The Effect of Feedback-Texts on the Sellers Performance on the Crypto Market

A Thesis in the Sociology bachelor's program of Utrecht University in the research group of Wojtek Przepiorka.

Utrecht University

Author: Pim P.M. Bakker

Student ID: 5991110

Supervisor: Dr. Wojtek Przepiorka

Coordinator: Prof. dr. Ineke Maas

Date of Submission: 14 June 2021

Location: Utrecht

Abstract

Collaboration and trust in humans still pose significant questions for social and behavioural sciences. Reputation systems where individuals can share information about others with different motives have been found to promote cooperation and trust. However, these findings mainly were researched on legal, regulated markets. For illegal online crypto markets outside governmental regulation, there is not much known. Illegal crypto markets are online marketplaces on the dark that are only accessible through a so-called Tor, which conceals users' location and identity. The encrypted technology on these illegal online crypto markets makes it almost impossible for law enforcement to get involved in these market exchanges. Using a unique dataset of a closed down crypto market called Silk Road, which sold illegal drugs, I reconducted research of Przepiorka, Norbutas, and Corten (2017) to see if I get the same results. I found similar results which proved that sellers with a better rating charge higher prices and sell their product faster than a seller with a bad or no rating history. Hence reputation systems create real incentives for cooperative behaviour among anonymous actors without law enforcement. Also, I added new variables to the previous research, which showed that moral norms affect reputation systems and sellers' performance. Moral norms play an essential role in trust and cooperative behaviour.

Keywords: reputation systems, illegal markets, moral norms, crypto markets, online markets, trust

Introduction

The internet has significantly expanded over the past 20 years (Răzvan, 2019). With this growth, the number of online markets has grown enormous, offering numerous chances to buy and sell items online. Online markets such as eBay, Amazon and Bol have had an increasing amount of buyers and sellers over the past decade (Haucap, Heimeshoff, 2014; Lubbers, 2013). eBay, Amazon and Bol are online platforms where buyers and sellers meet; these meetings can take place between a business to a customer or between customer to customer. These platforms guarantee a refund or a new item when the customer is not satisfied with the purchased item. Generally, these refunds last for up to 30 days after purchasing a particular good (Winn, 2016). Unfortunately, the rapid growth of the internet also opened up opportunities for illegal markets. These illegal crypto markets operate on the darknet, and it is impossible to access the darknet through regular search machines. These markets are only accessible through the use of a Tor. A Tor browser routes web page requests through a series of proxy servers operated by thousands of volunteers worldwide, rendering an IP address that makes IP address untraceable and unidentifiable (Jadoon et al. 2019).

On the dark web, everyone can purchase all types of illegal goods ranging from weapons, drugs to credentials and illegal porn. In the form of feedback, reputation systems effectively sustain cooperation in these illegal online markets. These reputation systems collect information about the illegal transaction once a buyer has bought something from a seller. After the trade, they can submit an evaluation to the marketplace through a detailed description or a rating scale. Transactions on illegal platforms are fully anonymize since they can use Crypto-currencies (such as Bitcoins) and by the use of pseudonyms. These markets do not benefit from legal protection as in the Clearnet marketplaces such as eBay, Bol and Amazon. Previous research showed that reputation systems enable sellers to successfully show their trustworthiness and reliability (Przepiorka and Berger, 2017; Resnick and Zeckhauser, 2002) while simultaneously affecting their business success regarding the number of sales and prices (Jiao, Przepiorka, and Buskens, 2021). The reputation system also showed their success on the illegal online market, also known as crypto markets which operate on the darknet (Norbutas, Ruiter, and Corten, 2020; Przepiorka, Norbutas, and Corten, 2017).Since crypto markets are tough to access and illegal, scientists have not researched them a lot.

There is no need for social institutions to control the market, according to previous studies. A reputation creates a framework that incentivizes sellers to deliver quality service to buyers despite the absence of law enforcement and the anonymity of the buyers (Hardy & Norgaard, 2016). For reputations systems, quantitative feedback that buyers leave is vital to sustain. That quantitative feedback provides factual information of the seller and can use by future buyers to, e.g. assess someone's trustworthiness, product quality, delivery time. Positive quantitative feedback leads to a positive reputation, and negative feedback vice versa.

While the known research assumes that market participants read the feedback text (Chevalier & Mayzlin 2006), there is almost no information on the impact of sellers' textual evaluations and their reputation in illegal online markets. There are different reasons to leave feedback; it could be an emotional basis, inform other buyers, punish or reward the seller or follow what others do. (Diekmann et al. 2014; Hennig-Thurau et al. 2004; Picazo-Vela et al. 2010). There is not much known about how different feedback text affects the seller's prices, sales, and reputation.

This study will research whether and how the feedback text "help other buyers" written with a positive or negative motive in mind affects sellers' performances. First, this paper will further elaborate on different illegal markets and the presence of a reputation system. After, this study will explain the role of moral and immoral behaviour and give different hypotheses. Then I will reproduce the work of Przepiorka, Norbutas, and Corten (2017) to see if I get the same results. I will use a part of an existing behavioural, social science framework encompassing one primary cue: Helping other buyers (Macanovic & Przepiorka 2021). Afterwards, this information complements quantitative feedback information and measures the differences in the numbers of feedback texts regarding the described cue. To what extent does the motive of helping other buyers affect the performance of sellers on illegal markets?

Theory and hypotheses

This section develops an account of how the feedback motive "help other buyers" affects the seller's performance. Consistent with the general theorizing and social relevance, this review focuses on the negative and the positive feedback of illegal online markets and the judgement of others behaviours in domains around which there is consensus about what is moral and immoral, e.g. 'products not arriving or good quality. As explained below, the expectation is that more positive feedback based on the motive "help other buyers" significantly positively affects the seller's performance.

Reputation systems

Acquiring a good reputation is challenging; a good reputation allows sellers to charge their customers an extra fee, increasing sellers' incentive to increase their reputation to profit from this extra fee. Sellers can charge an extra fee because they have established themselves as trustworthy and reliable in a market with no legal rights. Customers are willing to pay additional for ensured quality and delivery. However, the seller first has to establish the reputation. The seller can do this by lowering its price or giving away freebies to compensate potential buyers for the risk buyers take when buying with unestablished sellers. So first, the seller must invest and maybe secure a loss before charging extra and earning back these costs (Hardy & Norgaard, 2016). This will lead to the reasoning that sellers with a better reputation can achieve higher prices because buyers are willing to pay more for established sellers with good reputations.

Legal and illegal markets

The argument that seller reputation affects product sales and selling price has been confirmed in more than two dozen studies (Diekmann et al., 2014). Building a good reputation is an important deterrent for sellers with fraudulent purposes; while the legal system of legal online markets deters fraud, it also promotes trust and cooperation.

In legal markets, there is primarily asymmetric information regarding the seller and the buyer (Akerlof, 1970; Coleman, 1990; Kollock, 1994). This asymmetry creates a trust problem if the buyer cannot access the same information as the seller. The trust problem is the uncertainty regarding the trustworthiness or the competence of the trustee that the trustor faces. Trustworthiness is the trustee his intention to meet the trustor his advance while simultaneously distinguish it from competence. Competence is the trustee's ability to meet the trustor's advance in regards to knowledge and skill. The definition of *trust* is the trustor's belief that the trustee is trustworthy or competent; based on that, the trustor decides whether to make the advance or not. An example is that a product will be delivered in an assured quantity, although the trustee can choose to deflect the agreement (Diekmann & Przepiorka, 2019).

There are several mechanisms in which legal markets counter these trust problems. For example, there are legal regulations regarding buying items. The customer has many legal rights that he can call upon, whereby he/she can get his money back (Hodgson, 2002). Usually, the market where a customer buys items already has a system in which the seller gets punished, and the buyer gets compensated when the quality does not match the description (Finer, Monchel & Jenkins, 2010). Finally, a social norm states that being a fraud/thief/swindler is not desirable. Being a fraud is not desirable because it could lead to fewer friends and a shameful life (Moore, 2016). A reputation system in online legal markets might work very well to promote trust and cooperation. In legal online markets, reputation systems may only function as a coordination device, making it easier for buyers to choose a seller when there are many sellers of the same product (Beckert, 2009; Przepiorka and Aksoy, 2017; Frey and van de Rijt, 2016). Reputation systems might fail in markets with no legal or moral assurances because they might give an insufficient safeguard for economic exchange.

These legal markets operate whereby the identity of the buyer and seller is known. There is a lot more anonymity in online crypto markets, which takes away the mechanisms in which a legal market ensures purchases (Wang, 2010). Also, there is no social norm and no legal regulation present. There are, however, two ways in which online crypto marketers try to ensure a purchase conducts fairly. First of all, there can be an escrow service that will withhold the transaction of the buyer. Once the buyer confirms receiving the order, the money transfers to the seller. This method is to protected buyers from fraud. However, there is mostly the possibility of 'finalizing early' in these illegal markets, which the seller could request. The buyer would then release the funds before receiving the order (Christin, 2013). The second way of protecting buyers from scammers is by the reputation system. A reputation is hard to obtain and risky to lose. The reputation system allows people to fill in a feedback form after a completed trade. New sellers must first build a reputation, and to do so, they can give away free samples or lower their prices (Friedman and Resnick 2001; Shapiro 1983). Still, established sellers with a good reputation can charge more for their product, compensating for their earlier investments. Thereby reputation systems could solve the problem of ensuring fair trades by trustworthiness and reliability (Przepiorka, Norbutas & Corten, 2017).

Reputation system in online markets

The results of previous studies show that a marketplace without the existence of government regulation can function exceptionally well. The feedback mechanisms that a reputation system provides allow an informal institutional framework within traders to exchange goods with trust (Milgrom, North & Weingast 1990). This marketplace demonstrates the change of institutional structure in which crypto markets react to new threats and technology. The role of reputation systems is compelling since the buyer's and seller's entire existence relies on it. To sell at a higher price once a seller has a good reputation makes the crypto market partly autonomous.

Reputation systems promote cooperation and trust in online markets without providers of legal guarantees, positive self-selection or verifiable identities. In legal markets, the reputation system mitigates the trust problem but does not entirely solve legal and moral assurances (Przepiorka, Norbutas, and Corten, 2017). The incentive to charge higher prices once a seller has obtained a good reputation solidifies the theory that reputation mechanisms contribute to maintaining crypto markets without legal systems.

The role of moral and immoral behaviour.

As stated above, illegal crypto markets do not have problems with legal institutional interfering with the trades. The crypto markets, such as AlphaBay, Hansa and Silkroad, are illegal markets based on reputation systems that rely on moral behaviour. This moral behaviour consists of leaving feedback for other buyers and sellers, not abuse the system by anonymity (selling items and not shipping the items) and fairly state your feedback. However, previous research shows that reputation systems provide helpful information and an incentive to behave in a trustworthy manner. People tend to behave in a moral way when there is a reputation at stake, but before someone gets a reputation, they can behave in an immoral way. Scamming and being immoral to other people is a risk a buyer is willing to take to buy the same good for a lower price (Macanovic & Przepiorka, 2021). These moral norms take place at the transactions stage and at the feedback stage of a purchase. In the transaction stage, moral norms play a role for the seller. The seller can choose not to ship the item or maybe deliver a poor quality product. At the feedback stage, moral norms take place in a different form. On the one hand, moral norms motivate the provision of important information. On the other hand, moral norms create biases in the trader's reputation. Around 13 % of buyers feedback tries to balance between not harming the seller's reputation and still informing others about potential risks. On top of that, moral norms motivate around 27 % of all feedback texts in survey crypto markets (Macanovic & Przepiorka, 2021).

Nevertheless, when a buyer gets scammed, he or she can let other people know through the feedback text of a particular seller—the same counts for a positive experience. When a buyer has a positive experience, he or she can reward the seller through positive feedback. Hence the role of morality has shifted from the transaction stage to the feedback stage; buyers leave feedback because of moral norms. There are different types of motives to leave feedback. It could be that people want to share emotions or warn other buyers. Sometimes buyers want to state an objective experience of what has happened, and other times people wanted to punish the seller (Hennig-Thurau et al.2004; Picazo-Vela et al. 2010). In this study, I recreate the work of Przepiorka & Norbutas & Corten (2017). The study of Przepiorka & Norbutas & Corten showed that reputation systems create incentives for cooperation while law enforcement is absent at a large scale on the crypto market.

I use one cue in my research, which Macanovic & Przepiorka (2021) also researched with two reasons to leave feedback. This paper research uses the cue "help other buyers", which can be positive or negative. An essential reason for using this cue is that this cue can be both positive or negative and does not hint towards a direction. The cue is negative when the buyer leaves feedback texts in which he does not give a 5-star, the maximum rating. This cue is used if the author addresses other buyers directly or indirectly. Talking to the buyers is direct if the author is talking to other buyers. Addressing indirect is when the author talks about the seller in the third person. Direct or indirect addressing other buyers must include a recommendation or warning regarding the seller and/or product. Examples of this are (E.g., "beware!" or "recommended). This cue bases on the extrinsic other-regarding motive category. Extrinsic other-regarding motives: other-regarding motives are motives for people considering other people's outcomes regarding benefits and costs. Extrinsic other-regarding motives can be material, psychological or both. Other regarding motives are extrinsic when group solidarity comes into place. Group solidarity means that shared purposes, responsibilities and interest unite members of a collective (Macanovic & Przepiorka 2021). Extrinsic factors come into play when the feedback gives information to actors whose outcomes depend on the author's feedback. Extrinsic motives do not depend on the expectations of others or sanctioning threats; they are equalized with moral norms (Bicchieri, 2006).

As stated above, I will elaborate on the work of Przepiorka & Norbutas & Corten (2017). I will conduct the same research with the same data set to check if I get the same results. After, I will add one cue from Macanovic & Przepiorka (2021) to see how the counteracting forces of moral norms inter with the reputation system and shed more light on the bias that comes with moral norms. Since the cue "help other buyers' is equalized with moral norms, this will give an in-depth insight into the role of moral norms in the crypto market. Well-reputed sellers benefit by increasing prices while also selling more goods over the same period (Przepiorka, Norbutas & Corten, 2017). Hence I argue that the more positive feedback of the cue "helping other buyers, the more buyers are willing to buy from that trusted seller. Based on the theoretical argument in this paragraph, I formulate the following hypotheses:

- *Hypothesis 1:*The higher the proportion of positive feedback motivated by, help other buyers, the better the seller's performance.
- *Hypothesis 2:* The higher the proportion of negative feedback motivated by, help other buyers, the worse the seller's performance.

Data

The data used in this paper relies on earlier collected data from Christin (2013). The data is from a publicly accessible tor network on the website Silk Road. It focuses only on the seller's account since buyers do not have a public buyers page. Stealth listings and sellers who operate in stealth are not collected. This data was collected using 'crawls' and recorded time stamps whenever a page is visited. A crawl collects data of users, items and category webpages. Crawls are used daily and approximately collects 244MB of data, of which 124 MB were images. The crawls averagely ran for about 14 hours and skipped pages that had not changed (Christin, 2013).

In this study, there are 24,385 items previous collected by Christin (2013) between February 3, 2012, and July 24, 2013. Not all drugs sold on Silk Road are sold in the same forms; LSD, for example, is sold in pills, blotter and power, whereby there is a variation in weight and subsentence concentration. Because of the different forms of drugs, calculating and comparing items at prices per gram is too tricky. Hence this study will use the same seven categories of illegal drugs used by Przepiorka, Norbutas & Corten (2017). This list contains the illegal drugs: Ketamine, Hash, Weed, Cocaine, Meth, MDMA and heroin. These items are chosen based on their sizes and the comparability of these items within each category. In total, these items account for 24.6% of all items listings (6005) and 37.3% of all feedback messages. There are also 211 items listed in the general categories "Drugs" and "Cannabis," the seven categories cover them. In total, there are 6216 items.

Of these 6216 items, 430 are left out because they have no information on weight or have weight information comparable to items of other categories (e.g. pre-rolled joints within the category ‘Weed’; the majority sells in grams). Also, there are 111 items included as a custom listing for a specific buyer or given away as freebies, samples or lotteries.

At last, there are 2522 (44.4%) items that received no feedback message while the crawls were active. Since feedback is the main subject, they are distracted. Hence the primary analyses are based on 3153 items sold by 445 different sellers.

Variables and Model Estimations

This paper elaborates on the work of Przepiorka, Norbatus and Corton (2017). I reconducted their research and used the same variables. A five-star rating is automatically awarded after a finished transaction; for these reasons, my approach provides an accurate estimation of the number of items sold. (Soska and Christin, 2015; Décary-hetu, Paquet-Clouston and Aldridge, 2016). This approach is in line with the work of Przepiorka, Norbatus and Corton (2017). The descriptive statistics show close to similar results but vary only at five-star ratings and non-five-star ratings. This is because there is no aggregation of the five-star and non-five-star ratings across the items not included in my analyses in this research.

To test hypotheses 1 and 2, I use a regression model with the dependent variable log-transformed item price per gram in US dollars. After I use the log-transformed number of sales per day in a regression model as the dependent variable, this is done because both variables measure the seller's performance.

The main explanatory variables are the amount of positive and negative feedback texts with the cue "help other buyers", which a seller has. The data set already provided variables containing the described cue's positive, neutral and negative feedback texts. As described in the theory section, I argue that a negative rating is anything lower than a 5-star rating which, is in this data set a 4-3-2-1 star rating. Neutral ratings in this data set are ratings between four, three, and two stars, and negative ratings are 1-star ratings; hence, I added the cue's neutral and negative feedback texts "help other buyers" together to create one new variable. This results in only positive and negative ratings. When this cue contained a five-star rating, it was used as positive feedback. In the theory and hypotheses section, the argumentation for using the cue "help other buyers" is presented and gives a more in-depth look at the cue itself.

As described above, all variables used in Przepiorka, Norbatus and Corton (2017) are used in this research; this also includes the same control and dummy variables. In Table 1, the descriptive statistics of the main variables are shown in my analyses.

As in the original paper, there is no information on the seller's rating before starting the data collection. Hence the reputation is measured by summing up the five-star ratings and non-five-star ratings these sellers received during the observation period. This results in data analysis at the item level whereby the seller's ratings are received by the time an item was first listed in the market as an indicator of the reputation. This allows my research to capture the change over time and see the effect of different feedback text left with the ratings given.

Table 1. The table lists descriptive statistics of the main variables used in the analyses.						
Variable name	*N*	*Mean*	SD	Median	Minimum	Maximum
Item sales and duration online			-			
# item sales	3153	21	59	5	1	1501
item online in days	3153	50.44	56.17	28	0.5	382
# item sales per day	3153	0.45	0.69	0.25	0.01	10.83
Seller ratings at time item was first seen						
# five-star ratings	3153	178.77	306.17	57	1	2601
# non-five-star ratings	3153	7.81	17.05	2	1	149
Low-price products (weed, hash)						
weight in g	2297	18.15	65.57	6	.25	1000
price in USD per gram	2297	15.5	7.3	14.61	1.46	115.8
Medium-price products (ketamine, MDMA, cocaine)						
weight in g	562	7.17	45	1	0.05	1000
price in USD per gram	562	92.26	57.52	80.58	8.41	464.1
High-price products (meth, heroin)						
weight in g	294	1.40	3.87	0.5	0.10	56
Price in USD per gram	294	217.6	140.4	173.8	33.72	992.8
Feedback texts with the cue “help other buyers”						
Positive feedback with the cue “help other buyers”	3153	18.65	31.81	6	0	310
Negative feedback with the cue “help other buyers’’	3153	1.65	3.97	0	0	28

Notes: The data comprise N =3153 items which generated 21 sales within 50 days on average. Only the items of which at least one transaction was recorded are used whereby each item has been calculated the number of 5-star ratings and non-five star ratings. An average seller has 148 five-star ratings and five non-five-star ratings. In this replication study all items are divided in three categories, low, medium and high prices just as in Wojtek 2017. For the low-price items (N=2297) weed and hash are compromised and sold for an average of 15,5 USD in average packages of 18 gram. For medium-price items (N=562) ketamine, cocaine and MDMA are compromised which are sold for an average of 92 USD per gram in numbers of 7gram. The last, the high-price items (N=294) compromise heroin and meth which are sold for an average of 218 USD per gram in average packages of 1g. Positive feedback with the cue help other buyers (N=3153) and negative feedback (N=3153) show that with the cue “help other buyers” positive reasoning occurs more often 18.65 than negative reasoning 1.65.

Results

Table 2 shows the regression model estimations without the seller fixed effects which Przepiorka, Norbutas & Corten in 2017 did add. The results are not the same but in line with the previous study (Przepiorka, Norbutas & Corten, 2017).

Looking at the table in model 1, the log number of five-star ratings is positive, and the coefficient of the log number of non-five-star ratings is negative. On top of that, these coefficients are statistically significant. These results are in line with results and provide support for the research of Przepiorka, Norbutas & Corten in 2017. When looking at model 2, we see the same results; the coefficients are the same as the results of the replicated study. The coefficient of the log number of five-star ratings is in the correct direction and is statistically significant. The log number of non-five-star ratings is also in a negative direction, which is statistically significant. Hence these results provide support for the previous study. All other results are in the same direction and are also statistical significant except for foreign shipment, unknown shipment and poor quality. Table two shows that in model 1, foreign shipment is statically significant while also being negative. Model 2 shows that poor quality is in a negative direction, which is in the previous work in a positive direction. At last, unknown shipment is, in contrasts with the previous work, statistical significant. These results are not in line with the research from Przepiorka, Norbutas & Corten.

Table 2. Regression models of item price and sales per day

Variable name	Log(item price per gram USD) M1	Log(# item sales per day) M2	Log(item price per gram USD) M3	Log(# item sales per day) M4
Const.	2.877***	0.429**	2.891***	0.454**
	(0.018)	(0.166)	(0.018)	(0.167)
Item variable				
Log(item price per gram in USD)		-0.641***		-0.643***
		(0.053)		(0.053)
Log (weight in gram)	-0.237***	-0.448***	-0.237***	-0.446***
	(0.005)	(0.018)	(0.005)	(0.018)
Low price	(reference)	(reference)	(reference)	(reference)
Medium price	1.460***	0.914***	1.459***	0.914***
	(0.018)	(0.095)	(0.018)	(0.095)
High price	2.150***	1.390***	2.141***	1.404***
	(0.024)	(0.136)	(0.024)	(0.136)
Poor quality (weed and hash)	-0.855***	-0.073	-0.857***	-0.081
	(0.05)	(0.161)	(0.05)	(0.161)
Last 2 days	0.047***	0.036	0.045**	0.038
	(0.015)	(0.046)	(0.015)	(0.046)
Seller variables				
Log(# five-star ratings +1)	0.098***	0.427***	0.031	0.328***
	(0.01)	(0.029)	(0.021)	(0.064)
Log(non-five-star ratings +1)	-0.132***	-0.571***	-0.155***	-0.396***
	(0.017)	(0.053)	(0.033)	(0.1)
Log(#item sales)	-0.068***		-0.068***	
	(0.006)		(0.006)	
Seller ships to				
Unknown	-0.022	-0.335***	-0.002	-0.325***
	(0.03)	(0.092)	(0.03)	(0.093)
Domestic only	(reference)	(reference)	(reference)	(reference)
Foreign	-0.085***	0.028	-0.082***	0.023
	(0.013)	(0.041)	(0.013)	(0.041)
Positive feedback with the cue “help other buyers”			0.114***	0.147
			(0.031)	(0.095)
Negative feedback with the cue “help other buyers’’			0.017	-0.302*
			(0.044)	(0.136)
N	3153	3153	3153	3153
Adjusted R^2	0.888	0.213	0.888	0.214

Notes: (***P < 0.001, **P<0.01, * P<0.05, for two sided tests) whereby the target variable in model M1 and M3 is the log-transformed item price per gram in USD. And in Model M2 and M4 is the log-transformed number of item sales per day. There is no account for the seller fixed effects. In model M3 and model M4 the researched cue is added to show the effect of ‘help other buyers’.

Comparing models 1 and 2 with models 3 and 4, we see that all variables have the same direction and statistical significance except for one variable. Log five-star rating is not statically significant in model three but is in the right direction. This log variable is not in line with the research from Przepiorka, Norbutas & Corten.

Table 2 also shows that positive feedback with the cue “help other buyers” is in the expected positive direction. Not all negative feedback is in the expected negative direction. Although not all directions are correct, in both model 3 and model 4, there is evidence for hypothesis one and hypothesis two. These findings are in line with the theory. If the number of positive feedback with the cue “help other buyers” goes up by a factor of 10, the item price per gram increases by 100 x [0.114 x ln(10)) -1] = 30 per cent. For model four, there is no statistical significance when looking at the positive effect on the sales per day. Hypothesis two, in return, does not find any statistical significance in the item price per gram. In model four, however, there is the statical significance of negative feedback on item sales per day. If the number of negative feedback with the cue “help other buyers” goes up by a factor of 3, item sales per day decrease by 100 x [-0.302 x ln(3)) -1] = -39.34 per cent. A possible answer for the insignificance and unexpected direction with negative feedback with the cue “help other buyers” in model three and the insignificance of positive feedback with the cue “help other buyers’’ in model four, could be that other variables are more important for the dependent variables or that other buyer do not react to the negative cue “help other buyers”.

Discussion

This study researched whether the higher the positive proportion of the cue "help other buyers", the better the seller's performance. This research uses a longitudinal data set of a primary crypto market for illegal goods, called 'Silk Road', to test both the positive and negative aspects of the above-described cue. Only one of seven cues of the data sets were used whereby the seller's performance was measured with the price per item sold and the item sales per day. The regression analyses show that having proportional, more positive ratings with the cue help other buyers; it does significantly increase the seller's performance. Also, having a proportional, more negative rating of the same cue significantly lowers the seller's performance. This study shows that moral norms in the feedback stage play an important role in the reputation system by influencing the seller’s performance.

Although not all findings are statistically significant, they are in line with the theory. Market places without the existence of government regulation can work exceptionally well. The feedback mechanisms are a working alternative for the absence of the law (Milgrom, North & Weingast 1990). All the researched variables are in the direction in which the theory suggests they would, e.g., positive feedback "help other buyers" is in a positive direction". Also, this paper shows that customers are willing to pay additional for ensured delivery and quality. This is in line with Hardy & Norgaard's paper written in 2016, whereby a seller first has to invest in their reputation before energising extra and earning back previously made costs. This research shows that without trust, cooperation never gets off the ground. Scamming and immoral behaviour are punished through feedback texts whereby sellers have to lower their prices to regain trust. Hence, this paper shows that trustworthiness and trust are essential for a market whereby legal law is absent (Gambetta 1990; Hardin 2002).

Typical surface web markets such as Bol, Amazon, and eBay have in common with crypto markets that sellers and buyers can meet, whereby there an overlap in fixed-price sales. Reputation effects for fixed-price transactions are found to be effective (Przepiorka, 2013). Hence this paper contributes to the existing literature about fixed prices and their effects.

At last, these findings contribute to the still unknown and shady crypto markets on the dark web. These findings give a better understanding of the crypto markets and how these crypto markets can function without a legal system. Mainly in regards to feedback texts, and the different functions of these texts are now more tangible. This paper contributes to a broader set of knowledge about illegal crypto markets.

If someone replicates or further investigates this topic, there are a couple of concepts to keep in mind. First of all, researching why and how the difference between different feedback text with the cues is still underexposed. This paper does not give a clear and structural answer to why there is no statistical significance for negative feedback on item price per gram and positive feedback on sales per day. Researching the difference between the positive and negative aspects of the cue “help other buyers” could be a logical next step. Conducting more research on this topic could give a more in-depth insight into markets without a legal system and how these markets can survive for an extended period. On top of that, a comparison could be made between different markets. In this paper, only the market Silk Road is investigated. Comparing other closed-up markets, e.g. Hanza market and AlphaBay, could confirm the findings of this research. Thereby a global and structural overview of illegal crypto markets could give more information on the method of these markets, which the police may even use to shut down illegal crypto markets.

References

Akerlof, George A. 1970. “The Market for ‘Lemons’: Quality Uncertainty and the Market Mechanism.” *The Quarterly Journal of Economics* 84(3):488–500.

Beckert, J. (2009). The social order of markets. Theory and Society, 38, 245–269.

Bicchieri, Cristina. 2006. *The Grammar of Society*. Cambridge: Cambridge University Press.

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.

Christin, N. (2013, May). Traveling the Silk Road: A measurement analysis of a large anonymous online marketplace. In *Proceedings of the 22nd international conference on World Wide Web* (pp. 213-224).

Coleman, James S. 1990. *Foundations of Social Theory*. Cambridge, MA: Harward University Press.

Décary-Hétu, D., Paquet-Clouston, M., & Aldridge, J. (2016). Going international? Risk taking by cryptomarket drug vendors. *International Journal of Drug Policy*, *35*, 69-76.

Diekmann, A. et al. (2014). Reputation formation and the evolution of cooperation in anonymous online markets. American Sociological Review, 79, 65–85.

Diekmann, A., & Przepiorka, W. (2019). Trust and reputation in markets. In *The Oxford handbook of gossip and reputation* (pp. 383-400). Oxford: Oxford University Press.

Finer, M., Moncel, R., & Jenkins, C. N. (2010). Leaving the oil under the Amazon: Ecuador's Yasuní-ITT Initiative. *Biotropica*, *42*(1), 63-66.

Frey, V. and van de Rijt, A. (2016). Arbitrary inequality in repu- tation systems. Scientific Reports, 6, 38304.

Friedman, Eric J., and Paul Resnick. 2001. “The Social Cost of Cheap Pseudonyms.” *Journal of Economics & Management Strategy* 10(2):173–99.

Gambetta, Diego. 1990. Trust Making and Breaking Cooperative Relations. Oxford, UK: Blackwell.

Hardin, R. (2002). *Trust and trustworthiness*. Russell Sage Foundation.

Hardy, R. A., & Norgaard, J. R. (2016). Reputation in the Internet black market: an empirical and theoretical analysis of the Deep Web. *Journal of Institutional Economics*, *12*(3), 515-539.

Haucap, J., & Heimeshoff, U. (2014). Google, Facebook, Amazon, eBay: Is the Internet driving competition or market monopolization?. *International Economics and Economic Policy*, *11*(1), 49-61.

Hennig-Thurau, Thorsten, Kevin P. Gwinner, Gianfranco Walsh, and Dwayne D. Gremler. 2004. “Electronic Word-of-Mouth via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on the Internet?” *Journal of Interactive Marketing* 18(1):38–52.

Hodgson, G. M. (2002). The legal nature of the firm and the myth of the firm-market hybrid. *International Journal of the Economics of Business*, *9*(1), 37-60.

Jadoon, A. K., Iqbal, W., Amjad, M. F., Afzal, H., & Bangash, Y. A. (2019). Forensic analysis of Tor browser: a case study for privacy and anonymity on the web. *Forensic science international*, *299*, 59-73.

Jiao, R., Przepiorka, W., & Buskens, V. (2021). Reputation effects in peer-to-peer online markets: A meta-analysis∗. *Social Science Research*, 102522.

Kollock, Peter. 1994. “The Emergence of Exchange Structures: An Experimental Study of Uncertainty, Commitment, and Trust.” *American Journal of Sociology* 100(2):313–45.

Lubbers, L. (2013). *Operational data quality: A case study about the quality of net purchase prices in the catalog of bol. com*(Master's thesis, University of Twente).

Macanovic, A., Przepiorka, W. (2021). The Moral Foundations of Immoral Markets: Text Mining Feedbacks on Economic Exchanges in the Darknet* Unpublished manuscript, The Netherlands: Department of Sociology/ICS, Utrecht University.

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

Moore, A. (2016). Shame on you: The role of shame, disgust and humiliation in media representations of ‘gender-fraud’cases. *Sociological Research Online*, *21*(2), 118-135.

Norbutas, Lukas, Stijn Ruiter, and Rense Corten. 2020. “Believe It When You See It: Dyadic Embeddedness and Reputation Effects on Trust in Cryptomarkets for Illegal Drugs.” *Social Networks* 63:150–61.

Picazo-Vela, Sergio, Shih Yung Chou, Arlyn J. Melcher, and John M. Pearson. 2010. “Why Provide an Online Review? An Extended Theory of Planned Behavior and the Role of Big-Five Personality Traits.” *Computers in Human Behavior* 26(4):685–96.

Przepiorka, W. and Aksoy, O. (2017). Social Order in Online Markets and the ‘Collapse’ of Institutions. Unpublished manuscript, The Netherlands: Department of Sociology/ICS, Utrecht University.

Przepiorka, W., & Berger, J. (2017). Signalling theory evolving: signals and signs of trustworthiness in social exchange. *Social Dilemmas, Institutions and the Evolution of Cooperation. Berlin: De Gruyter Oldenbourg*, 373-392.

Przepiorka, W., Norbutas, L., & Corten, R. (2017). Order without law: Reputation promotes cooperation in a cryptomarket for illegal drugs. *European Sociological Review*, *33*(6), 752-764.

Răzvan, Ș. (2019). Several contemporary economy features, consequences of internet expansion and ict innovations in the world. *Studies in Business and Economics*, *14*(3), 175-181.

Resnick, P., & Zeckhauser, R. (2002). Trust among strangers in Internet transactions: Empirical analysis of eBay's reputation system. In *The Economics of the Internet and E-commerce*. Emerald Group Publishing Limited.

Shapiro, Carl. 1983. "Premiums for High Quality Products as Returns to Reputations." *The Quarterly Journal of Economics* 98(4):659–80.

Soska, K., & Christin, N. (2015). Measuring the longitudinal evolution of the online anonymous marketplace ecosystem. In *24th {USENIX} security symposium ({USENIX} security 15)* (pp. 33-48).

Wang, Z. (2010). Anonymity, social image, and the competition for volunteers: a case study of the online market for reviews. *The BE Journal of Economic Analysis & Policy*, *10*(1).

Winn, J. K. (2016). The secession of the successful: The rise of Amazon as private global consumer protection regulator. *Ariz. L. Rev.*, *58*, i.