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# Opportunistic seller behavior on the Silk Road: An empirical study.

The dark web provides both buyers and sellers with anonymous, untraceable marketplaces for online person-to-person transactions, henceforth referred to as cryptomarkets. This study will focus on the first major cryptomarket, Silk Road, as no other cryptomarket has achieved similar stability in combination with as long of a lifespan, suggesting that it is the best source of data of a well-functioning cryptomarket. Cryptomarkets have security measures in place that are aimed at protecting buyers from sellers, as the anonymous environment may incentivize sellers to behave opportunistically. One of these measures is the reputation system, like one would find on most legal marketplaces as well. These reputation systems exist to replicate the trust-based mechanisms on which real life interactions are based. Good behavior from sellers is encouraged, because opportunistic behavior may lead to negative feedback, which may impact the likelihood of other buyers interacting with that seller. However, multiple ways in which sellers are able to circumvent these measures to fraudulently earn money have been identified. This study analyses data acquired from both the Silk Road marketplace itself, as well as the Silk Road forums, in an attempt to identify characteristics of the sellers that behave opportunistically despite the preventive measures in place. Multiple linear regression models were used to test the effects of amount of sales, forum activity and the interaction between these two on the likelihood of a seller behaving opportunistically. It was found that the amount of sales a seller has, has a significantly positive effect on the likelihood of said seller behaving opportunistically, although this effect is smaller for sellers that are more active on the forums. This research has however not been able to identify a profile of opportunistic sellers, which is something further research could look into, using this study as a place to start.

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*Bachelor thesis*

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*June 13th 2019*

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# Table of contents


1. Introduction ... 3
2. Theoretical framework ... 6
   2.1 System-level scams ... 6
   2.2 Opportunistic seller behavior ... 6
      2.2.1 Exit scams ... 7
      2.2.2 Selective scams ... 7
   2.3 Rational choice ... 7
   2.4 Social bonds ... 9
3. Data & methods ... 11
   3.1 Datasets ... 11
      3.1.1. Marketplace dataset ... 11
      3.1.2. Forum dataset ... 12
      3.1.3. Final dataset ... 12
   3.2. Variables used in the analysis ... 13
      3.2.1. Independent variables ... 13
      3.2.2. Dependent variables ... 14
      3.2.3 Control variables ... 15
   3.3. Methods ... 16
4. Results ... 16
   4.1. Descriptive statistics ... 16
   4.2. Regression analyses ... 19
5. Conclusion and Discussion ... 24
6. Limitations and future research ... 26
7. References ... 27

## 1. Introduction

Since the uprising of the internet in the 21st century there has been an abundance of online marketplaces such as eBay or Amazon where both people and companies can sell their products. On a relatively unknown corner of the internet, the dark web, however, these marketplaces do not provide solely legal products. The dark web provides both buyers and sellers with anonymous, untraceable marketplaces for online person-to-person transactions, henceforth referred to as cryptomarkets. Cryptomarkets can offer a wide range of products, such as child pornography, illicit drugs, weapons or information (passwords, credit card information), but also legal products such as books (Demant, Munksgaard & Houborg, 2018). This study will focus on the first major cryptomarket, Silk Road, as no other cryptomarket has achieved similar stability in combination with as long of a lifespan, suggesting that it is the best source of data of a well-functioning cryptomarket (Aldridge & Décary-Hétu, 2016).

In February of 2011 the first cryptomarket went online, Silk Road. Silk Road was online until the 2nd of October 2013, when it got seized by the FBI, although by that time Silk Road was not the only operating cryptomarket. Within weeks of its closure multiple new cryptomarkets were opened, one of which was Silk Road 2.0(Aldridge & Décary-Hétu, 2016). Even though the trade of goods happening on these marketplaces most likely contributes only a small part to the total amount of illicit trading globally, Silk Road alone facilitated person-to-person trading worth close to 90 million dollars in its' last year of operating (Aldridge & Décary-Hétu, 2016). The success of these markets can be partially attributed to the security measures that have been put in place. Cryptomarkets require payments to be done in cryptocurrency, which is difficult to trace and does not pass through regular financial institutions such as banks. In addition to this these cryptomarkets can only be reached through the use of anonymizing browsers such as TOR. This last measure makes it exceptionally hard for law enforcement to trace not only the servers of the marketplace itself, but also the locations of both vendors and consumers. Furthermore, cryptomarkets have measures that are aimed at protecting buyers from sellers, as the anonymous environment may incentivize sellers to behave opportunistically. First of all, there is often an escrow system in place, where the payment is withheld by the cryptomarket until the buyer confirms that he has received the product, upon which the cryptomarket will release the funds to the seller (Aldridge & Décary-Hétu, 2016). In addition to this cryptomarkets generally have dedicated forums where buyers can, among other things, discuss their experiences with particular sellers. Lastly, cryptomarkets use reputation systems, which will be explained further in the following paragraph.

Within these cryptomarkets sellers are rated by buyers through a reputation system much like you'd find on most regular online marketplaces such as eBay. On Silk Road the reputation system consisted of a feedback rating, where one is the lowest and five is the highest, in combination with a feedback message, explaining the number rating (Hardy & Norgaard, 2016). These reputation systems exist to replicate the trust-based mechanisms on which real life interactions are based, as explained by Resnick, Kuwabara, Zechkhauser & Friedman (2000). In order for online marketplaces to function optimally there needs to be trust between buyers and sellers. In regular interactions between people good behavior is encouraged, as it increases the chance of reciprocation, whereas bad or opportunistic behavior increases the chances of retaliation. Because of the anonymous and non-traceable nature of cryptomarkets however, legal forms of retaliation are nigh impossible. This creates a trust problem, as it removes part of the incentive for sellers to behave cooperatively (Przepiorka, Norbutas & Corten, 2017). The reputation system attempts to solve this problem by having buyers leave feedback on how the interaction(s) with the sellers went, so that other buyers can form expectations on how their interaction with the seller will go. Therefore, good behavior from sellers is encouraged, because opportunistic behavior may lead to negative feedback, which may very well impact the likelihood of buyers to interact with that seller. The reputation system thus attempts to eliminate the incentives of scamming buyers by simulating the real-life mechanisms of trust-based decision making.

Bolton, Katok & Ockenfels (2004) explain the effectiveness of these reputation systems, found through an experimental study. First of all, buyers are often, rightfully so, reluctant to interact with new sellers. Because sellers can create a new account without costs, there is no certainty that a new seller is not just an opportunistic seller that created a new account to get rid of a bad reputation. Also, buyers tend to put more weight on negative feedback than on positive feedback, which creates an environment in which sellers have to be trustworthy in order to continue sales. In addition to this, buyers also generally put more weight on feedback that is more recent, creating the incentive for sellers to keep up their trustworthiness even after accumulating a large number of positive feedback (Bolton et al., 2004). These mechanisms together show clear incentives for sellers to continuously behave in a trustworthy manner, as not doing so may hurt future sales.

Aforementioned security measures like escrow and reputation systems are not exclusive to cryptomarkets, “regular” online marketplaces such as eBay often use the same type of security measures in order to protect buyers (Resnick, Zeckhauser, Swanson & Lockwood, 2006). However, these preventive measures have not been capable of completely eliminating opportunistic seller behavior. Multiple ways in which sellers are able to circumvent these measures to fraudulently earn money have been identified, which are mostly similar across regular marketplaces and cryptomarkets (Sun & Liu, 2012; Moeller, Munksgaard & Demant, 2017), the most common of which will be explained in the theory section. So, despite the proven effectiveness of the preventive measures in place, some sellers still behave opportunistically. The question then arises, what kind of sellers is this? Cryptomarkets are an ideal place to analyze the characteristics of opportunistic sellers, as although they mostly employ the same security measures as legal online marketplaces, sellers do not have to worry about the legal system tracking them down. Therefore the risks for a seller that behaves opportunistically go down significantly, giving a better view of general characteristics of opportunistic sellers, as well as the effectiveness of the preventive measures in an ‘isolated’ environment, which may provide cryptomarkets, and online marketplaces in general, with information that could be used to further solidify the security measures put in place to protect buyers.

Existing studies of opportunistic seller behavior in cryptomarkets often focus on information gathered directly from market participants and/or the cryptomarkets’ forums (e.g. Pace, 2017), or on data acquired through scraping the marketplace itself (e.g. Christin, 2013). This study aims to expand the academic knowledge by combining data acquired from the reputation system with forum data, in an attempt to get a more complete overview of what the characteristics of opportunistic sellers are. Opportunistic behavior will be operationalized as transactions in which the seller either does not ship the item, delivers sub-par or different items or in any other way dupes the buyer. The characteristics this study will analyze relate mainly to the market activity of sellers (e.g. activity on the forums and sales volume), providing a general overview upon which further studies can build. This study will thus attempt to answer the following research question:

*What are the main characteristics relating to market activity of opportunistic sellers within cryptomarkets?*

## 2. Theoretical framework

In this section I'll first explain how it is possible that sellers can circumvent the measures put in place to prevent opportunistic behavior, as well as what types of opportunistic behavior of sellers are most commonly found within cryptomarkets. Next, the rational choice and social bond theories and their mechanisms will be used to formulate hypotheses regarding the characteristics of opportunistic sellers.

### 2.1 System-level scams

Cryptomarkets have a lot of mechanisms in place to prevent sellers from behaving opportunistically. Sellers however are not the only ones that can walk off with other people's money. As mentioned cryptomarkets often use an escrow system for transactions made on the market. This escrow system however opens up the possibility of scams on the system-level. In a bitcoin heist an outside party attacks or exploits the way in which the cryptomarket handles the transactions in order to steal the bitcoins within the escrow system (Moeller et al., 2017). In a marketplace exit scam the administrators of the cryptomarket take off with the bitcoins themselves, which often eventually leads to the shutdown of the cryptomarket (Moeller et al., 2017). The relatively short lifespan of cryptomarkets can be attributed more to these types of system-level scams than to the efforts of law enforcement (Aldridge & Décary-Hétu, 2016).

### 2.2 Opportunistic seller behavior

Although cryptomarkets generally have an escrow system in place, there is often also an option not to use this, called finalizing early. When finalizing early the cryptomarket is cut out of the transaction and the buyer's transaction funds are directly transferred to the seller, rather than withheld until arrival has been confirmed (Moeller et al., 2017). There are multiple reasons as to why buyers comply to sellers that require or request finalizing early. Not only does it eliminate the aforementioned risks of the escrow system, it also eliminates the seller's risk of losing money due to the volatile exchange rates of bitcoins (Moore & Christin, 2013). In addition to this finalizing early also cuts out the costs that the cryptomarkets charge for using the escrow system (Moeller et al., 2017). In a study done by Christin (2013) the feedback of 20,884 out of 184,803 transactions mentioned finalizing early, which is 11,3% of analyzed transactions, ignoring those where it was used but not mentioned in the feedback. When finalizing early the seller immediately receives the money, and there is nothing that the buyer or the market can do when the seller refrains from shipping the item whilst claiming he did. So, although finalizing early has its benefits, one can see that it eliminates a barrier for sellers looking to scam buyers.

### 2.2.1 Exit scams

The first commonly documented way in which sellers scam is through exit scams. The idea behind this is a bit different than that of the aforementioned marketplace exit scam. In an exit scam the seller starts their operation by building up a good reputation. Once the seller has achieved a satisfactory rating, they will come up with a reason for their sales to be finalized early, if this wasn't already required. The seller then eventually leaves the market without shipping the products sold through the finalize early option. (Moeller et al., 2017). As mentioned in the introduction, building up a reputation is costly, and provides big future advantages, such as an increase in sales and the ability to price products higher because of your good reputation (Bolton et al., 2004), which should theoretically prevent sellers from exit scamming. However, the benefits of a good reputation can be abused by someone looking to exit scam, as through their reputation the benefits of absconding with buyers' funds increases as well, making it more feasible that this type of scamming would occur despite the cost of losing a good reputation. Within cryptomarket forums there are quite some documented cases of this type of scamming, buyers on the forums also speculate that the sellers that pull this type of scam register a new account and repeat the practice (Moeller et al., 2017). Ross Ulbricht, the creator of Silk Road, confirmed this practice, stating cases of sellers that were banned from Silk Road but returned later under a new username to repeat their practices (Pace, 2017).

### 2.2.2 Selective scams

The second type of scamming that is well documented is selective scamming. A selective scam is a continuous type of scamming, where sellers behave cooperatively on most transactions, but refrain from shipping a small portion of their sales (Moeller et al., 2017). By doing this the seller can keep up a good reputation whilst also scamming some costumers. This type of scam often targets buyers that are new to the site and thus do not have a buyer rating. When done successfully a selective scam can be kept up for a long period of time without losing much business from regular sales (Moeller et al., 2017).

## 2.3 Rational choice

The rational choice theory is a theory that assumes that all acts are the result of a rational analysis of the situation, where one chooses to act in a way that correspondents with the best net result for the actor (Scott, 2000). This cost-benefit analysis takes into account not only the economic consequences of acting, but also context dependent factors and other implications that may follow from acting. Opportunistic behavior within a cryptomarket has one clear benefit, being the monetary gain from the transaction. When looking at costs on the other hand, it becomes a bit more complicated. One of the costs that would exist on a regular marketplace would be that of law enforcement cracking down on a vendor for opportunistic behavior, but because of the anonymous and nigh untraceable nature of transactions within cryptomarkets this generally does not apply there. A cost that may occur though is that of potentially lost sales due to negative feedback left by the buyer.

Within an isolated transaction there is no loss of future sales to be had, transactions on a cryptomarket however are generally not isolated. Buskens & Raub (2013) explain three mechanisms through which an actors' decisions affect the decision of others to enter into a trust game with that actor, all of which may apply to trading on cryptomarkets. First of all is "dyadic embeddedness", which states that how the seller chooses to act, influences the way in which the buyer makes his decision to interact with the same seller again. Second is "network embeddedness", which states that how the seller chooses to act affects the wat in which others related to the buyer make their decision to interact with the seller, so if a buyer has a network containing others that also make use of cryptomarkets, his experiences may influence whether those people interact with said seller. Lastly is "institutional embeddedness", which may also enhance the two mentioned earlier. Institutional embeddedness refers to the way in which institutions may affect actors' choices, for cryptomarkets one could for example look at the forums as an institution that does this. If a seller acted opportunistically, discussions on the forum may affect the choice of other buyers to interact with that seller, in such an instance the institution thus creates network embeddedness.

The rational choice theory provides a theoretical model which can be used to predict behavior assuming that people act completely rational (Scott, 2000), and are thus fully aware of all potential costs and benefits. So, when looking at the mechanisms that influence potential future sales, one would argue that sellers only behave opportunistically when they can avert these mechanisms enough so that the benefits offset the costs. Resnick et al. (2006) found that most buyers tend to base their decision of whether or not to trust a seller solely on the overall score of the seller, or the percentage of trustworthy transactions. Taking this into account one could argue that large volume sellers are most capable of averting the mechanisms that would reduce future sales after opportunistic behavior. This is because negative feedback becomes less relevant the more positive feedback there is, as it affects the average feedback score less than it would for a seller with a small amount of sales. Although Bolton et al. (2004) did identify that buyers tend to put relatively more weight on recent negative feedback, a larger volume of sales will also diminish the relative recency of specific feedback faster. The idea that large volume sellers are more likely to act opportunistically would be in line with the two identified types of opportunistic seller behavior, exit scams and selective scams, as those are more profitable the higher the volume of sales is. Also, larger sellers may be able to earn more money from opportunistic behavior than their smaller counterparts, as the larger clientele would create more opportunities to behave opportunistically. In addition to this, when a seller pulls an exit scam before completely disappearing from the market, so without registering a new account, the loss of future sales would not have to be considered as a cost. Following this logic, we can formulate the following hypothesis:

*H1: Opportunistic seller behavior within cryptomarkets is more likely to be done by sellers that have a large amount of sales.*

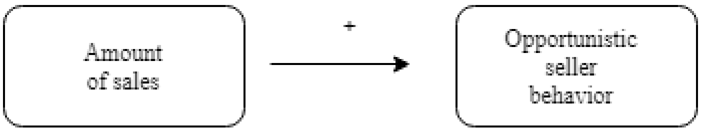


*Figure 1: Mechanism of H1.*

2.4 Social bonds

In addition to purely economic costs, the rational choice theory can also encompass social factors, which will be explained later on. These social factors can also be looked at on their own in order to predict characteristics of opportunistic sellers. Social control theories state that opportunistic types of behavior arise when an individual's connection to society, or a specific community, is weak or broken (Hirschi, 1967.) The underlying assumption these theories make is that people are not pushed to delinquent behavior, but rather are being constrained from it. Hirschi (1967) identified four types of social bonds that increase a person's connection to society, and thus strengthen the constraint on opportunistic acting: attachment, commitment, investment and belief. These types of bonds will be explained in the following paragraph, explaining how they can be adjusted to fit the separate community of a cryptomarket.

Attachment refers to the attachment one holds to others, which is generally operationalized as attachment to family and peers (Krohn & Massey, 1980). The more attached one is to others, the less likely they are to behave opportunistically, as doing so may hurt the bonds they have with others. When looking at a cryptomarket one could look at the attachment one holds to peers within the cryptomarket, such as fellow buyers and sellers, where behaving opportunistically may hurt these bonds. Commitment refers to the participation within the community and its' activities (Krohn & Massey, 1980). For this study commitment will be seen as one with involvement, which refers to the amount of time invested participating within the community and its' activities (Krohn & Massey, 1980). Commitment and involvement within a cryptomarket can be seen as the amount of activity an actor spends on the forums, engaging with other participants. Behaving opportunistically may hurt the sellers' opportunities to interact with others, as they may be ignored or shunned. Finally, is belief, which refers to the belief one has in the conventional values present within the community (Krohn & Massey, 1980). For a cryptomarket this would refer to the general values held within the cryptomarket community. For all types of bonds, we can argue that within a cryptomarket, they would strengthen through one's participation on the forums. Through interacting with other users on the forum, a seller may become more attached to their peers. In addition to this participation would increase commitment and involvement, as more time would be spent participating in the community and its' activities. Lastly, by participating on the forums a seller would come into contact more often with the general beliefs held by the community. Following this logic, we can formulate the following hypothesis:

*H2: Opportunistic seller behavior within cryptomarkets is less likely to occur the more a seller participates on the forums.*

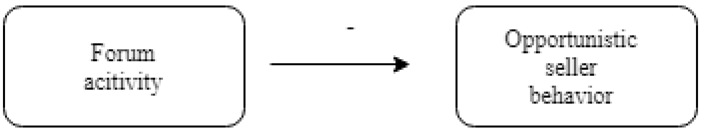


*Figure 2: Mechanism of H2.*

In addition to this, these social bonds would also change the cost-benefit analysis that a completely rational seller makes when considering opportunistic behavior, as they add an additional cost to the analysis. Bouffard & Petkovsek (2014) tested whether social bonds could be integrated into rational choice theories and found that those individuals that scored higher on social bonds were indeed less likely to behave opportunistically. In other words, social bonds impose themselves as an additional cost in the cost-benefit analysis through creating social implications for opportunistic behavior. It can be argued that these social implications are harder to avert for a seller than the reputation costs associated with opportunistic behavior, as these may be less likely to get put to the background by positive transactions. One could thus argue that the positive effect of number of sales on likelihood of opportunistic behavior argued for in hypothesis one, gets smaller or disappears when moderated for participation on the forums, because costs of opportunistic behavior rise, while benefits do not. This is formulated in the following hypothesis:

*H3: The positive effect of number of sales on the likelihood of opportunistic seller behavior gets smaller the more a seller participates on the forums.*

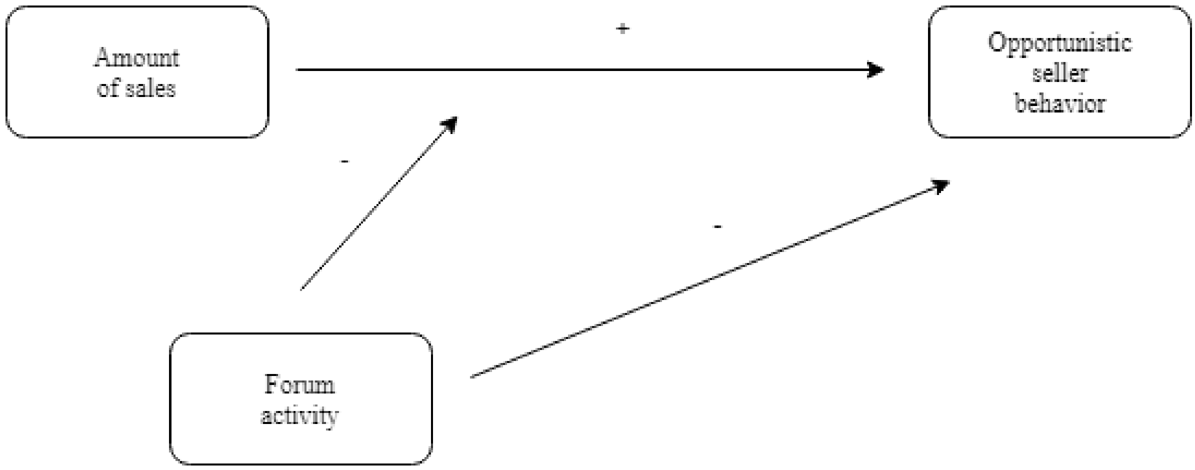


*Figure 3: Mechanisms of H3.*

## 3. Data & methods

For my research I will be using two different datasets. One is a dataset regarding sales and the corresponding feedback for transactions made on Silk Road, the other is a dataset of forum messages left by sellers on the Silk Road forums.

### 3.1 Datasets

#### 3.1.1. Marketplace dataset

The marketplace data of transactions has been gathered by Christin (2013) over a six-month period starting in February of 2012. The data has been obtained by "crawling" through Silk Road, scraping data from the website. The site was attempted to be scraped nearly daily from February 3, 2012 through July 24, 2012, only leaving out days where the crawl from the day before took so long that it passed over into the next day. Unfortunately, not all attempted scrapes yielded useable data. Because of a periodic change in how Silk Road displayed feedback, all data collected between March 7$^{th}$ and March 12$^{th}$ had to be discarded. In addition to this there were some days were the scrape was unsuccessful, either because of Silk Road being down for maintenance or due to human error. These crawls only registered seller, item and feedback data, as buyer's data is not publicly accessible. Because Silk Road has a mandatory feedback system, where if the buyer forgets or neglects to leave feedback Silk Road automatically finalizes the order and leaves a 5 out of 5 feedback score (Przepiorka et al., 2017), the feedback data can be easily used as a proxy for sales, as it gives a fairly accurate estimate. Using this method, Christin gathered data from 184,781 transactions done on Silk Road between February and July of 2012. The dataset was complemented by Branwen et al. (2015), who added seller handles to the transactions.

#### 3.1.2. Forum dataset

The data from the Silk Road discussion forums has been collected by Branwen et al. (2015). This dataset contains messages from the Silk Road discussion forums throughout its' existence. The dataset itself was composed out of 3 archives of the Silk Road forums, all of which were created in October of 2013, after Silk Road went offline, but before the forums went offline. Unfortunately, after Silk Road went offline a lot of users started to delete or censor their posts, which creates missingness in the dataset. Branwen et al. (2015) estimate to have gathered a coverage of about 75% of what was left of the forums after this deleting and censoring happened. The posts on the forums were nested into threads which itself were nested into subforums. In addition to containing these details on where on the forums a post was left, the dataset also includes statistics on the person that left the comment, such as total amount of posts on the forums and reputation score on the forums. The dataset only contains users that have left 1 or more messages on the forums, so those that only lurked but did not post are excluded from this dataset. This specific version of the dataset has been edited so that it only contains messages left by sellers that could be identified through their seller handle (N = 140,768). This seller handle is important because it allows the forum dataset to be merged with the marketplace dataset, using the seller handle as the identifying variable. This dataset will be used to identify how active sellers were on the forums

#### 3.1.3. Final dataset

The first point of action was to merge these datasets into one, using the seller handle to identify sellers across both datasets. This was done by sorting the datasets by seller handle in SPSS, after which the datasets could be merged using the merge file command. Because the marketplace data was from a specific time period, not all sellers that left forum messages had recorded sales in the dataset, in addition to this not all sellers that had recorded sales were active on the forums. This made it so that the new dataset had an N of 299.398. Because for this research only the cases that had a sale, and thus a review, are relevant, I then filtered the dataset to only show cases that had a valid value for feedback rating (1 through 5), which left an N of 184.780.

Because of the way the dataset was structured after operationalization, each case referred to a sale, but had the same value for all used variables for all sales done by the same seller. Although a longitudinal analysis of the data would have been possible, as all transactions were time-stamped, I opted to aggregate all data to the seller level and perform linear regression analyses. This choice was made because this study is meant as a first step to test the hypotheses, leaving room for more complex longitudinal design for future studies. After aggregating all data to the seller level the final dataset remained, which had an N of 1017.

## 3.2. Variables used in the analysis

### 3.2.1. Independent variables

In order to rate how active a seller is on the forums I have made use of the post count variable; this variable aggregated the amount of posts a seller had made on the forums since registering to them. A new variable for forum activity was created. Within this variable, each seller was assigned the highest found value within the database for the post count variable, which would be the accurate amount of posts that seller had made on the forums. Those sellers that remained with a missing value, were assigned a value of 0, as it meant they had not made any identified posts on the forum. The forum activity variable was then divided by 10, as the effect of one forum posts on opportunistic behavior was too small to interpret.

Number of sales done by each seller was operationalized by the amount of recorded feedback a seller had gotten within the dataset. As mentioned earlier the amount of recorded feedback can be used as a relatively accurate proxy for number of sales, as leaving feedback is mandatory on Silk Road, and when a buyer neglects to do so Silk Road leaves an automated 5/5 review. This method of operationalizing sales has also been used in prior research (Christin, 2013; Décary-Hétu, Paquet-Clouston & Aldridge, 2016). In order to do this an identifier variable had to be created first, which assigns a unique value to each case within the dataset. Next, the number of times a seller appeared within the dataset could be aggregated into a new variable, which reflects the total amount of sales a seller has made within this dataset. To keep in line with the forum activity variable, amount of sales was also divided by 10.

### 3.2.2. Dependent variables

Operationalizing opportunistic seller behavior was a non-trivial task, for which nobody has really used a good measure, as these are not reported anywhere. Therefore, opportunistic seller behavior was operationalized by using proxies in two ways, which were then also merged into a third operationalization.

First of all, a variable was computed based on the feedback rating, which had a value of 0 for transactions with a feedback score of 3 or higher, indicating a trustworthy transaction, and a value of 1 for transactions with a feedback score of 1 or 2, indicating a transaction in which the seller behaved opportunistically. Although this threshold is somewhat artificial, it was chosen because it is the bottom half of the 1-5 rating distribution, where 4 and 5 can be seen as above average or positive, 3 average or neutral, and thus 1 and 2 as below average or negative.

In addition to this, a random sample of approximately 10% of the transactions in which the seller was identified as behaving opportunistically was taken, and the feedback messages corresponding to the transaction were analyzed. Doing so identified a few words and phrases which were often used by buyers that felt like the seller behaved opportunistically, these being: “scam”, “warning”, “warned”, “beware”, “not received”, “nothing arrived”, “never received” “never arrived”, “do not trust”, “low quality”. Using these words and phrases another variable for opportunistic behavior was created, where the value was 0 for transactions of which the feedback message contained none of these words or phrases, again indicating a trustworthy transaction, and 1 for transactions of which the feedback message did contain one of these words or phrases, again indicating a transaction in which the seller behaved opportunistically. Between the two variables indicating opportunistic seller behavior, there was an overlap of approximately 35%.

Despite the relatively small amount of overlap, the choice was made to also merge the two variables into one additional dependent variable, where if either the feedback rating or the feedback message indicated the seller behaving opportunistically the value was put to 1, and if neither of the two indicated the seller behaving opportunistically the value was put to 0. The choice to combine the variables into one was made because I believe it gives a better view on opportunistic behavior, as it includes the feedback where the buyer was negative in the feedback message but not in the rating. Since buyers may forget to change the rating away from 5/5(default when leaving feedback) or choose 3 while not really being satisfied, this combined variable will most likely flag opportunistic transactions the most accurately. All 3 dependent variables were aggregated, so that they indicated the total amount of times a seller was flagged as behaving opportunistically when looking at the specified conditions.

#### 3.2.3 Control variables

Multiple control variables were added to the analysis to strengthen it, these were firstly structured as dummy variables. First of all, shipment origin was used as a control variable. Shipment origin may affect a buyers' decision to order an item, and thus affect the amount of sales a seller has. In addition to this the shipment origin is likely to be the place in which the seller is located. Sellers from different locations may be either more or less likely to participate on the forums or behave opportunistically, based on different cultures and socio-economic situations. For shipment origin there were 5 origins that had a substantially larger amount of sales than others, those being USA, UK, Germany, The Netherlands and Canada. For each of these 5 origins a dummy was created, where 1 indicated that the shipment origin was that place, and 0 indicated it was not. Lastly a dummy was created combining all other shipment origins, where a 1 indicated it was sent from somewhere other than these 6 destinations, and a 0 indicated it was not.

In addition to this, shipment destination was used as a control variable. Shipment destination can affect the total number of sales a seller has, as where the seller is willing to ship to also affects how large their potential clientele is. Furthermore, shipment destination may affect the likelihood of a seller being flagged as behaving opportunistically, as some shipment destinations may have harsher control on incoming mail, increasing the likelihood of some getting intercepted and thus not arriving at the buyer. Lastly, shipment destination may also affect forum activity, as sellers that only ship to certain places may have less incentives to use the forums if those places are not largely represented on the forums. For shipment destination there were 6 destinations that had a substantially larger amount of sales than other, those being worldwide, USA, USA or Canada, UK, EU and worldwide except USA. For each of these 6 destinations a dummy was created, where 1 indicated the shipment destination was that place, and 0 indicated it was not. Lastly a dummy was created combining all other shipment destinations, where a 1 indicated it was sent to somewhere other than these 6 destinations, and a 0 indicated it was not.

Lastly, the type of item that was sold was used as a control variable. The item category may affect the sellers amount of sales through the desirability of the product, a sellers' opportunistic behavior through the value of the product(e.g. higher value is more benefits from behaving opportunistically) and the forum activity of the seller through the demand for the product(e.g. if the demand is low the seller may want to advertise it on the forums). For item categories the 9 most commonly sold categories were used, in addition to the category digital goods. Digital goods was chosen as an extra category as it does not require shipment and has a fast delivery time, thus making finalizing early less likely to happen, therefore making opportunistic behavior also less likely. The other 9 categories were: weed, cocaine, hash, pills, mdma, prescription drugs, benzos, books and white (commonly heroin). For all these categories a dummy was created, where 1 indicated the sale being in that category, and 0 indicated that not being the case. Lastly a dummy was created combining all other item categories, where a 1 indicated the item sold was in another category than these ten, and a 0 indicated it was not.

All dummy variables were then aggregated to the seller level, creating new, non-dummy, categorical variables. Where a 1 indicated that the seller had at least once shipped an item from or to the corresponding place, or had sold an item in the corresponding category.

### 3.3. Methods

Three models were constructed to test the hypotheses. All three models were ran separately for all 3 dependent variables: opportunistic seller behavior based on feedback rating, opportunistic seller behavior based on feedback messages and finally opportunistic seller behavior based on both feedback rating or messages.

The first model consists of a multiple linear regression, where amount of sales and forum activity act as the independent variables, and opportunistic seller behavior as the dependent variable. This model was constructed to test hypotheses 1 and 2 in isolation. The second model adds the interaction variable to the equation, in order to test the third hypothesis. The third and final model adds the control variables, in order to see if the results from model 1 and 2 hold when controlled for whether the seller has ever sold from a shipment origin, to a shipment destination or an item of a certain category.

## 4. Results

### 4.1. Descriptive statistics

In table 1 the descriptive statistics of the independent and dependent variables are depicted.

Table 1.

*Descriptive statistics of independent and dependent variables per seller.*

| | N | Min | Max | M | SD |
|---|---|---|---|---|---|
| Opportunistic transactions per seller based on feedback rating | 1017 | 0 | 87 | 2.53 | 7.7 |
| Opportunistic transactions per seller based on feedback messages | 1017 | 0 | 91 | 1.91 | 6.76 |
| Opportunistic transactions per seller based on both feedback rating and messages | 1017 | 0 | 139 | 3.77 | 11.44 |
| Amount of sales per seller /10 | 1017 | .10 | 484.70 | 18.17 | 40.97 |
| Amount of posts on the forums per seller /10 | 1017 | 0 | 1361.90 | 8.52 | 47.36 |

As can be seen in table 1, the average Silk Road seller in the database had made 181.7 sales in the time period in which the data was collected, in addition to this the average seller had made 85.2 posts on the Silk Road forums. When looking at the amount of transactions in which a seller operated opportunistically, we see that when looking solely at feedback rating this averages at 2.53 times, when looking at solely feedback messages it averages at 1.91 times, and when looking at both of these together it averages at 3.77 times. When comparing this to the max values of respectively 87, 91 and 139, the average numbers appear to be relatively low, which may indicate that opportunistic behavior is mainly done by a relatively small number of sellers.

In table 2 the descriptive statistics of the control variables are depicted. For each category a 1 indicates that a seller has at least once shipped something from or to that place, or has at least once sold an item in that category.

Table 2.

Descriptive statistics of control variables per seller.

| | N | Min | Max | M | SD |
|---|---|---|---|---|---|
| *Seller has shipped from origin* | 1017 | 0 | 1 | | |
| USA | | | | .51 | .50 |
| UK | | | | .11 | .31 |
| Germany | | | | .05 | .22 |
| The Netherlands | | | | .07 | .26 |
| Canada | | | | .05 | .22 |
| Other | | | | .35 | .48 |
| *Seller has shipped to destination* | 1017 | 0 | 1 | | |
| Worldwide | | | | .50 | .50 |
| USA | | | | .40 | .49 |
| USA or Canada | | | | .09 | .29 |
| UK | | | | .06 | .24 |
| European Union | | | | .10 | .30 |
| Worldwide except USA | | | | .03 | .17 |
| Other | | | | .18 | .38 |
| *Seller has sold item from category* | 1017 | 0 | 1 | | |
| Weed | | | | .22 | .42 |
| Cocaine | | | | .10 | .30 |
| Hash | | | | .10 | .31 |
| Pills | | | | .07 | .25 |
| MDMA | | | | .08 | .27 |
| Prescription Drugs | | | | .13 | .33 |
| Benzos | | | | .13 | .34 |
| Books | | | | .03 | .16 |
| White | | | | .03 | .18 |
| Digital Goods | | | | .04 | .19 |
| Other | | | | .83 | .37 |

Table 2 shows some interesting statistics. First of all, we see that at least some sellers sent their goods from different origins, as well as deliver them to several destinations, because the sum of the means from these categories are above 1(respectively 1.14 and 1.36). The US is the place from which most sellers have at least once sent products with 51%, followed by the UK with 11%, which corresponds with earlier research on cryptomarkets (Norbutas, 2018; Kruithof et al., 2016). Furthermore, most sellers appear to be willing to ship their product worldwide, with 50% of sellers having done so at least once followed by the US with 40%, which also corresponds with earlier research on cryptomarkets (Broséus, Rhumorbarbe, Morelato, Staehli & Rossy, 2017). Lastly, we see that there are at least some sellers that sell items from different categories, as again the sum of the mean is above 1(1.76). For item categories weed is the most popular, with 22% of sellers having at least once sold it, followed by benzos and prescription drugs, both coming in at 13%. Although this does not correspond with earlier research (e.g. Norbutas, 2018), there could be a simple explanation for this, as most studies have looked at the total amount of sales per category, rather than the number of sellers that have sold items within a specific category.

### 4.2. Regression analyses

Table 3 shows the results of the regression analyses, where opportunistic seller behavior based on feedback rating and opportunistic seller behavior based on feedback messages are separately used as dependent variables. Feedback has been shortened in the table to fb for formatting purposes.

Table 3

*Regression analyses predicting opportunistic seller behavior based on either feedback rating or messages*

| | Model 1 | | | | Model 2 | | | | Model 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Opportunistic seller behavior based on fb rating | | Opportunistic seller behavior based on fb message | | Opportunistic seller behavior based on fb rating | | Opportunistic seller behavior based on fb message | | Opportunistic seller behavior based on fb rating | | Opportunistic seller behavior based on fb message | |
| | B | S.E. | B | S.E. | B | S.E. | B | S.E. | B | S.E. | B | S.E. |
| Constant | .534* | .215 | .294 | .197 | .30 | .22 | .148 | .200 | -3.73*** | .738 | -.788 | .665 |
| Salescount/10 | .111*** | .004 | .090*** | .004 | .129*** | .006 | .101*** | .005 | .110*** | .006 | .090*** | .005 |
| Forum posts/10 | -.003 | .004 | -.002 | .004 | .028*** | .007 | .018** | .007 | .027*** | .007 | .019** | .006 |
| ForumxSales | | | | | -.001*** | .000 | -.001*** | .000 | -.001*** | .000 | -.001*** | .000 |
| *Seller has shipped from* | | | | | | | | | | | | |
| USA | | | | | | | | | 3.16*** | .758 | .817 | .682 |
| UK | | | | | | | | | 2.70** | .918 | 1.39 | .826 |
| Germany | | | | | | | | | 4.72*** | .971 | 1.09 | .874 |
| The Netherlands | | | | | | | | | 6.73*** | .929 | 7.61*** | .836 |
| Canada | | | | | | | | | 1.92* | .966 | 1.041 | .870 |
| Other | | | | | | | | | 2.86*** | .568 | 1.038* | .512 |
| *Seller has shipped to* | | | | | | | | | | . | | . |
| Worldwide | | | | | | | | | .296 | .468 | .496 | .421 |
| USA | | | | | | | | | -1.14 | .653 | -.350 | .588 |
| USA or Canada | | | | | | | | | .075 | .669 | .470 | .602 |
| UK | | | | | | | | | -1.44 | 1.10 | -1.59 | .992 |
| EU | | | | | | | | | -1.15 | .672 | -.956 | .605 |
| Worldwide except USA | | | | | | | | | -2.88** | 1.11 | -1.90 | .997 |
| Other | | | | | | | | | -1.10* | .547 | -1.06* | .493 |
| *Seller sold item from category* | | | | | | | | | | | | |
| Weed | | | | | | | | | .393 | .474 | -.600 | .427 |
| Cocaine | | | | | | | | | 2.01** | .622 | .692 | .560 |
| Hash | | | | | | | | | 2.55*** | .630 | .670 | .567 |
| Pills | | | | | | | | | 3.55*** | .800 | 3.82*** | .720 |
| MDMA | | | | | | | | | 1.28 | .721 | 1.54* | .649 |
| Prescription Drugs | | | | | | | | | .948 | .565 | .428 | .508 |
| Benzos | | | | | | | | | -.471 | .566 | -.225 | .509 |
| Books | | | | | | | | | 2.45* | 1.15 | -3.43** | 1.04 |
| White | | | | | | | | | 2.21* | 1.04 | .005 | .937 |
| Digital Goods | | | | | | | | | -2.38* | .994 | -1.43 | .894 |
| Other | | | | | | | | | .548 | .515 | -.512 | .464 |
| $R^2$ | .349 | | .293 | | .365 | | .301 | | .460 | | .433 | |

***Sig*** **P<.05, **P<.01, ***P<.001*

The first model, which used only amount of sales and amount of posts made on the forum by sellers as independent variables had an $R^2$ of .349 for opportunistic seller behavior based on feedback rating, and an $R^2$ of .293 for opportunistic seller behavior based on feedback messages, explaining the variation by respectively 34.9% and 29.3%. It also shows that both when looking at opportunistic seller behavior based on feedback rating, as well as opportunistic seller behavior based on feedback messages a significant positive effect of the amount of sales made is found (respectively b=.111; p<.001 and b=.090; p<.001). These findings support the first hypothesis:

*H1: Opportunistic seller behavior within cryptomarkets is more likely to be done by sellers that have a large amount of sales.*

When looking at the effect of forum posts however, there were no significant effects found in model 1(respectively b=-.003; p=.439 and b=-.002; p=.685), meaning in model 1 no support was found for the second hypothesis:

*H2: Opportunistic seller behavior within cryptomarkets is less likely to occur the more a seller participates on the forums.*

When adding in the interaction variable in model 2 the effect of amount of sales changes slightly, but stays significantly positive, for both opportunistic seller behavior based on feedback rating (b=.129; p<.001) and opportunistic seller behavior based on feedback messages (b=.101; p<.001). A bigger change is found in the effect of forum messages, which is now also significantly positive for both dependent variables (respectively b=.028; p<.001 and b=.018; p<.001). The explained variation in the form of $R^2$ also increases to respectively 36.5 and 30.1 percent. We also find a small, yet significant negative interaction effect of forum activity and amount of sales for both dependent variables (b=-.001; p<.001 for both DVs), meaning that the positive effect amount of sales has on opportunistic seller behavior is smaller for sellers that have more posts on the forum. These finding support the first hypothesis, as well as the third:

*H3: The positive effect of number of sales on the likelihood of opportunistic seller behavior gets smaller the more a seller participates on the forums.*

The second hypothesis however is not supported by model 2, as the significant effect is positive rather than the hypothesized negative effect.

The third and final model shows that when controlled for shipment origin, shipment destination and category of item sold, the results from the second model hold. With the effect of amount of sales on the opportunistic behavior based on feedback rating(b=.110; p<.001) and based on feedback messages(b=.090; p<.001) remaining significantly positive, as well as the effect of forum activity(respectively b=.027; p<.001 and b=.019; p<.01). The interaction effect between these independent variables remained significantly negative (b=-.001; p<.001 for both DVs). This model also explained the variation the best, with an $R^2$ of .460 for opportunistic behavior based on feedback rating and an $R^2$ of .433 for opportunistic behavior based on feedback messages. Based on these analyses support has been found for both the first and third hypotheses, but no support has yet been found for the second hypothesis.

Finally, Table 4 shows the results from the last regression analysis, which used the dependent variable of opportunistic seller behavior based on both the feedback rating and the feedback messages. For model 1 this analysis shows similar results as the others, providing a significant positive effect of amount of sales on opportunistic seller behavior (b=.173; p<.001) and finding no significant effect for amount of posts on the forums on opportunistic seller behavior (b=-.003; p=.605). With an $R^2$ of .384, model 1 provided a 38.4% explanation of variance for the dependent variable. So, again support was found for the first hypothesis, and again not for the second.

The second model's results were also in line with those found earlier, finding once more a significant positive effect of amount of sales on opportunistic seller behavior (b=197; p<.001). In addition to this, the effect of forum activity has become significantly positive again (b=.038; p<.001). The interaction effect of forum activity and amount of sales was once more significantly negative (b=-.002; p<.001). The $R^2$ for this model was .397, explaining 39.7% of the variance of the dependent variable.

Lastly, the third and final model's results were also in line with the results found earlier. The effect of amount of sales on opportunistic seller behavior was significantly positive (b=.171; p<.001), the effect of forum activity on opportunistic seller behavior was significantly positive (b=.039; p<.001) and the interaction effect of these variables was significantly negative (b=-.002; p<.001). This model explained 50.7% of the variance in opportunistic seller behavior. Once more, all results were in line with the first and third hypotheses, but no support was found for the second hypothesis. An additional finding that is interesting to note is that the origin from which a seller has shipped seems to have a large effect on the likelihood of the seller behaving opportunistically, with 5 out of the 6 categories having large, significant results.

Table 4.

*Regression analyses predicting opportunistic seller behavior based on both feedback rating and messages*

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | B | S.E. | B | S.E. | B | S.E. |
| Constant | .653* | .007 | .345 | .315 | -3.75*** | 1.05 |
| Salescount/10 | .173*** | .006 | .197*** | .008 | .171*** | .008 |
| Forum posts/10 | -.003 | .315 | .038*** | .010 | .039*** | .010 |
| ForumxSales | | | -.002*** | .000 | -.002*** | .000 |
| *Seller has shipped from* | | | | | | |
| USA | | | | | 3.26** | 1.08 |
| UK | | | | | 3.24** | 1.30 |
| Germany | | | | | 4.84*** | 1.38 |
| The Netherlands | | | | | 11.96*** | 1.32 |
| Canada | | | | | 2.32 | 1.37 |
| Other | | | | | 3.23*** | .807 |
| *Seller has shipped to* | | | | | | |
| Worldwide | | | | | .670 | .664 |
| USA | | | | | -1.23 | .928 |
| USA or Canada | | | | | .413 | .949 |
| UK | | | | | -2.32 | 1.56 |
| EU | | | | | -1.69 | .954 |
| Worldwide except USA | | | | | -4.21** | 1.57 |
| Other | | | | | -1.71* | .777 |
| *Seller sold item from category* | | | | | | |
| Weed | | | | | -.177 | .673 |
| Cocaine | | | | | 2.20* | .883 |
| Hash | | | | | 2.78** | .895 |
| Pills | | | | | 5.83*** | 1.14 |
| MDMA | | | | | 2.62* | 1.02 |
| Prescription Drugs | | | | | 1.04 | .802 |
| Benzos | | | | | -.723 | .803 |
| Books | | | | | -.172 | 1.63 |
| White | | | | | 1.91 | 1.48 |
| Digital Goods | | | | | -3.27* | 1.41 |
| Other | | | | | .028 | .732 |
| $R^2$ | .384 | | .397 | | .507 | |

***Sig** *P<.05, **P<.01, ***P<.001*

## 5. Conclusion and Discussion

This paper set out to identify market activity characteristics of sellers that behave opportunistically within cryptomarkets, which have mostly the same measures in place to protect buyers as regular online marketplaces, sans the threat of legal action. By doing so I hoped to build a framework upon which further research can build, and from which new preventive measures could possibly arise. In order to do so, the following research question was formulated:

*What are the main characteristics relating to market activity of opportunistic sellers within cryptomarkets?*

I argued that through rational choice mechanisms, the sellers that were most likely to behave opportunistically would be those sellers that were best able to avert the costs associated with this type of behavior. This because the rational choice theory (Scott, 2000) provides a theoretical framework in which people weigh off costs and benefits associated with acting in a certain way, thus being able to avert costs makes it more likely that the cost-benefit analysis would turn out in a net benefit for acting. Using findings on the workings of reputation systems from Resnick et al.(2006) and Bolton et al.(2004) it was argued that the sellers with the largest volume of sales would be the sellers that would be best able to avert the costs associated with opportunistic behavior, as a negative feedback rating has less impact on their overall rating than it does for smaller sellers, as well as their larger volume of sales diminishing the relative recency of the negative feedback faster. Following this logic, the following hypothesis was formulated:

*H1: Opportunistic seller behavior within cryptomarkets is more likely to be done by sellers that have a large amount of sales.*

In addition to this, social bond theory (Hirschi, 1967) was used to formulate an expectation of the effect of a sellers' forum activity on their likelihood to behave opportunistically. Social bond theories that opportunistic types of behavior arise when an individual's connection to society, is weak or broken. Using the mechanisms of social bonds as explained by Krohn & Massey (1980), this theory was applied to the community of a cryptomarket, arguing that through forum participation one would create a strong connection to the community, thus lessening the likelihood of a seller behaving opportunistically. This was formulated in the second hypothesis:

*H2: Opportunistic seller behavior within cryptomarkets is less likely to occur the more a seller participates on the forums.*

In addition to this, the social bond mechanisms were paired with the rational choice theory. Bouffard & Petkovsek (2014) found that social bonds impose an additional cost to the cost-benefit analysis done by an actor, as behaving opportunistically could damage those bonds. Using this mechanism, it was argued that the positive effect a seller's volume of sales has on opportunistic behavior gets smaller the more that seller participates on the forums, as the social costs can not be as easily averted as the reputation costs. Following this logic, the following hypothesis was formulated:

*H3: The positive effect of number of sales on the likelihood of opportunistic seller behavior gets smaller the more a seller participates on the forums.*

Using Silk Road marketplace data collected by Christin (2013) and complemented by Branwen et al. (2015) in combination with Silk Road forum data collected by Branwen et al. (2015) these hypotheses were tested. The tests were done on a seller level, controlling for whether or not a seller had once shipped from or to a certain place, and whether or not a seller has once sold items from a certain category. The dependent variable was operationalized in three different ways, as operationalizing opportunistic seller behavior was a non-trivial task, for which nobody has really used a good measure, so that the results would be as exhaustive as possible. All dependent variables were ran through 3 multiple linear regression models, one containing only the two independent variables, one adding the interaction variable and the last adding the control variables. The variance explained by these models ranged from 29.3% to 50.7%.

Across a total of 9 models ran, the amount of sales a seller had made had a significant positive effect on their likelihood to behave opportunistically. These results support the idea of the rational choice mechanisms, and are in correspondence with the most common types of opportunistic seller behavior identified by Moeller et al. (2017), as these were all types of opportunistic behavior that could most easily be committed by large volume sellers. The first hypothesis is thus supported based on the results from this study

When looking at the effect of forum activity on opportunistic seller behavior however, no significant effect was found in 3 out of the 9 models, in the other 6 models a significant positive effect was found, meaning the more active a seller was on the forums the more likely they were to behave opportunistically. Because of this the second hypothesis has to be rejected. A possible reason for this could be that cryptomarkets do not lend themselves as communities upon which general social theories can be applied, as through anonymity the effects of social control and bonds may be absent or dampened.

For the interaction effect formulated in hypothesis 3 a small, negative significant effect was found for all 6 models in which it was included, meaning that the positive effect of volume of sales on opportunistic seller behavior found is indeed smaller when a seller is more active on the forums. Meaning that the third hypothesis is supported by these findings.

In regards to the research question, the only main characteristic related to market activity of sellers that behave opportunistically in cryptomarkets is that they tend to be higher volume sellers. This research has however not been able to identify a profile of opportunistic sellers, which is something further research could look into, using this study as a place to start.

## 6. Limitations and future research

This paper has several limitations. First of all, the Silk Road marketplace data only contained transactions from a set period of time. This means that a large volume seller that just happened to not make much transactions within that time-period was seen as a small volume seller in this study, which may impact the results. Future research should in part be aimed at obtaining more complete datasets, ranging over a longer period of time. In addition to this future research could use a longitudinal analysis, rather than the linear regression models used in this study, as those can give results on the transaction level, rather than the seller level, which may give more trustworthy results. Secondly, this paper has only looked at seller characteristics on the surface, future research may want to go further, either through case studies or by using more complete data, to get a better picture of who the opportunistic seller is.

In addition to this, the results from this study have raised several other points on which further research may want to focus. First of all, this study found that large volume sellers are more likely to behave opportunistically than their low volume counterparts, despite the fact that raising reputation is costly and the future benefits of a good reputation are evident. More information is needed as to why reputation systems are not capable of achieving the theoretical effects that they should have. Secondly, the control variables used in the analysis showed that both geographical location of the seller as well as the goods the seller sells may have a reasonably large impact on the likelihood of a seller behaving opportunistically, which is something future research may want to look into.  Lastly future research should be focused on finding a more exhaustive measure with which to operationalize opportunistic behavior, as these are not reported anywhere, by doing so future studies can use corresponding operationalization and thus create results that are more generalizable and replicable.

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