

**Trust and cooperation without governmental supervision: The influence
feedback text polarity has on item sales in an illegal online marketplace.**

Written by:

Karel van Dijck (5543401)

Supervised by:

Wojtek Przepiorka

Date:

07-06-2021

Type of document:

Bachelor thesis

Abstract

From the marketplaces of ancient Rome until the modern day era of online shopping reputation systems have always been crucial in promoting trade and creating trust. Newly created anonymous and illegal online marketplaces have given rise to a new dimension of these reputation systems. Customers have to put their trust in an anonymous seller without any governmental supervision or functioning system of law. One of the most used illegal online market places named SilkRoad will be subject of this research. With a newly coded dataset the effect of written feedback texts can be researched for the first time on this platform. By looking at written reviews on SilkRoad and specifically the effect these reviews have on sales more information about the functioning of reputation systems in illegal online market places will be obtained.

Keywords

SilkRoad; Reputation system; Feedback text polarity; crypto market

1. Introduction

Reputation systems have been used and proven to be successful in promoting trade and therefore successfully providing a solution for trust problems between potential buyers and sellers. The grain market in ancient Rome had a 'peer monitoring system' (Temin, 2013) (Diekmann & Przepiorka, 2019). During the times of the Dutch East India Company ship owners in Amsterdam blocked potential investors from having information about previous shipments; Investors were allowed to buy stocks in shipments from Asia. If this ship made it home safely investors made profit. But owners of these ships made sure that previous information about their shipments was not accessible for the public. Fear of losing reputation was the underlying reasoning for this but in the end it seriously harmed the trust in some of these companies. People stopped buying stocks due to this lack of trust, and the prices of these stocks took a huge tumble (Helleman, 2011).

In more recent times we saw the emergence of online markets. Research in online markets has been plentiful since the foundation of the internet. For this research, which focuses on an illegal online market place (SilkRoad), other research into legal online market places is very relevant. A popular subject for this kind of research on legal online market places is eBay. Dewan and Hu found a significant effect of the eBay numeric reputation system on likelihood of

sale. Findings of Cabral and Hortac (2005) supported this notion. However, findings in other research have not always been consistent with the notion that negative numeric feedback decreases the likelihood of sales. McDonald and Slawson (2002) found that more negative feedback can increase the number of bids in secondary market auctions. Jiao et al (2021) combined these researches and many others in their meta-analysis. This meta-analysis found an overall positive effect between positive feedback and sales and a negative relationship between negative feedback and sales. Even though some individual researches in this meta-analysis pointed at an insignificant or opposite relationship between feedback and sales

Due to presumably practical reasons (Ghose et al, 2009) most of the research that focused on reputation systems in online market and their effects on sales has been on numeric ratings. Focusing mostly on the polarity of these numeric ratings. However, focusing on just the polarity of numeric ratings and not including the written reviews can lead to inaccurate conclusions. Research has suggested that polarity of numeric ratings does not accurately portray the information available in the accompanying textual feedback of the review. Macanovic and Przepiorka (2021) found that 79.4% of the time a neutral rating is not accompanied by a neutral text. On the other hand, Ghose et al (2007) suggest that textual feedback can portray information in numeric variable accurately, since the information retrieved from the textual feedback is significantly more accurate in predicting the eventual amount of sales.

Feedback text polarity sees on whether a written review is positive, neutral or negative. When looking at numeric ratings the polarity is very easy to measure. A 1/5 rating is very negative and a 5/5 rating is very positive. With textual feedback this is more difficult. This information has to be extracted through manually or automated coding methods (Ghose et al, 2009). In the data and methods section the coding methods used in this research will be explained further.

Even though the polarity of textual feedback and the effect on sales has been a relatively under researched topic, the importance of these written texts has been proven in several researches. Chevalier and Mayzlin (2006) have proven that favorable reviews lead to an increase of book sales. Negative books reviews on the other hand have a negative effect on the amount of sales. Another interesting finding of this study is that a negative review is more powerful in decreasing book sales than a positive review is in increasing sales. Nan Hu (2014) found that both moderately positive and moderately negative textual feedback has more influence on sales

then strong positive or strong negative sentiments have on sales.

So from the marketplaces of ancient Rome until the modern-day era of online shopping researches have shown us the influence a reputation system has on the amount of sales. Yet the recently founded illegal online and anonymous markets and their reputation systems have been relatively undiscovered. Przepiorka et al (2017) have shown us the significant impact numeric ratings have on the amount of sales in such a marketplace. Macanovic and Przepiorka (2021) have actually researched textual feedback in illegal online markets, but only in the context of the motivational landscape of these reviews.

In contrary to legal online market research no relevant research has been done on the polarity of textual feedback and the effect on sales in illegal online markets. This is why this will be looked at in this research. This research will focus on the online sales of narcotics on the illegal crypto marketplace SilkRoad.

For this research the following research question will be answered:

What is the influence of the polarity of textual feedback on the eventual amount of sales of narcotics on SilkRoad?

Why this research question is chosen will be elaborated further on in the theory section. Before trying to answer this question it is important to understand why the answers to this question can provide relevant and useful information. User-generated online reviews are an important source of information when deciding whether to buy a product or not while shopping online (Nan hu et al, 2014). The total revenue of E-commerce in 2020 amounted to 4.28 trillion US dollars and is only expected to grow the upcoming years (Sabanoglu, 2020).

Silk road functions under different circumstances than other legal online markets that are embedded in functioning legal systems. But that does not mean that knowledge gained about Silk road cannot apply to other legal online markets. Since there are no legal assurances and limited assurances provided by the marketplace itself it is possible to study a more isolated effect of customer feedback compared to research on legal markets. Furthermore, we are living in an increasingly globalizing world. Trading is becoming more and more international. How much legal insurance do you really have when ordering product directly from China? From this perspective anonymous trading with little to no legal assurance is not something that is just happening in illegal markets and is becoming more and more a normal way of doing business. Even though Silk road was a small and illegal marketplace, the potential of crypto marketplaces

is enormous. After 1 bitcoin breaking the mark of being worth 50.000 euro and the crypto based company Coinbase entering Nasdaq at an estimated value of 86 billion dollars it seems likely that the cryptocurrencies are more than just a hype and are becoming a serious economic entity (Wilson, 2021) (Yen & Cheng, 2021). Having early knowledge about the works of such marketplaces working with crypto currencies can therefore be extremely valuable.

In the next section a theoretical framework will be given as to why a good reputation leads to an increase of sales and a bad reputation leads to a decrease of sales. Also, an explanation of the important role feedback text polarity plays in the amount of sales of an item will be given.

2. Theory

Problems of trust in online markets

Buying something is a risk. Beforehand it is almost impossible to be sure if you will be satisfied with your new acquisition.. Logging into an online store of a big retailer and deciding whether to buy a sweater or not can already be a big decision for some people: Does it really fit? Is the quality of the fabric good? What we see here is a situation of asymmetric information (Diekmann & Przepiorka, 2019). The buyer can't confirm the quality of the product with certainty. Now imagine buying a used sweater from an online marketplace such as eBay. This will create even more uncertainty for the buyer. An official retailer as described can generally be trusted to send you the item what was promised. Dealing with another user of an online marketplace is more difficult. Maybe the seller of the sweater is a scammer and you won't even receive a product.

There are a lot of potential uncertainties that can make a person decide to not proceed with a transaction. In case of the examples given this could lead to a sub optimal outcome of both the parties involved. Maybe the sweater of the online retailer is of great quality after all and the online seller of the sweater on eBay is actually very well intentioned. In these cases, both the parties involved lose out on a mutually beneficial exchange (Diekmann & Przepiorka, 2019) due to problems of trust. This interaction between a seller and a buyer can accurately be portrayed by a trust game as seen very often within game theory. In this example $T > R > P > S$. Meaning T is the best outcome and S is the worst outcome. In the standard trust game (**Figure 1, See next page**) a seller has no incentive to ship the goods. If a buyer gives his trust (and therefore his money) to the seller, the seller will always abuse this trust because $T > R$. This leads to the buyer not buying

because $P > S$. Which at the end leads to a situation that is suboptimal for both parties since $R > P$.

In reality (**Figure 2**) there are negative incentives (C) and positive incentives (B) for the seller to ship the goods. These incentives can change the old equilibrium (figure 1: P,P) to a new one (R, R+B). As displayed here creating these incentives is the key of solving the trust problem

Figure 1 (jiao et al, 2021)

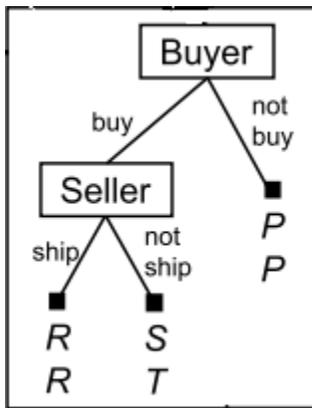
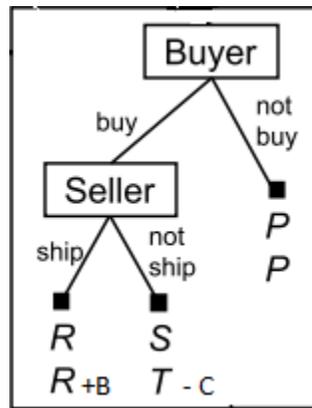


Figure 2



Solutions of trust problem in online markets

As said before we see that there are incentives for sellers in online markets to deliver (quality) goods. By creating incentives for the seller to uphold his side of the bargain the trustworthiness of the seller will increase. These incentives for sellers to deliver are commonly referred to as ‘solutions of the trust problem’ in the relevant literature (Milgrom, North, and Weingast 1990). Creating more trust will allow the seller to have more success in the market he is operating in. The seller will see an increase of sales or is able to increase his or her prices (Obloj & Capron, 2011).

The solutions for the trust problem, from now on trust buildings mechanisms, can be categorized in three categories first, by means of **repeated exchanges**; second, by **regulation** of the exchanges; and third, by **reputational incentives** (Diekmann & Przepiorka, 2019).

Repeated exchanges: If buyers can condition their actions based on interactions they have had in the past with the same seller they have a possibility to reward or punish the seller for his behavior (Milgrom et al, 1990).

Regulations: In most markets there are an uncountable amount of different regulations for numerous amounts of different kind of transactions. These regulations can be used to (partly) solve the trust problem. Among other possibilities regulations can be used to punish scammers or

making it more difficult for sellers and buyers to actually perform dishonest transactions. In relevant literature a distinction between exogenous and endogenous regulations is made (Ostrom, 1990) (Diekmann & Przepiorka, 2019). Exogenous regulation could be state laws and self-organized regulations being for example the payment of a deposit. In the context of online markets this thesis argues that a three-way division between regulations created by the authorities, providers and users would be more sensible.

Examples of a regulation formed by the authorities would be the Dutch system of private law. If a consumer feels wronged he or she can take legal actions against a company or other individual to demand compensation (Kralingen, 2016).

An example of regulations created by the providers is eBay creating a system in which scammers are banned. Lastly, an example of a regulations created by users is a transaction in which two eBay user would come to an agreement to withhold a certain amount of the payment until the deliver is successful

Reputation of the seller: The trust building mechanism of repeated exchanges focuses on multiple exchanges between the same two actors. However, the trust building mechanism of the reputation of the seller focusses on the past transaction of other costumers with a buyer. The reputation of the seller will create (dis)trust on the basis of experiences of other costumers with a specific product or seller (Diekmann &Przepiorka, 2019). Information on the trustworthiness of seller can be passed on through all sort of communication. Through direct in person communication but also through online reviews and ratings (lee et al, 2007). If a seller receives bad reviews online potential buyers will perceive this seller as untrustworthy. Acquiring a good reputation can be very costly. New entrants of the market with very little reviews need to compete with competitors that already have a good reputation. Therefore, they will need to charge lower prices or accept a relatively low amount of sales compared to other vendors with a established reputation (Jiao et al, 2021)

Typically, reputation in electronic markets is encoded by a “reputation profile” that provides potential buyers with information about past transaction of the seller in question. Usually in the form of generic ratings and/or textual feedback. If a seller has a lot of positive feedback or ratings or a potential buyer will be more inclined to trust this seller (Ghose et all,2011)

Silk road

As described there are several trust building mechanisms to overcome the trust problem between buyer and seller. However, the trust building mechanisms of repeated exchanges and regulations are not very present on SilkRoad. The majority of online markets are embedded in functioning legal systems (Przepiorka et al, 2017). As stated before this legal system is an example of a regulation formed by authorities which mitigates the trust problem. SilkRoad is not imbedded in a legal system since transactions are anonymous and therefore making it virtually impossible for law enforcement to intervene. The trust building mechanism of repeated exchanges is also limitedly present. Through the dark web it is easy to offer your services to a lot of people. An online seller on SilkRoad can ship nation or worldwide (Christin, 2013). Therefore, it would be possible to have a successful business without making more than one transaction with the same person.

The success of SilkRoad therefore relies for the most part on the reputation system present on this marketplace. However, there is some regulation system provided by the operator of the marketplace. An escrow service. Money will be withheld by the escrow until the actual product is received. This will prevent a buyer from not delivering at all, but it won't guarantee a high-quality product or stealth delivery. A seller can still cheat a buyer by delivering low quality or low quantity products (Przepiorka et al 2017)

The second main trust building mechanism present on SilkRoad is the reputation system every seller is subjected to. After making a purchase a 5-star rating is given to the seller. The buyer can change this rating to a 1-4 rating if he pleases. Also, the seller is allowed to leave textual feedback (Christin, 2013).

In the first part of the theory it was described why the reputation system on SilkRoad is an important part of enabling sellers to create trust and therefore to make sales. In the next part of the theory it will be discussed why and how the written reviews also known as feedback texts are hypothesized to have an effect on the amount of sales of an item on SilkRoad.

Feedback text polarity and effect on sales

Studies found that around 65 percent of people spent around 10 minutes reading reviews before purchasing a product. 78 percent of people say that they trust written reviews from other costumers (Nan hu et al, 2013). Chevalier and Mayzlin (2006) found that review length has an

effect on the eventual amount of sales. This was seen as proof that most people actually read the reviews. The proof that people read and trust feedback text is an indication that these feedback texts can have a negative or positive effect on sales. Ghose et al (2011) used text mining tools to confirm the effect feedback text has on sales. In this research different product attributes were divided into different categories. Meaning that different positive or negative mentions about something like product quality or delivery were split into different categories. Almost all of these categories had a significant effect on sales.

The previously mentioned researches (Ghose et al,2011) (Nun Hu et al, 2013) (Chevalier and Mayzlin, 2006) were all focused on legal online markets. Due to the smaller amount of moral and legal assurances SilkRoad provides the reputation systems on SilkRoad has a more important role as a trust building mechanism between buyer and seller (Przepiorka et al, 2017) (Macanovic et Przepiorka, 2021) compared to legal online markets. This is an argument for expecting a similar or stronger effect of feedback text polarity on sales on SilkRoad compared to earlier legal online market research. Expecting an insignificant or reversed effect when the importance of this feedback is increased is not logical.

In contrary to the effect of feedback text polarity on sales, the influence of numeric ratings on sales in illegal online markets has been proven (Przepiorka et al, 2017). Numeric ratings and feedback texts both are an important part of a reputation system (Alnemr & Meinel, 2011). This leads to the expectation that feedback text, just as numeric ratings, have a significant effect on sales. Similar conclusion as the earlier mentioned research to numeric ratings in SilkRoad are to be expected (Prezpiorka et all, 2017). A negative feedback text has a negative effect on sales. A positive feedback text has a positive effect on sales.

Based on the previously mentioned arguments two hypothesizes can be derived:

H1: Positive feedback text polarity has a positive effect on the total amount of sales on SilkRoad

H2: Negative feedback text polarity has a negative effect on the total amount of sales on SilkRoad

An online feedback text does not always have to be positive or negative. A significant part of textual reviews are neutral. This can be because they contain positive and negative elements or because these reviews are indifferent (Sonnier et al, 2011). The theory behind these neutral reviews and their effect on sales is very inconsistent. Some theory suggest that effect of this

neutral reviews will be negative since people tend to look for a positive experience. Meaning that a neutral experience is something below their desired outcome of the purchase (Mudambi & Schuff, 2010). Other theory suggest a positive effect of neutral reviews on sales. Neutral reviews will spread more awareness of a product. Therefore it will have a positive effect on sales (Sonnier et al, 2011). Lastly an insignificant effect of neutral reviews is predicted in consumer behavior theory. People supposedly tend to only read the negative or positive review texts. Not paying much attention to the neutral ones (Salehan & Kim, 2016). Probably all these different theories are true in some way. Some people interpret neutral reviews as negative, some as positive and others do not pay attention to neutral reviews at all. In the end this will most likely lead to an insignificant effect of neutral reviews on sales:

H3: The amount of neutral reviews has an insignificant effect on the amount of sales

Behavioral research has proven that people read reviews and find them important before purchasing a product online (Nan Hu et al, 2013). Suggesting that looking at numeric ratings alone is not enough for accurately predicting the sales of a product. Research from Archak (2007) confirmed that numeric ratings are not sufficient for accurately predicting sales. Adding the information from feedback text to the numeric ratings increases the accuracy of the prediction of sales drastically.

Macanovic and Przepiorka (2021) confirmed that numeric ratings do not always accurately mirror all the information present in the accompanying feedback text. In this research it was specifically proven that the feedback text polarity does not always match the polarity of the numeric rating on SilkRoad. Since it is proven that people read reviews and that numeric ratings do not capture the same information as feedback texts in both legal and illegal online markets the following hypothesis is formulated:

H 4: Using both the information on feedback text polarity and numeric ratings will lead to a more accurate explanation of the amount of sales per day compared to using only the information on numeric ratings

In the following section these hypotheses will be checked for by analyzing data extracted from SilkRoad (Cristin, 2013). But first a description of this data set and the variables used in the analysis will be given.

3. Data

The data on SilkRoad used in this paper was collected by Christin (2013) between the end of 2011 and 2012. The data was obtained by automatically browsing and downloading the snapshots of marketplace webpages. To finalize an order customer on SilkRoad were obligated to leave a numeric rating (Christin, 2013). Implying a 100 percent feedback rate based on numeric ratings. Furthermore, it was found that 98 % of feedback contained a text (Christin, 2013). The original data found a total of 24,385 unique items. Mostly narcotics but also fake money and illegal books (Christin, 2013). This research however only considers seven different types of narcotics: weed, hash, cocaine, ketamine, MDMA, heroin, and meth. These items are chosen because they are listed relatively often and have high item homogeneity since they are usually sold in the same form (Przperiorka et al, 2017). Furthermore, by using the types of narcotics as in similar research (Przperiorka et al, 2017) (Macanovic & Przperiorka, 2021), it will be easier to draw comparisons between results in this research and the results of these two similar researches.

Looking at just the seven different categories of narcotics leaves us with 5,675 items, 2,522 items received no feedback rating (Przperiorka et al, 2017). Since 100 percent of the sales lead to a feedback message it is safe to say that the posting of these 2,522 items did not lead to any sales. We cannot be sure that the sellers of these items actually had the intention to sell these items (Przperiorka et al, 2017). This is why these 2,522 items will be excluded from the analysis.

The feedback extracted from SilkRoad contained a numeric rating and a textual description of the feedback (Christin, 2013). These feedback texts were coded for sentiments in text (polarity, emotionality and, where applicable, subjectivity) (Macanovic & Przperiorka, 2021). Creating new variables from the SilkRoad data that have not been analyzed before. This coding was done by students who were not familiar with the study and received compensation for this. The students, including myself, who worked on a thesis subject surrounding SilkRoad also coded some of the feedback texts. The information collected by these coders was used to automatically assess the same dataset using the Random Forest algorithm (Macanovic & Przperiorka, 2021).

Variables used

In the regression analysis of this research the amount of sales per day will be used as the dependent variable. As independent variables the variables representing the feedback text polarity will be looked at. The same control variables as in the research of Przepiorka et al (2017) will be used. As well as the same dependent variable. Not only will this allow to reproduce old results of this paper, but it will also give a possibility to compare existing knowledge of the effect on numeric ratings on sales with new insights into the influence of feedback text polarity on sales. An explanation and justification of the variables used in this regression analysis will now follow. In **table 1** the descriptive statistics of the most important variables used are shown.

Dependent variable:

The dependent variable used in the regression is the log Number of item sales per day. Silkroad cannot provide with direct information on total amount of sales. However, a sale is always accompanied by a numeric rating (Christin, 2013). This means that the total amount of sales is equal to the total amount of numeric ratings (Przepiorka et al, 2017). By dividing the total amount of numeric ratings by the amount of days an item is observed online the dependent variable is obtained. To normalize the distribution of this dependent variable a log transformation of this variable is done. (Ives, 2015). Since item without sales are filtered out before hand it is not necessary to add a plus 1 to this log transformed data.

Independent variables:

The available data on SilkRoad regarding feedback text polarity is collected and divided into three different variables. Positive, neutral, and negative feedback texts. Similar research on numeric ratings put 1 to 4-star ratings together in one category (Prezpiorka et al, 2017). To put neutral and negative feedback into one category was also a consideration for this research. But this would deny the opportunity to draw conclusion about neutral feedback texts specifically. Also, data analysis (**Table 4, p. 20**) shows that neutral feedback has an insignificant effect on sales. Negative feedback has a significant effect. Meaning that grouping together these two variables as one would always lead to a misleading effect of significance for one or two of the variables included into the new variable.

For a certain item the total amount of negative, neutral and positive feedback texts of the

seller of this item are taken up until the point of the listing of this item (Macanovic & Przepiorka, 2021)

To draw conclusions about the effect of feedback text polarity on sales these three independent variables are added to the regression. By using all three of these variables all information available in the dataset on feedback text polarity is used. In the dataset there is no distinction between moderately positive or negative feedback texts and strongly positive or negative feedback texts. Therefore, no comparison can be drawn between earlier research that did discuss moderately negative or moderately positive feedback texts (Nan Hu, 2014).

Control variables:

The first control variables added to the regression are the logged weight in grams and the item prize per gram. It would make sense that these variables have a negative effect on sales. If a product is more expensive and/or is offered in a high quantity, demand for this product will decline most likely (Aldridge & De´cary-He´tu, D, 2016).

Secondly the seven types of different drugs as discussed earlier are added as control variables. Since it is very likely that some types of drugs are more in demand than others (Jardine, 2019). To reduce the total amount of control variables these seven types are divided into three categories (Przepiorka et al, 2017). Three sets of dummy variables are used with low price item as the reference category.

Furthermore, a dummy variable for items of poor quality is added as a control variable. Some items in the low-price category (Hash and weed) are labeled by the seller as being of ‘poor quality’. The expectation is these labels of low quality have a negative effect on the amount of sales per day. Research on the illegal sales of marihuana in New York showed that buyers of marihuana rather pay more than to receive low quality products (Sifaneck et al, 2007). Since the data is right censored a dummy variable to mark items that were listed on the last two days is also included (Przepiorka, et al, 2017).

Lastly the locations where the seller ships to will be controlled for. The data collected by Christin (2013) provides this information. Three sets of dummy variables are used with seller only ships domestically as the reference category. These variables are controlled for since it would be expected that sellers who ship to more locations have more sales, since they have more potential customers (Revell,2017).

Numeric ratings will be added as control variables in a second regression (**model 2 in table 4, p. 20**). These numeric ratings are added in a separate regression due to expected multicollinearity issues. In **table 2** and **table 3 (p. 16)** the potential problems of multicollinearity between numeric ratings and feedback text polarity are displayed. The Pearson correlation matrix (**table 3**) also shows the high correlation between these seller variables. The results of both the regressions will be analyzed and compared with earlier research (Przepiorka et al, 2017) (Ghose et al, 2009). One regression with numeric variables added as control variables and one regression without numeric variables added as control variables. On the basis of this analysis and comparison it will be decided which information of which regression will be used to formulate answers to the hypothesizes

Another variable that has a potential problem of multicollinearity is the variable of price per gram (**table 2**). However, further data analysis showed that adding or removing this variable as a control variable did not influence the coefficients of other variables in a drastic manner. Furthermore, since this research aims to draw comparisons between the similar research of Przepiorka et al (2017) it would be unwise to use add or remove control variables used in this research. Meaning that the variable of price per gram will be controlled for in the regression

Table 1: Descriptive statistics of main variables used in the analysis

Variable name	N	Mean	SD.	Minimum	Maximum
Item sales and duration					
# item sales	3,153	20.72	58.94	1	1501
Item online in days	3,153	50.44	56.17	1	382
# item sales per day	3,153	0.45	0.69	0.01	10.83
Numeric ratings					
# five-star ratings	3,153	177.78	306.18	0	2600
# non-five-star ratings	3,153	6.81	17.01	0	148
Feedback text polarity					
# positive feedback	3,153	140.51	241.55	0	2018
# neutral feedback	3,153	22.13	48.72	0	598
# negative feedback	3,153	15.14	26.06	0	215
Low-price products					
Weight in g	2,297	18.15	63.57	0.25	1000
Price in USD per g	2,297	15.50	7.30	1.46	115.76
Medium-price products					
Weight in g	562	7.17	45	0.05	1000
Price in USD per g	562	92.26	57.51	8.41	464.13
High-price products					
Weight in g	294	1.40	3.87	0.10	56
Price in USD per g	294	217.55	140.40	33.72	992.82

Table 2: Multicollinearity (N=3153)

Variable name	Dependent variable: non-5-star	Dependent variable: 5-star
	M1 VIF:	M2 VIF:
Item variables		
Log (price per gram)	8.67 (*)	8.57 (*)
log (weight in gram)	2.24	2.23
Medium price	3.37	3.57
High price	4.41	4.27
Poor quality product	1.12	1.12
Last 2 days	1.05	1.04
Seller variables		
Log (#positive feedback+1)	213.07 (*)	9 (*)
Log (#neutral feedback+1)	10.61 (*)	9 (*)
Log (#negative feedback+1)	9.92 (*)	9.8 (*)
Seller ships to		
Unknown	1.06	1.08
Foreign	1.20	1.22

* = Potential problem of Multicollinearity

Table 3: Matrix of correlation (N=3153)

Variable name	1	2	3	4	5
(1) Log (#five-star ratings+1)	-				
(2) Log (#non-five-star ratings +1)	0.728*	-			
(3) Log (#positive feedback+1)	0.997*	0.728*	-		
(4) Log (#neutral feedback+1)	0.926*	0.821*	0.917*	-	
(5) Log (#negative feedback+1)	0.929*	0.835*	0.927*	0.929*	-

* $P < 0.001$ (2-tailed)

4. Results

Table 4 shows that adding the control variable of numeric ratings changes the output of especially the other seller variables significantly. The coefficient of neutral ratings changes from insignificantly negative to significantly positive. Furthermore, the already significant coefficients of both positive and negative feedback texts both substantially increase. The substantial changes in the coefficients of these variables after adding the control variables of numeric ratings is another sign of problematic multicollinearity (Alin, 2010). Adding to the argument of an expected problematic multicollinearity already discussed and displayed in **table 2** and **table 3**.

Model 2 of table 4 also displays an effect of the added control variables of numeric ratings that is rather strange. Five-star rating seem to have a significantly negative effect on the amount of sales. An even larger negative effect than non-five-star ratings have on sales to be exact. This is so much out of line with results found in earlier research (Przepiorka et al, 2017)(Ghose et al, 2009) that this is another argument for assuming that the multicollinearity between numeric ratings and feedback text polarity leads to inaccurate results when adding numeric ratings as a control variable. Because of the high probability that the results of **model 2 of table 4** are inaccurate only the results of **model 1 of table 4** will be used in the following sections of this paper.

In the theory section two hypotheses were formed regarding positive and negative feedback text polarity:

H1: Positive feedback text polarity has a positive effect on the total amount of sales on SilkRoad

H2: Negative feedback text polarity has a negative effect on the total amount of sales on SilkRoad

Model 1 of table 4 shows the significant effect positive and negative feedback texts have on the amount of sales per day.

The coefficient of the log number of Positive reviews is significantly positive ($b = 0.290$, $SD = 0.027$, $t = 10.863$, $p < 0.001$).

The coefficient of the log number of negative reviews is significantly negative ($B = -0.015$, $SD = 0.036$, $T = -7.498$, $P < 0.001$).

Considering that the range of the positive feedback texts is considerably larger than the range of negative feedback texts an 8-fold increase in positive feedback texts and a 3-fold increase in negative feedback texts is used to calculate the effect of these reviews on the amount of sales per day (Przepiorka et al, 2017). If the number of positive feedback texts increase by a factor 8 the sales per day increase by $100 \times [\exp(0.290 \times \ln(8)) - 1] = 82.77\%$. If the number of negative feedback texts increase by a factor 3 the number of sales per day decrease by $100 \times [\exp(-0.299 \times \ln(3)) - 1] = (-)28\%$. These results clearly support hypothesis 1 and 2. Not only because the effect of these reviews is significant, but also since the calculations with the fold increase show how much a difference these reviews can make in percentage of sales that will potentially be made.

In the theory section the following hypothesis regarding neutral feedback text polarity was formulated:

H3: The amount of neutral reviews has an insignificant effect on the amount of sales.

Model 1 of table 4 shows that the effect of neutral reviews on the amount of sales per day is not only close to zero but also insignificant ($b = -0.015$, $SD = 0.036$, $t = -0.400$, $p=0.689$).

Supporting hypothesis 3.

The last hypothesis that will be checked for is hypothesis four:

H4: Using both the information on feedback text polarity and numeric ratings will lead to a more accurate explanation of the amount of sales per day compared to using only the information on numeric ratings

To test this hypothesis an incremental F-test will be used (**table 5**). Model 1 of this table contains the numeric ratings as independent variables plus the control variables also used in the regression of **model 1 of table 4**. In **model 2 of table 5** the three variables representing feedback text polarity are added to the first model. Both Models have sales per day as a dependent variable. Adding the three variables representing feedback text polarity improves the first model with just the numeric ratings significantly ($R^2 \text{ change} = .009$; $F\text{-change} = 11.920$; $p < .001$). Meaning that the added information on feedback text polarity will lead to a more accurate explanation regarding the amount of sales per day. Even though the improvement is significant, the improvement is still very small (0.9 % more accurate). The hypothesis is confirmed but the improvement is not substantial.

By answering these hypotheses the research question is answered as well.

The research question of this paper was the following question: *What is the influence of the polarity of textual feedback on the eventual amount of sales of narcotics on SilkRoad?*

The first three hypotheses have specifically addressed what kind of influence negative, neutral and positive feedback texts have on the sales of narcotics on SilkRoad. Therefore, not only proving there is an influence of feedback text polarity on sales but also explaining what kind of influence these different kind of feedback texts have on sales. Hypothesis four proved that this is indeed the influence of feedback text polarity on sales and not just the correlated effect of numeric ratings.

Table 4: Regression with Log (#Item sales per day) as dependent variable

Variable name	M1 (not including numeric variables)		M2 (including numeric variables)		
	B	SD	B	SD	
Const.	0.322*	0.168	0.460**	0.168	
Item variables					
Log (price per gram)	-0.608***	0.054	-0.639***	0.054	
log (weight in gram)	-0.436***	0.019	-0.440***	0.018	
Low price	(Reference)		(Reference)		
Medium price	0.848***	0.96	0.907***	0.095	
High price	1.357***	0.138	1.429***	0.137	
Poor quality product	-0.068	0.162	-0.102	0.160	
Last 2 days	0.045	0.047	0.057	0.047	
Seller variables					
Log (#positive feedback+1)	0.290***	0.027	0.666***	0.128	
Log (#neutral feedback+1)	-0.015	0.036	0.140***	0.042	
Log (#negative feedback+1)	-0.299***	0.040	-0.127**	0.045	
Log (#five-star ratings+1)	-	-	-0.468***	0.132	
Log (#non-five-star ratings +1)	-	-	-0.259***	0.031	
Seller ships to					
Unknown	-0.406***	0.093	-0.339***	0.092	
Domestic only	(Reference)		(Reference)		
Foreign	0.012	0.042	0.035	0.042	
Adjusted R-square		= 0.205	Adjusted R-square		= 0.221
N1 (number of items)		= 3153	N1 (number of items)		= 3153
N2 (number sellers)		= 445	N2 (number sellers)		= 445

Note: The coefficients are noted with level of significance: ***P < 0.001, **P < 0.01, *P < 0.05, for two-sided tests.

Table 5: Incremental F-test (N=3153)

Model	R ²	Adjusted R ²	R ² -change	F-Change	Sig. F-Change
Model 1	0.216	0.213	0.216	86.501	<0.001
Model 2	0.225	0.221	0.009	11.920	<0.001

5. Discussion

Earlier research on SilkRoad data confirmed that numeric ratings have a significant effect on the amount of sales per day (Przepiora et al, 2017). This research added to this by showing that positive and negative feedback texts also have a significant effect on the amount of sales per day. Once again proving that people actually read reviews online, not just on legal online markets but also in illegal online markets (Chevalier& Mayzlin, 2006). Unfortunately, the effects of feedback text polarity are not controlled for by numeric ratings in **model 1 of table 4** The multicollinearity between numeric ratings and feedback text polarity did not allow adding numeric ratings as control variables to this regression. This could have led to inaccurate results since it would still be possible that some potential buyers just look at numeric ratings. This could be something that is not accounted for in **model 1 of table 4** On the other hand, **table 5** does consider both information of numeric ratings and feedback text polarity, adding validity to the results. The results in **table 5** showed that adding the information of feedback text polarity to the model of numeric ratings increased the accuracy of explaining the amount of sales per day. In legal online markets it was already proven that numeric ratings do not capture all the information of accompanying feedback text polarity (Ghose & all, 2007). Now this is also proven to be the case in an illegal online market place such as SilkRoad.

As described earlier the data used in this research is collected between 2011 and 2012 (Christin, 2013). But the variables on feedback text polarity used have just been recently created through coding work performed at the University of Utrecht (Macanovic & Przepiora, 2021). It is very interesting to look at data that is not coded before in such a manner. One thing that is not covered by the data on feedback text polarity is which aspect of the feedback texts is either positive, negative or neutral. By not knowing this we cannot say things about the priorities or specific demands of (potential) costumers. Maybe speed of delivery is very important and something negative or positive about this is weighted more strongly by costumers. This is something that could be looked at in further research

Furthermore, it is interesting to see that these reputation systems in illegal online markets seem to work as trust building mechanisms. Positive feedback texts contribute to more sales and there were a lot of sales on SilkRoad. All this without any control from governments or other official institutions. This points out a huge potential for the cryptocurrencies in general. The idealistic origin of these cryptocurrencies lies partly in the fact that people are able to make transactions and have control over their money without being subjected to government control (Levy, 2001). By showing that certain market places without government control can actually function just on the basis of a working reputation mechanisms shows the potential of illegal and legal online crypto markets.

6. Literature

Alin, A. (2010). Multicollinearity. *Wiley Interdisciplinary Reviews: Computational Statistics*, 2(3), 370-374.

Aldridge, J. and De´cary-He´tu, D. (2016). Hidden wholesale: the drug diffusing capacity of online drug cryptomarkets. *International Journal of Drug Policy*, 35, 7–15.

Alnemr, R., & Meinel, C. (2011, October). Why rating is not enough: A study on online reputation systems. In *7th International Conference on Collaborative Computing: Networking, Applications and Worksharing (CollaborateCom)* (pp. 415-421). IEEE.

Archak, N., Ghose, A., & Ipeirotis, P. G. (2007, August). Show me the money! Deriving the pricing power of product features by mining consumer reviews. In *Proceedings of the 13th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 56-65).

Branwen, G. (2011). *Silk Road 1: Theory & Practice*.

Cabral, Luis, Ali Hortac, su. 2005. The dynamics of seller reputation: Theory and evidence from eBay. Working Paper EC-04-05, Stern School of Business, New York University.

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.

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).

Dewan, Sanjeev, Vernon Hsu. 2004. Adverse selection in electronic markets: Evidence from online stamp auctions. *Journal of Industrial Economics* 52 497–516. 5

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.

Ghose, A., & Ipeirotis, P. G. (2010). Estimating the helpfulness and economic impact of product reviews: Mining text and reviewer characteristics. *IEEE transactions on knowledge and data engineering*, 23(10), 1498-1512.

Ghose, A., Ipeirotis, P. G., & Sundararajan, A. (2009). The dimensions of reputation in electronic markets. *NYU Center for Digital Economy Research Working Paper No. CeDER-06-02*.

Helleman, J. (2011). Financiële verantwoording door de VOC. *Management Control & Accounting: Tijdschrift voor Organisaties in Control*, 2011(2), 26-31. http://www.finance-control.nl/module/article/download_free.aspx?id=9040

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.

Ives, A. R. (2015). For testing the significance of regression coefficients, go ahead and log-transform count data. *Methods in Ecology and Evolution*, 6(7), 828-835.

Jardine, E. (2019). The trouble with (supply-side) counts: The potential and limitations of counting sites, vendors or products as a metric for threat trends on the dark web. *Intelligence and National Security*, 34(1), 95-111.

Kralingen, M. J. (2016). Onrechtmatige daad en schadevergoeding. *Ars Aequi KwartaalSignaal*, 2016(140), 8110-8112

Levy, S. (2001). *Crypto: How the code rebels beat the government--saving privacy in the digital age*. Penguin.

McDonald, Cynthia Goodwin, Vester Carlos Slawson. 2002. Reputation in an internet auction market. *Economic Inquiry* 40(3) 633–650.

No'aman, M. A., & Novikov, B. (2021, January). A Multi-Source Big Data Framework for Capturing and Analyzing Customer Feedback. In *2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus)* (pp. 185-190). IEEE.

Obloj, T., & Capron, L. (2011). Role of resource gap and value appropriation: Effect of reputation gap on price premium in online auctions. *Strategic Management Journal*, 32(4), 447-456.

Przepiorka, Wojtek, Lukas Norbutas, and Rense Corten. "Order without law: Reputation promotes cooperation in a cryptomarket for illegal drugs." *European Sociological Review* 33.6 (2017): 752-764.

Revell, T. (2017). US guns sold in Europe via dark web. *New scientist*, (3136), 12.

Salehan, M., & Kim, D. J. (2016). Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics. *Decision Support Systems*, 81, 30-40.

Shin, H. S., Hanssens, D. M., Kim, K. I., & Gajula, B. (2011). Impact of positive vs. negative sentiment on daily market value of high-tech products. In *Working paper*.

Sonnier, G. P., McAlister, L., & Rutz, O. J. (2011). A dynamic model of the effect of online communications on firm sales. *Marketing Science*, 30(4), 702-716.

Subanoglu, T. (2021, 26 maart). Retail e-commerce sales worldwide from 2014 to 2024. *Statista*. <https://www.statista.com/statistics/379046/worldwide-retail-e-commerce-sales/>

Temin, Peter. 2013. *The Roman Market Economy*. Princeton, NJ: Princeton University Press.

Wilson, T. (2021, 14 april). Coinbase valued at \$86 bln in choppy Nasdaq debut. *Reuters*. <https://www.reuters.com/technology/coinbase-heads-89-bln-valuation-nasdaq-debut-2021-04-14/>

Yen, K. C., & Cheng, H. P. (2021). Economic policy uncertainty and cryptocurrency volatility. *Finance Research Letters*, 38, 101428.