Exploring the Structural and Cultural Features of the Darknet Market AlphaBay* (Master thesis). Oslo: Grafisk Senter. <http://urn.nb.no/URN:NBN:no-61917>
- Lee, Z., Im, I., & Lee, S. J. (2006). The effect of buyer feedback scores on internet auction prices. *Journal of Organizational Computing and Electronic Commerce*, 16(1), 51–64.
<https://doi.org/10.1080/10919390609540290>
- Macanovic, A., & Przepiorka, W. (in press). The Moral Foundations of Immoral Markets: Text Mining Feedbacks on Economic Exchanges in the Darknet. *Utrecht University*.
- Norbutas, L. (2020, March). *Trust on the dark web: An analysis of illegal online drug markets* (Dissertation). Utrecht University. <https://doi.org/10.33540/189>
- Norbutas, L., Ruiter, S., & Corten, R. (2020). Reputation transferability across contexts: Maintaining cooperation among anonymous cryptomarket actors when moving between markets. *International Journal of Drug Policy*, 76,
<https://doi.org/10.1016/j.drugpo.2019.102635>

- Pavlou, P. A., & Dimoka, A. (2006). The Nature and Role of Feedback Text Comments in Online Marketplaces: Implications for Trust Building, Price Premiums, and Seller Differentiation. *Information Systems Research*, 17(4), 392–414.
<https://doi.org/10.1287/isre.1060.0106>
- Przepiorka, W., & Berger, J. (2017). Signaling Theory Evolving: Signals and Signs of Trustworthiness in Social Exchange. *Social Dilemmas, Institutions, and the Evolution of Cooperation*, 373–392. <https://doi.org/10.1515/9783110472974-018>
- Shin, H. S., Gajula, B., & Hanssens, D. (in press). Positive vs. Negative Online Buzz as Leading Indicators of Daily Price Fluctuation. *Anderson School of Business, UCLA*.
- Standifird, S. S. (2001). Reputation and e-commerce: eBay auctions and the asymmetrical impact of positive and negative ratings. *Journal of Management*, 27(3), 279–295.
<https://doi.org/10.1177/014920630102700304>
- Statt, N. (2017, July 15). *Dark Web drug marketplace AlphaBay was shut down by law enforcement*. The Verge. <https://www.theverge.com/2017/7/14/15975140/alphabay-dark-web-drug-marketplace-police-shutdown-silk-road>
- Wilson, T., Wiebe, J., & Hoffman, P. (2005). Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. *Proceedings of Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing*, 347–354.
- Winstock, A. R. (2020, May 15). *Global Drug Survey 2019*. Global Drug Survey.
<https://www.globaldrugsurvey.com/wp-content/themes/globaldrugsurvey/results/GDS2019-Exec-Summary.pdf>
- Ye, Q., Li, Y., Kiang, M., & Wu, W. (2009). The Impact of Seller Reputation on the Performance of online sales. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, 40(1), 12–19. <https://doi.org/10.1145/1496930.1496935>

Appendix A: Tables

Table 2: Coefficients regression Hypothesis 1 & 2 (N=1655)

<i>Independent Variables</i>	<i>Sales</i>		<i>Prices</i>	
	b	SE.	b	SE.
'cml # seller feedback texts'	-0,003	0,003	-0,035*	0,014
'cml # seller feedback ratings'	0,003	0,002	0,024*	0,011
'cml # of forum mentions'	0,022**	0,008	-0,085*	0,041
Control Variables	-	-	-	-
'item's weight in grams'	-0,002	0,001	-0,020**	0,006
'sellers vendor level'	0,559**	0,183	2,371*	0,967
'sellers trust level'	-1,193***	0,337	0,539	1,777
'days item was online'	0,165***	0,035	-0,263*	0,131
'price category "medium"'	0,872	0,654	49,927***	3,450
'price category "high"'	2,644**	0,916	108,303***	4,835
'shipping category "international"'	0,432	0,718	-11,430**	3,789
'shipping category "regional"'	0,258	0,842	-3,723	4,440
'shipping category "unknown"'	-2,101*	0,927	-17,893***	4,891
R²	0,056		0,281	

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

Table 3: Coefficients regression Hypothesis 3 & 4 (N=1655)

<i>Independent Variables</i>	<i>Sales</i>		<i>Prices</i>	
	b	SE.	b	SE.
'cml # of positive forum mentions'	0,070	0,036	-0,218	0,189
'cml # of positive feedback ratings'	0,004*	0,002	0,021	0,011
'cml # of positive feedback texts'	-0,006*	0,003	-0,029	0,015
Control Variables	-	-	-	-
'item's weight in grams'	-0,002*	0,001	-0,02**	0,007
'sellers vendor level'	0,454*	0,186	2,584**	0,986
'sellers trust level'	-1,259***	0,339	0,658	1,793
'days item was online'	0,165***	0,025	-0,263*	0,131
'price category "medium"'	0,819	0,653	50,02***	3,452
'price category "high"'	2,564**	0,915	108,462***	4,84
'shipping category "international"'	0,246	0,719	-10,989*	3,802
'shipping category "regional"'	0,192	0,844	-3,433	4,463
'shipping category "unknown"'	-2,413**	0,936	-17,259***	4,953
'nonpositive qualitative feedback''	0,012	0,007	-0,054	0,037
R²	0,061		0,281	

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

Table 4: Coefficients regression Hypothesis 5 & 6 (N=1655)

Independent Variables	<i>Sales</i>		<i>Prices</i>	
	b	SE.	b	SE.
'positive qualitative texts'	-0,001	0,001	0,002	0,003
'nonpositive qualitative texts'	0,020***	0,006	-0,078*	0,031
Control Variables	-	-	-	-
'item's weight in grams'	-0,003*	0,001	-0,021***	0,006
'sellers vendor level'	0,499**	0,186	2,771**	0,981
'sellers trust level'	-1,227***	0,337	1,199	1,780
'days item was online'	0,165***	0,025	-0,268*	0,131
'price category "medium"'	0,776	0,653	49,701***	3,453
'price category "high"'	2,417**	0,915	108,104***	4,836
'shipping category "international"'	0,414	0,717	-10,641**	3,791
'shipping category "regional"'	0,481	0,833	-4,242	4,405
'shipping category "unknown"'	-2,398*	0,937	-16,693**	4,952
R²	0,057		0,279	

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