Relationship Between Vendor Popularity and Prices on Dark Web Marketplaces

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ABSTRACT

Illicit drugs take up by far the largest market share out of all categories of illicit items sold on the dark web marketplaces. With the rapid growth of darknet users over the last decade, and the notorious popularisation of the Silk Road business model, drug vendors, both new and established, have been becoming adept in marketization of their goods. The cryptomarket platforms became reminiscent of traditional e-commerce websites, such as Amazon or eBay, with item descriptions, vendor ratings, reviews, and discounts. There exists a gap of knowledge regarding the effects of vendor popularity on the price of drugs, created by the new "black e-commerce" business model. This research uses secondary forms of data analysis to discover if a relationship exists between vendor popularity and prices on dark web marketplaces.

Keywords

Drug Trafficking, Dark Web Marketplaces, Analysis, Drug Vendors, Drug Pricing, Vendor Popularity

1. INTRODUCTION

The existence of modern dark web marketplaces (DWMs) can be attributed to the emergence of the infamous Silk Road in 2011, which revolutionized trade in illicit items, most notably drugs [2, 8]. The cryptomarket utilized famous e-commerce models, like those used on Amazon and eBay, for the creation of its own marketplace, which later became known as "black e-commerce". Customer friendly interfaces, user profiling, vendors and consumers, reviews, ratings, and product descriptions, all notable attributes for an online market [2, 9]. Although the platform was shut down in late 2013, multiple variants based on the model developed by Silk Road began to saturate the dark web with contemporary cryptomarkets, becoming some of the most popular websites on the darknet.

While onion routing is not widely popularised in the public, it is one of the most common ways people are able to access the darknet, namely using the Tor browser. Because of its anonymity functions [11], it has been one of the leading factors in the rapid increase of users on the darknet and subsequently on the DWMs [9]. In combination with cryptocurrencies being the general payment method, which provide another layer of anonymity in the form of no direct traceability to personal identity [4], the lucrativeness of the DWMs has attracted many new customers and in turn, vendors.

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Existing research shows that the average lifespan of DWMs tends to be 8 months. The frequent shutdowns are mainly facilitated by exit scams or law enforcement intervention, making it difficult for vendors to build and preserve their reputation. As a result of this problem, vendors found a way to maintain their recognisability through building their brand around their username, as to ensure market success during transition periods to other DWMs. A study found that two accounts belonging to the same vendor are most likely to have similar usernames on different DWMs, however two accounts that belong to the same vendor that operate in the same marketplace tend to be different [9].

As previously mentioned, the cryptomarkets predominantly operate with the use of cryptocurrencies. There is a bidirectional relationship between drug listing prices and the exchange rate of Bitcoin [13]. Prices change depending on the exchange rate. Subsequently, a visual representation can be seen at the time of closure of the Silk Road. The Bitcoin price dropped from \$145.70 to a low of \$109.76 [15]. The prices of drugs also depend on the quantity sold. It is estimated that approximately one quarter of all revenue generated by cryptomarkets are wholesale transactions, implying business to business affairs, however the market is dominated by purchases on a smaller scale, implying personal use or small social distribution [7]. In both cases similar product marketability applies, as well as the branding of vendors. Apart from cryptomarkets resembling traditional drug markets in terms of revenue and distribution [3], the success is directly related to the vendors reputability. From this, an assumption can be made, that more reputable vendors can sell their product for a higher price, than that of an unknown vendor.

While there has been a substantial amount of research done regarding the price of drug listings on the DWMs that correlate and fluctuate with cryptocurrencies, the effect that the vendor has on the price has been untouched. This paper will analyse data of vendors and their product listings scraped from various DWMs to discover if there is a relationship between drug vendors and product prices by comparing the price listings of popular vendors to less popular vendors on similar products.

Therefore, the purpose of this research is to find the answer to whether or not does drug vendor popularity affect drug prices. The research questions (**RQ**) below are used as sub-questions to answer the main question and are as follows:

RQ1: What are the core factors that dictate vendor popularity on the dark web marketplaces?

RQ2: Using data gathered from **RQ1**, how do less popular vendors set prices upon entering the market compared to the prices of popular vendors?

RQ3: What are the subsequent changes in vendors price over time depending on their popularity?

This paper focuses on filling the gap on knowledge regarding the factors that go into pricing of illicit substances on the dark web marketplaces, using descriptive data analysis, statistical analysis and employing comparative research techniques, hypothesising a relationship between drug vendors and product prices. The research will provide a better understanding of vendors and their interactions on cryptomarkets, as well as the pricing of illicit goods.

The paper is split into multiple sections. Related work covers all the necessary literature that is going to be used for this research, mainly to discover vendor popularity factors. Methods of research is a detailed description on how the answers to the research questions will be achieved. Data discusses the used dataset, as well as the changes it underwent. Results depict the findings related to the research questions followed by their discussion. Finally, the conclusion which contains the summary of everything beforehand.

2. RELATED WORK

The most important research contribution towards the understanding the DWMs and their inner workings can be attributed to the largest publicly available data collection, consisting of web scrapes of all existing English language DWMs, which was manifested by Gwern et. all [6]. This collection of data has contributed to a wide spectrum of research on various disciplines connected to DWMs, that helped to shape our current understanding of the cryptomarkets, many of which are reviewed and used in our research [1, 4, 8, 9, 12, 13].

Furthermore, the formation of the raw data from Gwern et. al. into a readable CSV dataset was manifested by Isaak Ladegaard in coordination with Boston College [14]. This specific dataset is used for conducting this research.

The work of Shan produces a deep understanding of drug vendors on the DWMs with insights on vendor branding, account usage, and distribution across various cryptomarkets. Shaw found that vendors tend to use similar usernames across different DWMs, which is a descriptive factor of an established vendor [9].

Zaunseder and Bancroft assert a bidirectional relationship between cryptocurrency rate and the price of drugs on the DWMs, which was confirmed by their findings stating that there is a direct relationship between Bitcoin exchange rate and the price of drugs [13]. This is not surprising, seeing as an estimated ¼ of Bitcoin users are involved in illegal activity [5]. Being a core factor in the pricing of drugs, it will be considered when researching the relationship between vendor popularity and drug pricing.

Other contributing factors to both the vendors and the prices are implied by Bhaskar et. al. [1] stating that, as with legal online markets, the cryptomarket penalizes bad ratings, which leads to the reduction of sales and in the worst case to market exit. This leads to a relatively low portion drug deals receiving bad ratings. These factors are also important to note during the identification of vendor popularity and the subsequent effects on their listings.

3. METHODS OF RESEARCH

This section will go through the steps completed for finding the answers to the research questions.

First, a literature review of works relating to drug vendors and drug prices on the DWMs is conducted. Considering that there is no research done on the relationship between the two, the focus of the literature review will be to identify the factors of vendor popularity. Once these factors have been found, they are examined and compared with the existing rating metric for vendors within their respective markets. In this case the most defining characteristic of vendor popularity was the number of transactions they have completed. From this, a regression analysis was performed on vendors with various amounts of transactions, followed by hypothesis testing, which was validified by the student t-test analysis. The testing hypothesis is stated in the results section.

$$t = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{(s^2\left(\frac{1}{n_1} + \frac{1}{n_2}\right))}}$$

Formula 1: t-test

When the core factors of vendor popularity were identified, resulting in being the number of transactions a vendor has, using the dataset provided by Gwern et. al. factorization began on popular vendors and less popular vendors to compare their setting of price with set prices of popular vendors by extracting data on vendors, their products, and prices. Another t-test was performed using both groups to discover if they convey any differences. The hypothesis for this test is stated in the results section.

Finally, the lifespan of vendors is followed to find a correlation between their popularity and their product price. For this, trend analysis is used.

Ultimately, all information from the previous steps is compiled together to see if there is a relationship between vendor popularity and drug prices.

4. DATA

The dataset used for this research was provided by Ladegaard & Boston College [14]. Each row within the dataset represents a transaction between the vendor and a customer. These rows are split into columns: ID, Feedback, Item description, Market, Category, Sale date, Ships from, Price (USD) Median, Vendor rating, Vendor username.

4.1 Restructured Data

The data has been restructured for the purpose of excluding unnecessary information that is not related to the underlying study. Such columns as ‘ID’, ‘Feedback’ and ‘Ships From’ were removed.

Furthermore, specifically when working with pricing, the data that is being compared between each other must be of a similar nature to produce the most accurate results. To achieve this, the data was filtered by limiting the research to the sales of the two most popular drugs, namely cannabis and MDMA, on the top three trafficked platforms at the time, Agora, Silk Road 2.0, and Evolution. For each drug, a singular quantity was also chosen based on the frequency it was sold at. The most frequent were chosen for their larger containment of data entries. For cannabis, the quantity of five grams, whereas for MDMA only one gram. A representation of the restructured data can be seen in Table 1. The dataset was also stripped from entries that possessed a null or empty value in such fields as vendor rating and price.

Depending on the tests or analysis performed, the data has been structured accordingly. For regression analysis, t-tests, and trend analysis, outliers relevant to the values that were being tested were removed by excluding values above and below the 95^{th} and 5^{th} percentiles, respectively.

Market	*Vendors*	*Average Rating*	*Average Transaction Number*
Agora	253	0.98	92
Evolution	205	0.99	86
Silk Road 2.0	61	89	270

Table 1: Remaining Restructured Data

5. RESULTS

To gain the most accurate conclusion on whether vendors affect drug prices, following the laid-out research questions, multiple vendors were analysed and compared between each other based on various metrics, such as the product types, product quantity, their market, their ratings, or popularity, and their number of transactions.

5.1 Vendor Popularity

A literature review was done to find the core factors that dictate vendor popularity on DWMs.

It is important to note the existence of a vendor rating metric within the dataset that was used for this research. The said metric is not reliable enough to be a descriptive factor of vendor popularity due to the lack of contextual information behind it. To our knowledge, the rating can represent anything from the quality of the product to the quality of the delivery. Because of this, the metric will be used as a comparative for the information gathered from the literature review. This will both add soundness and validify to the metric, as well as verify the information collected form the literature review.

Reputation is incredibly important for drug vendors both in the physical and online worlds. More so online, where there is no guarantee for a successful purchase or sale of illicit substances. This is facilitated further by the anonymity offered by DWMs, where all transactions are anonymous, as well as the identity of vendors and customers. If the transaction ends up being a scam, regardless from which party, no legal action can be called upon, as the activity itself is illegal. As a result, positive vendor reputation is one of the key factors of success in the illicit business, where customer generated feedback acts as the judge of that reputation. Customers, especially new ones, are subject to risk when purchasing goods and therefore strive to minimize it by finding vendors with the most positive or neutral feedback for their desired product and avoiding those with no or negative feedback [9].

Another important piece of information concluded by Shaw is that vendors tend to uphold their reputation between markets by using their username as a brand. This is due to the short average lifespan of DWMs being 8th months. Without somehow branding themselves, vendors would be forced to rebuild their reputation every time their operable marketplace shutdown. This only amplifies the importance of feedback for vendors, especially when holding accounts on multiple marketplaces, where negatively affected reputation on one platform can subsequently negatively impact the reputation on other platforms leading to a decrease of sales [9].

In their reputation's analysis, Bhaskar et. al. state that the negative rating not only causes a decline in growth of sales, but also increases the rate at which more negative ratings come in [1].

Negative ratings are rarely given. In the four DWMs that Bhaskar et. al. have analysed, it was found that between 1.2% and 2.9% of ratings were negative, 1.8% to 3.7% neutral and between 94.5% and 96.9% were positive [1].

The market penalizes bad ratings, which in the worst case leads to market exit. The ratings include feedback, as there is usually an explanation to why the rating was negative. Negative feedback, which from now on will also mean negative rating unless stated otherwise, mostly is descriptive of the process, such as product shipment and not the product quality [1].

Vendors structure price and discounts to encourage feedback. And feedback in combination with signals of commitment and authenticity inform pricing. Product descriptions are an important feature in the successful marketization of goods, whereas product images are predominantly used as an aspect of recognisability and feature of the vendor's identity [13].

In their findings, the authors assert a bidirectional relationship between Bitcoin exchange rate and the price of drugs on the cryptomarkets. The connection does not increase or decrease the actual price of drugs. Due to DWMs using crypto currencies as a payment system, the prices set on the platforms fluctuate depending on the exchange rate while remaining true to the actual drug price. If the Bitcoin price rises, the crypto price of drugs on cryptomarkets decreases and vice versa if the price decreases [13].

Concluding from all aforementioned information, a single entry in the dataset represents a transaction, which also includes the metric of feedback. This means that every entry of feedback corresponds to a transaction. From this, it is safe to assume that the more transactions a vendor has, the more feedback they have and therefore a higher rating or popularity. Considering a high percentage of positive reviews, and low percentage of negative or neutral reviews, it implies that vendors with a low number of transactions on average should have a lower rating than vendors with a high number of transactions. From this, it can be stated that the more transactions a vendor has, the more popular they are. This can be cross-examined with the integrated vendor rating existing within the dataset.

5.1.1 Popularity Analysis

The findings state a direct connection between positive or negative feedback and vendor popularity, particularly that more popular vendors, or in other words vendors with higher amounts of positive feedback, tend to have higher sales. To further validify these findings in a manner that would integrate them for use in the research, a cross-examination is performed on the existing vendor rating metric within the dataset by applying regression analysis and hypothesis testing.

In the findings of Bhaskar et. al. [1], it is stated that negative feedback is rarely given on DWMs, due to the severity of consequences for the vendor it carries. This is confirmed by an unusually high average rating on each of the three platforms, as can be seen in Table 1 and Figures 1, 2, and 3.

Following the data from Table 1, it is found, that vendors below the market transaction quantity average had subaverage ratings, specifically:

- **86.7%** vendors on Agora below transaction average have subaverage rating.
- **87.2%** vendors on Evolution below transaction average have subaverage rating.

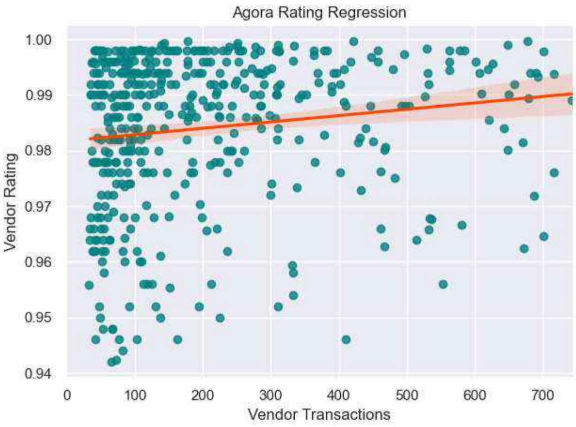

Figure 1: Agora Vendor Rating Regression

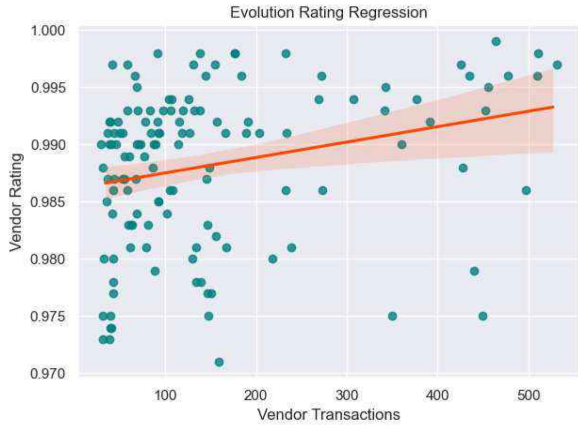

Figure 2: Evolution Vendor Rating Regression

- **94.1%** vendors on Silk Road 2.0 below transaction average have subaverage rating.

This information, however, is not sound enough to be relied upon, mainly due to many outliers and no statistical analysis for proof. Therefore, first, regression analysis is conducted for determining the relationship between vendor rating and the quantity of their transactions. The removal of outliers is manifested by the exclusion of data points above the 95th and below the 5th percentiles for both variables. The final results can be seen in Figures 1, 2, and 3, where each data point represents a single vendors average rating and total transaction amount. The shadow cast from the line depicts the confidence interval of 95%.

The regression lines show an upward trend, revealing that average rating of vendors increases with the number of transactions. To really see a substantial difference, t-test is performed. The vendors are split into two groups based on their number of transactions. Vendors below the transaction mean are put into group one, and vendors above the mean into group two, collectively defining the groups required for the test. The hypothesis for the test is as follows:

H_o: Average rating of low transaction vendors = average rating of high transaction vendors.

H_a: Average rating of low transaction vendors ≠ average rating of high transaction vendors.

Market	*Rating $\bar{x}$*	*Trans. $\bar{x}$*	*Gr. 1 $\bar{x}$*	*Gr. 2 $\bar{x}$*	*P-value*
Agora	0.984	207.5	0.982	0.986	0.002
Evolution	0.988	151.9	0.987	0.990	0.027
Silk Road 2.0	92.9	262.6	92.5	93.6	0.064

Table 2: Vendor Rating t-test

The p-value, or probability, is used as the main metric for determining the success of the test, which is set at 5%, meaning that if the results p-value is below five percent, they did not come by chance. The results of the test can be found in Table 2. Both markets of Agora and Evolution comfortably present a p-value below 5% dictating the rejection of the null hypothesis and accepting the alternative. Silk Road 2.0 comes close to rejecting the null hypothesis, however, ultimately rejects the alternative despite the upward regression trend. This potentially can be attributed to the low amount of data available, which is further discussed in the discussion section.

Together with the upward regression trend, these largely, yet non-completely, yield proof that the more transactions a vendor has, the higher the rating and therefore the more popular they are, validifying our assumptions and the rating metric withing the dataset.

5.2 Price Setting

Based on the findings from section 5.1, there now exists the ability to select groups based on their popularity. Similarly to the previous t-test, data for price setting was filtered for outliers by excluding values above the 95th and below the 5th percentiles for the variables that will be compared, namely vendor transaction count and price. The hypothesis for the test is as follows:

H_o: Average price of less popular vendors = average price of popular vendors.

H_a: Average price of less popular vendors ≠ average price of popular vendors.

Firstly, the test was conducted on the groups below and above the transaction average respectively, similarly to that of the previous test. The findings suggest no difference between the average prices of both groups, as can be seen in the MDMA example in Table 3 and for cannabis in Table 4.

Market	*Price $\bar{x}$ (USD)*	*Trans. $\bar{x}$*	*Gr. 1 $\bar{x}$ (USD)*	*Gr. 2 $\bar{x}$ (USD)*	*P-value*
Agora	55.1	102.0	57.2	44.7	0.155
Evolution	51.9	90.6	55.5	36.0	0.064
Silk Road 2.0	68.9	379.5	75.2	44.5	0.150

Table 3: MDMA Below and Above Transaction Mean t-test

Market	*Price $\bar{x}$ (USD)*	*Trans. $\bar{x}$*	*Gr. 1 $\bar{x}$ (USD)*	*Gr. 2 $\bar{x}$ (USD)*	*P-value*
Agora	70.2	93.8	69.1	76.4	0.271
Evolution	68.4	89.7	69.0	63.9	0.413
Silk Road 2.0	80.9	199.1	83.3	64.0	0.421

Table 4: Cannabis Below and Above Transaction Mean t-test

Market	Price $\bar{x}$ (USD)	Trans. $\bar{x}$	Gr. 1 $\bar{x}$ (USD)	Gr. 2 $\bar{x}$ (USD)	P-value
Agora	55.1	102.0	66.3	47.1	0.058
Evolution	51.9	90.6	51.8	43.8	0.444
Silk Road 2.0	68.9	379.5	62.2	43.6	0.313

Table 5: MDMA Price t-test with Group 1 Below 25th percentile and Group 2 above 75th percentile average transactions.

Market	Price $\bar{x}$ (USD)	Trans. $\bar{x}$	Gr. 1 $\bar{x}$ (USD)	Gr. 2 $\bar{x}$ (USD)	P-value
Agora	70.2	93.8	68.0	75.2	0.305
Evolution	68.4	89.7	67.7	67.7	0.998
Silk Road 2.0	80.9	199.1	81.6	81.7	0.995

Table 6: Cannabis Price t-test with Group 1 Below 25th percentile and Group 2 above 75th percentile average transactions.

Groups from all three markets fail to reject the null hypothesis with the p-value being above 5%.

The second test was performed on vendors on the further ends of the transaction average spectrums. The groups for this test consisted of values below the 25th and above the 75th percentiles in terms of transactions. Delving anywhere further past those limits would result in achieving maximally low samples for comparison, considering their initial low quantity. The results can be seen in Tables 5 and 6. The null hypothesis is again failed to be rejected, suggesting that there is no difference between the average price of both groups. This once again can be potentially attributed to small sample sizes.

Furthermore, the findings display an interesting discovery. The average price of vendors who are considered to be not so popular tends to be higher than that of the popular vendors. This can be seen by comparing Group 1 and 2 price means for both below and above the transaction mean t-test, as well as below and above the percentiles t-test. Although all of the price tests failed to reject the null hypothesis, the results lucratively suggest that there potentially is a difference in price setting between less popular and popular vendors. However, the size limitations of the dataset play their role in dampening these conclusions and it is left up for discussion whether a larger dataset could have yielded more accurate results.

5.3 Price Change in Vendor Lifespan

Price setting difference is not the only way we can confirm our main research question. Another way to discover, if there is a relationship between vendor popularity and price, would be to conduct a trend analysis on both the vendors price, as well as their rating over their time on the market. Successful results would mean that the trend of the price would react depending on the trend of rating over time.

For each of the markets, for each product type, five vendors with the highest amounts of transactions are selected, due to their large containment of data. Their price, as well as their ratings, are drawn out on their timeline on the market. Since the usernames of vendors maintain an encoding, they are marked with the first ten characters of that encoding. An example can be seen in Figures 4 and 5, where Figure 4 represents the price of each vendor set over the time those vendors have spent on the market, and Figure 5 represents the same vendors rating over their time on the market.

Figure 3: Silk Road 2.0 Vendor Rating Regression

Analysing their trends, no connection has been found between rating and price. The prices of vendors maintain predominantly a level trend, even when their respective vendors rating fluctuates. This can be demonstrated in the example of cannabis vendor 'c062e95e02' from Agora in Figures 4 and 5. Their average rating increased over time, however the price remained consistently level both at lower and higher ratings. Similarly, MDMA vendor '7c420b2fef' has seen a decrease in rating over time, however the price remained constant. These results, as well as the others, can be found in appendices A & B.

6. DISCUSSION AND FUTURE WORK

Ultimately the results attained from answering the research questions resulted in the inability to find a relationship between drug vendor popularity and drug price.

The rating metric withing the dataset turned out to be compliant with the assumption of that higher quantities of transactions result in higher ratings. There potentially could be many other factors that go into defining vendor popularity, however these were the ones used for this research. The strength of this metric to evaluate vendor popularity is low, as it is obvious. A high number of transactions implies that the vendor is producing consistent sales, which means their supply, and potentially their particular supply, is in demand. This in turn generates a higher volume of feedback, which as is already known, is predominantly positive [1]. Further research into the factors that dictate vendor popularity will produce more accurate selection of data, in turn leading to more accurate results. Shaw found that vendors tend to use similar usernames across platforms. This is one of the ways they maintain their brand, as the longevity of markets is relatively short at an average of 8 months [1]. Within this research such vendors were also found, at least by their encoded usernames. An example of that would be the vendor 'c062e95e02a90f627e30b147dbab781a80e81ecebfb7fa16118b55c0', who has the largest amount of cannabis related transactions on all three analysed markets. A potentially lucrative direction researchers could discover is how the rating of vendors, that operate on multiple markets, is affected by said other markets. Does a certain vendor maintain their rating from the previous marketplace when entering a new one?

Both the second and the third research questions results did not satisfy the assumptions of price difference based on popularity. At least not statistically. While the values received

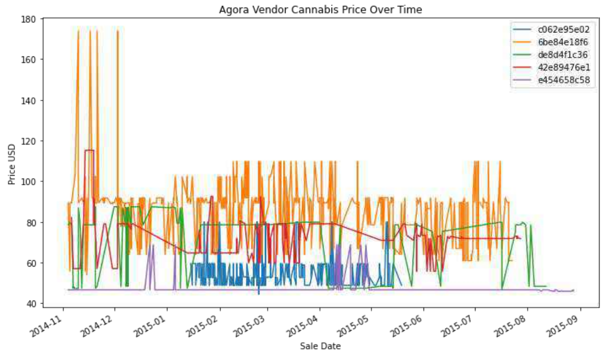

Figure 4: Agora Cannabis Price Trend

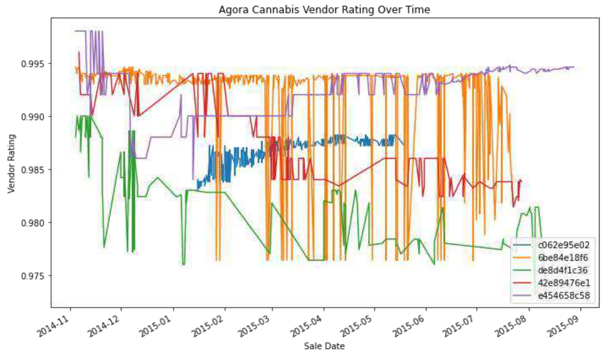

Figure 5: Agora Cannabis Vendor Rating Trend

from conducting the t-test on the setting of prices by popular and less popular vendors failed to pass the probability margin, they were considerably close. In fact, a personally unexpected outcome came in the form of less popular vendors, whilst not significant enough to be considered non-random, on average tend to have their prices higher, than that of their popular counterpart. It is difficult to give specific reasons as to why that is, however, it can be discussed from the economic angle of supply and demand [16]. The law of demand states, that at higher prices, buyers demand less of the economic good. Simultaneously, the higher price of less popular vendors diminishes their buyer's opportunity cost of purchasing, therefore generating less transactions, which subsequently leads to less positive feedback and a lower rating. Furthermore, an assumption can be made, that vendors generating large amounts of sales with a lower price acquire their supply in larger quantities, and therefore cheaper, than vendors generating a lower number of sales. Buying in bulk is always cheaper, more so if those vendors manufacture their own product. Both of these outcomes led to the ability of setting a lower market price. Potential future research could be done in finding out how do drug vendors that manufacture their own product set prices compared to those who buy in large quantities. This however is incredibly difficult to find out, given the anonymity and illicitness of the field.

7. CONCLUSION

This research paper attempts to find the relationship between drug vendor rating and drug prices on DWM's by first identifying their popularity factors, followed by a comparison of price setting between popular and less popular vendors, and finally analysing a vendors change of price over time based on their rating. Based on literature review, regression analysis and statistical testing, the core factor turned out to be the amount of positive feedback a vendor can generate. Subsequently, the positive feedback is further facilitated by the number of transactions a vendor achieves, leading to the conclusion that, on average, vendors with a higher number of transactions are more popular than their low transaction counterparts. The price setting of both of the aforementioned groups of vendors is compared between each other using statistical analysis, mainly t-tests. With the dataset in use, the results suggested no significant enough difference between both groups, however, did present a small variation in the form of less popular vendors having slightly higher prices than popular vendors. Lastly, a trend analysis was performed on vendors price and rating over time. The majority of the results suggest no connection between trends of both metrics, with most prices of vendors maintaining a level trend, even when their rating sustains positive or negative changes.

Ultimately, the relationship between vendor popularity and prices on DWMs was not identified. Implications of this work, that are explored in the discussion, point towards further research into the factors that go into the setting of prices on DWMs. This paper has identified a relationship between vendor popularity and the number of transactions that vendor has, providing grounds for identifying popular vendors. Perhaps the most important future work would be the manifestation of an updated scrape of the current markets, as the publicly available data is becoming outdated and for some research too small. This applies also to the underlying paper, considering that some results did show a difference in price between popular and less popular vendors, however, the limited nature of the data quantity produced statistically insignificant results to prove a connection.

8. AKNOWLEDGEMENT

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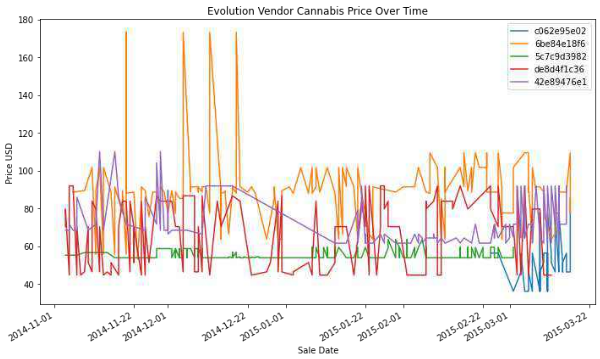
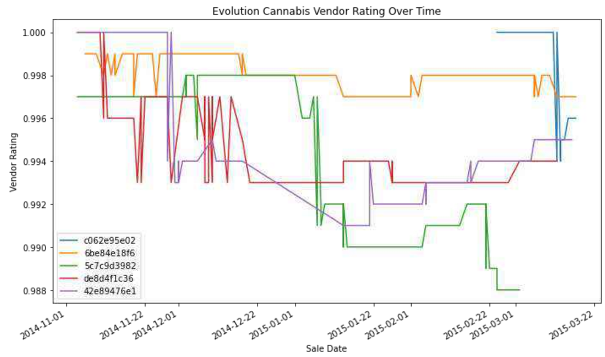
APPENDIX

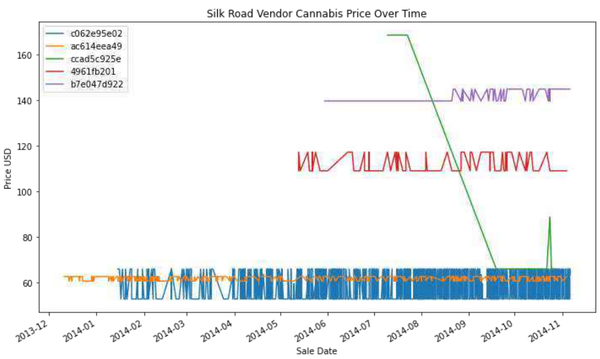
A. TREND ANALYSIS CANNABIS



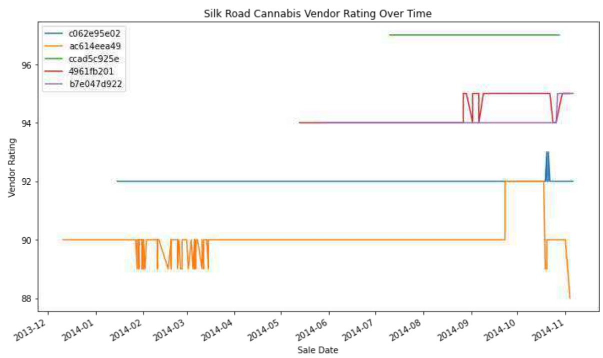
(**a**) *Evolution Cannabis Price Trend*



(**b**) *Evolution Cannabis Rating Trend*



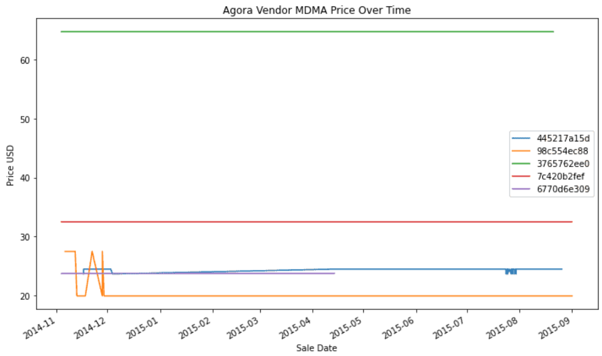
(**c**) *Silk Road 2.0 Cannabis Price Trend*



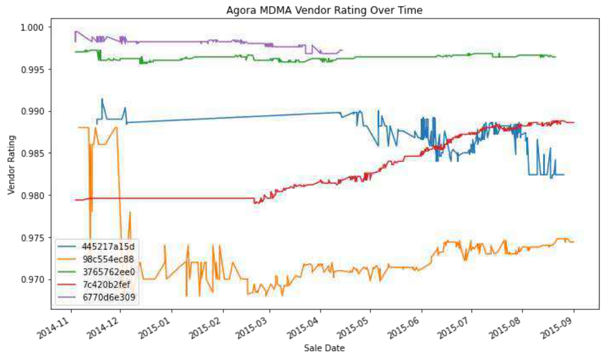
(**d**) *Silk Road 2.0 Cannabis Rating Trend*

Figure 6: Cannabis Price & Rating Trends

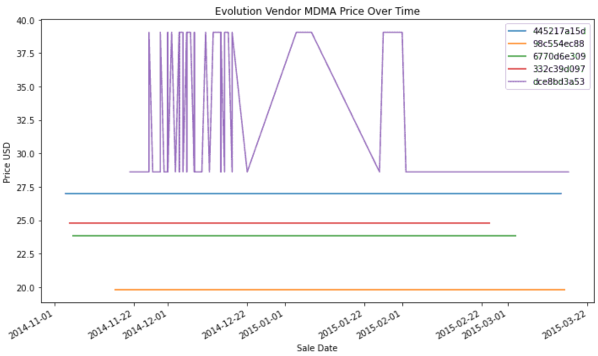
B. TREND ANALYSIS MDMA



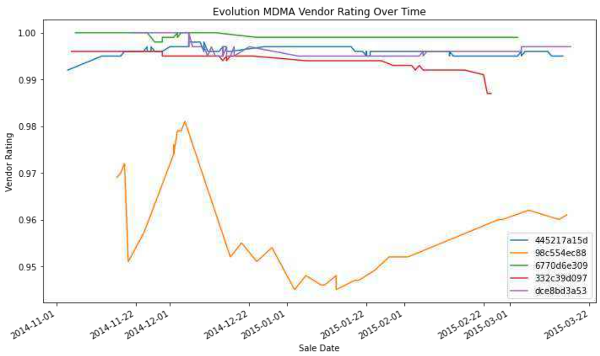
(**a**) *Agora MDMA Price Trend*



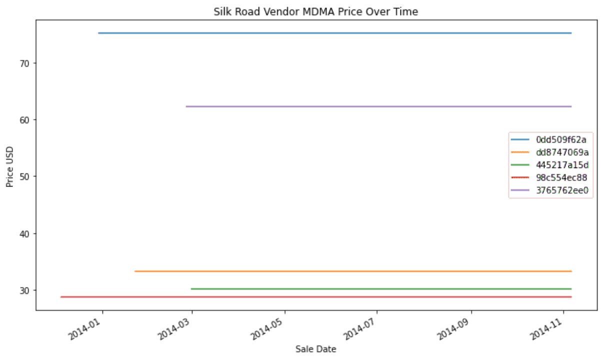
(**b**) *Agora MDMA Rating Trend*



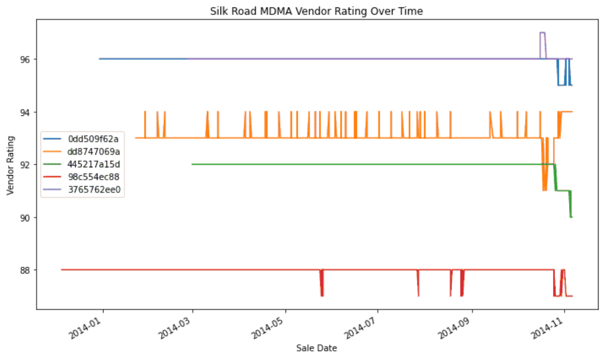
(**c**) *Evolution MDMA Price Trend*



(**d**) *Evolution MDMA Rating Trend*



(**e**) *Silk Road 2.0 MDMA Price Trend*



(**f**) *Silk Road 2.0 MDMA Rating Trend*

Figure 7: MDMA Price & Rating Trends