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Research Paper

Social influence in the darknet market: The impact of product descriptions on cocaine sales

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A R T I C L E I N F O

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A B S T R A C T

Background: The rise of the darknet market, supported by technologies such as the Tor Browser and cryptocurrencies, has created a secure environment in which illicit transactions can occur. However, due to the lack of government oversight in this hidden online domain, darknet markets face significant challenges in upholding social order. Hence, this study explores the social dynamics that promote social order in a darknet market, focusing on the impact of item descriptions on sales. In particular, the study examines how text contained in product listings can influence sales and contribute to social order.
Method: To conduct this analysis, we examined 4160 cocaine listings on AlphaBay, which was active from December 2014 to July 2017 and is one of the largest darknet markets in history. Using generalised additive models (GAMs), we assessed the impact of various listing description features, including content and semantic structure, on cocaine sales.
Results: The results showed that sales increased by 61.6 % when listings included delivery information in their description, compared to offers that did not. In addition, the standardised sentiment score (ranging 0,1) of the product description increased positively, and estimated sales increased by 260.5 %. We also found that international shipping reduced sales by 28.3 %. Finally, we found that listings stating the product origin increased sales for all continents except Asia.
Conclusion: The study sheds light on the characteristics of product advertising that facilitate social order within a darknet market. Listings that include delivery details in the description reduce uncertainty about a critical stage of the transaction process while using positive language increases trust. This study makes both an empirical and a theoretical contribution by demonstrating the influence of ad descriptions on sales and the intricate role of social influences in shaping market order.

Introduction

The expansion of darknet markets, facilitated by tools such as the Tor browser and cryptocurrencies, has created a safer and more efficient online space for conducting illicit transactions. Barratt et al. (2016) investigated the impact of using cryptomarkets to buy and sell drugs, exploring the dynamics between buyers, traffickers, and suppliers. They found that users value the relative safety and quality control of the darknet market compared to traditional drug markets. In addition, respondents who used cryptomarkets perceived significantly fewer threats and acts of violence than those who relied on other sources. These findings confirm that the darknet market has transformed illicit trade by providing a safer and more efficient means of conducting transactions. However, the absence of a legitimate government authority that regulates illegal online markets poses a challenge to maintaining social order, as there is no authorities protecting property rights, setting product quality standards, or prosecuting opportunistic actors. Indeed, previous study has reported that consumers who used darknet markets were more likely to report problems such as financial losses, long waiting times, and non-delivery of products (Barratt et al., 2016).

Therefore, the issue of social order within darknet markets has attracted the attention of social scientists interested in the underground economy. Social order occurs when actors involved in an economic transaction successfully coordinate their actions with each other (Beckert & Wehinger, 2013). In such circumstances, market exchange takes place because social actors can form expectations about others' behaviour and how that behaviour aligns with their own interests. Such alignment is a prerequisite for what is called the order of markets. While

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there is existing empirical and theoretical research on how social order emerges in darknet markets (Hardy & Norgaard, 2016; Przepiorka et al., 2017; Tzanetakis et al., 2016) certain elements, such as the role of product descriptions, remain unexplored. This article aims to fill this gap by investigating how product advertising affects sales. Specifically, it addresses the following research question: What are the characteristics of product advertising that promote social order and sales on darknet markets? By analysing product advertising on AlphaBay, one of the most popular darknet markets, this paper aims to better understand how social order emerges in darknet markets.

Cryptomarkets

Cryptomarkets, also known as darknet markets (Martin 2014), were first introduced in 2011 with the launch of Silk Road. These markets are revolutionary online platforms that allow multiple vendors to sell their products or services by combining two technologies – Tor, which provides anonymity to internet users, and Bitcoin, which enables anonymous digital transactions (Barrat & Aldridge, 2016, p. 1). These platforms have web designs similar to eBay and other marketplace, including reputation metrics, private messaging, platform intermediation, and customer review and comment sections. Cryptomarkets operate on the platform economy model and charge users a commission for facilitating transactions and disseminating information on their platform, benefiting both buyers and sellers. In addition, darknet markets use a hierarchical semantic categorisation system that helps sellers place their products in the appropriate categories on the platforms. This standardised system reduces uncertainty and creates a recognisable socio-technical structure (Kalberg, 2017; Tzanetakis et al., 2018). However, sellers have the flexibility to describe their products using messages and relevant tags and to use specific keywords to help buyers quickly find the products they are looking for.

In darknet markets, two payment options are available to sellers: the centralised escrow method and decentralised finalised early payment (FE). In the escrow method, the seller receives payment only after the buyer has confirmed receipt of the item. In this scenario, the platforms act as a third party, intervening in disputes to foster trust between buyers and sellers. However, sellers may view this approach as risky due to the uncertain nature of payments and the potential loss of funds in the event of seizure of the platform's assets (Moeller et al., 2017). In addition, both sellers and buyers are vulnerable to platform exit scams, where platform administrators shut down the marketplace by misappropriating cryptocurrencies held in the marketplace's escrow account. In contrast, the FE payment method allows sellers to receive payment before the item is shipped, which significantly reduces the risk of loss of funds due to seizure of the platform (Ladegaard, 2020; Van Buskirk et al., 2017).

Research into the trade of illicit goods on computer networks has provided insights into the problem of social order within darknet markets. Scholars have analysed various elements to better understand this phenomenon. Robust results suggest that reputation plays an important role in influencing social order by increasing sales (Hardy & Norgaard, 2016; Przepiorka et al., 2017; Tzanetakis et al., 2016). Similarly, studies adopting a social network perspective have found evidence that repeated interactions promote trust between sellers and buyers (Décary-Hétu & Quessy-Doré, 2017; Norbutas et al., 2020). In contrast, recent studies analysing the impact of escrow transactions have found that transactions outside escrow tend to be larger (Munksgaard, 2023). There is more complex evidence on the impact of reputation, rankings, and payment options on price. For instance, studies have shown that the payment option 'finalize early' is associated with price discounts (Munksgaard & Tzanetakis, 2022), while the results related to reputation are less conclusive. Munksgaard and Tzanetakis (2022) found that sellers neither consistently raise prices when they receive positive feedback nor lower prices when they receive negative feedback, which is supported by the observations of Červený and van Ours (2019) and Espinosa (2019). On the other hand, Przepiorka et al., (2017) found that a better reputation induces sellers to raise prices. However, as Tzanetakis (2018) points out, the mediation of socio-technical structures offered by platforms plays a prominent role in aligning the interests of buyers and sellers during transactions. To the best of our knowledge, research has yet to provide quantitative evidence demonstrating the effect of product advertising on promoting sales.

Modalities of social influence on cryptomarkets

Social influence is a key component of soft power tactics and is conceptualised as a social psychological process that facilitates the achievement of social order through non-coercive means (Sammut & Bauer, 2021). The main goal of social influence is to steer individuals' behaviour, attitudes, and beliefs in a particular direction (Sammut & Bauer, 2021). Different modalities of social influence can be identified according to the modality of social influence and modes, where the modality refers to the specific way in which social influence is exercised, and the mode refers to the tools used to exercise social influence. For example, a modality of social influence could be reputation systems, while the mode used to implement that modality could be online reviews or ratings.

Market administrators and sellers can use various forms and modalities of social influence on digital marketplace platforms to align buyers' and sellers' interests. These include reputation systems, third-party security mechanisms, and information categorisation systems operated by market administrators. Some of these modes of social influence are under the control of market administrators, while others are in the hands of sellers. The reputation system, for example, is a form of social influence controlled by platforms that provide a technological infrastructure that allows buyers to rate products. By contrast, the modality of third-party security, can be decided by platforms or sellers, as some market administrators may choose to prohibit transactions outside the escrow system or leave it up to sellers to offer their products with or without an escrow system. Other modalities of social influence, such as the description of the listing or the use of 'tags' for the product, are ultimately in the hands of the sellers, who can decide how to promote their products. While many empirical studies have focused on how reputation and third-party assurance, such as escrow, affect sales and prices (Hardy & Norgaard, 2016; Munksgaard, 2023; Przepiorka et al., 2017), no empirical research has examined the impact of the listing description on online sales in darknet markets. This study aims to fill this gap by exploring how product advertisement affects sales.

Examining applied social influence in the AlphaBay market

This research focuses on AlphaBay for two main reasons. Firstly, it was one of the largest darknet marketplaces from December 2014 to July 2017, with approximately 369,000 illegal listings on the platform, including counterfeit documents, illegal drugs, firearms, fraudulent services, malware, and more. Secondly, AlphaBay offers rich metrics and textual data, enabling us to test our empirical hypothesis (Tzanetakis, 2018). Despite the availability of other forms of communication, text remains one of the most common means of communication in online environments, including the darknet market. The AlphaBay market offered sellers the opportunity to describe their products with a text message that appeared on product listings when viewed by buyers (see supplementary material A1) (Laferrière & Décary-Hétu, 2022), which raises some important questions: What are the salient features of product descriptions on the darknet market? Which features of product descriptions have the most significant impact on sales?

Hypothesis 1: delivery information and sales

Asymmetric information between buyers and sellers can dramatically undermine the social order of the market, as it can threaten a crucial aspect of coordination that leads to market order: cooperation (Beckert, 2009). In this context, trust issues can hinder cooperation because, to obtain the promised benefits from the interaction, the trustees (buyers) must be willing to accept the associated risks (Luhmann, 1988, p. 97). Therefore, cooperation can break down if the involved actors are unwilling to assume the transaction risks.

The temporal discrepancy between the moment buyers place an order and the subsequent receipt of products in online transactions renders physical quality checking impractical. This gives rise to significant challenges in the form of asymmetrical information and adverse selection problems (Lewis, 2011) on online markets. Given these challenges, information about the product modality of delivery can help buyers assess the likelihood that a seller is trustworthy. This information can be categorised into expensive and cheap signals: expensive signals are only generated by sellers who commit to high-quality goods, while cheap signals can be easily falsified and are not a reliable indicator of a seller's true intentions. The benefit of sending a signal depends on the cost and expected profit (Gambetta, 2009; Przepiorka & Berger, 2017). Sellers may try to convince buyers of their positive intentions through item descriptions, but these can be easily falsified by both reputable and untrustworthy sellers. Hence, item descriptions should be seen as a cheap signal that provides information about the item's features and shipping details, helping to reduce negative selection.

An empirical study conducted by Houser and Wooders (2006) in the field of traditional e-commerce found that item descriptions play a significant role in influencing sales. For instance, Lewis (2011) demonstrated that photos and text posted by sellers on auction websites can strongly influence prices, while McDonald and Slawson (2002) found that highlighting expensive shipping and handling costs tends to lower the price of the winning bid on eBay. Thus, even though product descriptions are considered to be cheap signals, they can still affect buyers' decisions (Lewis, 2011; McDonald & Slawson, 2002; Snijders & Zijdeman, 2004; Ter Huurne, et al., 2017).

Transactions on the darknet markets can be fraught with various logistical risks (Aldridge & Askew, 2017), which increases the problem of adverse selection. The first risk involved in darknet market transactions is the danger of arousing suspicion in the postal system. To alleviate these problems, sellers in the illicit drug trade employ sophisticated 'stealth' strategies, such as using discreet packaging, to minimise the risk of interception or arrest (Martin, 2014; Van Hout & Bingham, 2014), especially in regard to large or international shipments (Décary-Hétu et al., 2016). Nevertheless, delivery remains one of the most critical stages of the darknet market transactions. Bhaskar et al. (2019) analysed 32,574 negative reviews and found that delivery issues accounted for 60.2% of negative feedback. Additionally, when placing an order, buyers may feel uncertain about whether or not to provide their real name or a pseudonym (Maddox et al., 2016) and how to communicate essential information such as their shipping address. They might also be concerned about potential consequences if the product is intercepted by law enforcement upon delivery. How, then, can sellers increase buyers' sense of security, mitigate adverse selection, and promote efficient coordination between buyers and sellers to support market order? The AlphaBay market offers sellers the opportunity to describe their products and services with a text message appearing on product listings when buyers view them. In addition to the listing description and its effects, this space can be used to provide information regarding factors such as the inclusion of real or pseudonymous names, and how address structure could contribute to uncertainty. By including delivery information in product descriptions, sellers can mitigate adverse selection and facilitate effective coordination. As Yamagishi (2011) suggests, trust issues become more prominent when social uncertainty is high. Consequently, any additional information that mitigates uncertainty can aid in overcoming trust-related challenges. Equally, a lack of comprehensive delivery information in product descriptions may deter potential buyers from purchasing, especially if they are not given explicit instructions on navigating the different stages of the delivery process. Therefore, it is reasonable to hypothesise that including comprehensive delivery information in item descriptions may positively influence the likelihood of sales.

H1: Including delivery-related information in product descriptions increases sales.

Hypothesis 2: Positive language and sales

Emotions, whether expressed positively or negatively, play a crucial role in signalling a person's attitudes and intentions in social interactions (Rocklage et al., 2018; 2021; Keltner & Haidt, 1999). Current research highlights the positive impact of using positive language to improve online market performance – a phenomenon that has been thoroughly investigated in comprehensive studies by Deng et al. (2018) and Ranco et al. (2015). Moreover, this guiding principle has found substantial application in the field of venture crowdfunding, where positive sentiments shared via Twitter have demonstrated their predictive utility in assessing the likelihood of successful fundraising. A comprehensive evaluation of this application of sentiment analysis was conducted by Greenberg et al. (2013). In addition, a Twitter study by Berger and Milkman (2012) revealed that tweets that are infused with positive language are more likely to be successful. In particular, online content that is characterised by positive emotions has a higher probability of going viral. Similarly, when influencers use an optimistic tone in promotional Instagram posts, it is expected to lead to more engagement. In the context of e-commerce, a study by Rocklage et al. (2021) showed that items such as movies, books, commercials, and restaurants do not consistently have the same success despite similar reviews. Indeed, online reviews are often unable to accurately predict people's behaviour and the success of different items. To overcome this challenge, the researchers investigated whether rating emotionality using computational linguistics could provide a more reliable signal. Their results indicated that measuring emotionality has predictive power for a wide range of articles on different platforms, including Metacritic, Amazon, Twitter, Yelp, Facebook, and OpenTable. This raises the question of whether positive language can contribute to higher sales and promote market order.

Research suggests that communicating through positive language provides a means of implicitly conveying intended attitudes toward others. It follows that using positive language in texts describing products or services can increase their success because they are perceived as more reliable (Berger & Milkman, 2012; Keltner & Haidt, 1999; Rocklage et al., 2018). This is particularly relevant in the context of darknet markets, where traders operate within a framework of trust and adhere to basic norms of reciprocity, as shown by Przepiorka et al. (2017) and Masson and Bancroft (2018). While a significant proportion of revenues fall into price brackets indicative of business-to-business trade, the majority of transactions are concentrated in the lower price brackets, suggesting a market orientation towards social dealing. However, darknet markets face cooperation challenges stemming from the risk of opportunistic behaviour, which can lead to coordination problems between participants. Sellers can convey their reliability and intentions by using positive language in product descriptions, as empirical studies in different contexts have shown the importance of positive language. Therefore, the use of positive language can indicate positive intentions, reduce the perceived risk of opportunistic behaviour by buyers, and contribute to market order on the darknet markets.

H2: Product descriptions that use positive language to describe the product are more likely to lead to a successful sale.

Data and methods

Our study analysed a dataset of 114,385 items, 6033 sellers, and 1270,000 reviews collected on AlphaBay's darknet market between 26 and 28 January 2017 by McKenna and Goode (2017). Most listings on the AlphaBay platform were included in the dataset, even if the items were not purchased. However, 1636 pages from Tor could not be downloaded, resulting in around 700 missing listings, but these only accounted for 0.01 % of all listings and were therefore unlikely to affect our results. We focused our analysis on cocaine listings for two main reasons. First, given the high price and potential dangers associated with the drug, consumers were expected to carefully examine the information in sellers' listing descriptions. Second, the text mining technique used in this study required a certain degree of homogeneity in the text content. Therefore, we began by selecting all products that fell within the 'cocaine' category (5485). Subsequently, we eliminated listings that lacked quantity information in their item descriptions (258). Lastly, we eliminated products that, despite being categorised as cocaine, were not genuine cocaine-related items, such as 'lidocaine' and similar substances (956) as well as products for which the listed weight in grams was not clearly expressed (109). Consequently, the final dataset encompassed 4160 cocaine listings by 714 distinct vendors.

Variable

The unit of analysis in this study was the cocaine listings on AlphaBay. Instead of using the number of reviews left by buyers, we used the number of transactions provided by the platform as the dependent variable to estimate sales. There are two main reasons for this approach. First, unlike other platforms, AlphaBay provides the specific number of sales for each listing. Second, we consider this platform measurement to be more reliable, as not all buyers leave feedback after a transaction. Rather, the seller's reputation is assessed at the seller level and is represented by two variables: the percentage of positive reviews, and the percentage of negative reviews plus neutral reviews. 'Days selling' indicates the number of days the product was on the market at the time of data collection.

Geographical origin serves as an additional factor for the analysis. In cases where sellers have not indicated their nationality, the platforms assign a 'worldwide' label to represent their geographical origin. We have categorised nations into continents – Asia, Africa, Europe, Oceania, North America, and South America – based on the number of cases in each region. Please note that there are currently no cocaine listings from Africa in this dataset. This macro-categorisation was necessary due to the limited number of cases in some countries. We also added a dummy variable for shipment, which was labelled 'international' if the origin was different from the destination and 'national' if the origin was the same as the destination. Regarding the characteristics of the listings, the variable 'grams' was generated by extracting the quantity of listings from the heading and the description of the listing. Consequently, the price per gram was calculated by dividing the price by the number of grams. In addition, a dummy variable was created to indicate the payment method. A value of 1 indicates products offered through an escrow payment, while a value of 0 indicates the option to 'finalize early payment' (FE).

Text variables

To test H1 and measure the extent to which providing information about delivery increases sales, we generated four topics using latent Dirichlet allocation (LDA). One of these topics focused specifically on semantic structure related to delivery. The details of this process, including the methodology and results, can be found in supplementary material A2. We then classified quotes as product descriptions containing delivery information if they had a probability of belonging to each topic three was higher or equal to 0.50.[1,2] This classification enabled us to analyse how the inclusion of delivery information in product descriptions influences customer purchasing behaviour and overall sales performance.

To test H2, we performed sentiment analysis, a procedure that facilitates the categorisation of sentiment polarity. For a product description, the aim of sentiment analysis is to assign a score to the text. We used the AFINN lexicon – a compilation of English terms, each assigned a score from -5 (for negative sentiment) to +5 (for positive sentiment). By adding the scores of each word classified in the AFINN lexicon, we calculated a total score for each text that was analysed (See supplementary material A3). As this variable represents results from texts of varying lengths, we utilised min-max scaling, a technique that transforms the data into a range between 0 and 1. This normalisation process ensures that the data values are confined within a specific interval.

We also created additional text measures, namely the linguistic diversity of product descriptions and text length. The first variable measures the linguistic diversity of each listing description by quantifying the unique words within a message. It is calculated by dividing the number of unique words by the total number of words and is designed to control for the effects of linguistic diversity on sales. We added this variable based on a study that found that text richness in terms of linguistic diversity can better capture users' attention and increase engagement (Berthold et al., 1998). In addition, we added the length of the description relative to the average length of the cocaine offerings by dividing the length of each listing description by the average length of all cocaine offerings on the market. If the resulting value was less than one, this meant that the length of the description was below average. If, on the other hand, the value was above one, it indicated that the length of the description was above average (Huffaker, 2010; Spitters et al., 2015). This variable controls whether sellers who provide a long description have an advantage on the market.

GAM model

The GAM with maximum likelihood estimation and the Tweedie distribution were used to investigate the relationship between the previously described variables and their effects on sales. In this context, the GAM enabled us to model non-linear and linear relationships, capturing potential interactions between the predictor variables and their effects on the response variable (sales) (Li et al., 2011). The Tweedie distribution is well-suited for data exhibiting characteristics such as skewness

[1] To establish this threshold, we followed the procedure outlined by Kigerl (2018). The LDA results produced a topic matrix indicating the probability that each product belongs to one of the four topics. This matrix of product-topic probabilities consists of rows representing products and four columns representing topics. The cell values represent the probability that a product belongs to a particular topic, and these probabilities are assigned so that the sum of the rows is 1.0. If a product is not associated with any of the four topics, the probability that it belongs to each topic by chance is 0.25 (1/ 4(number of topic)). To set a threshold for certainty in assigning a product description to a topic, a threshold of 0.50(0.25*2) was chosen.

[2] Three other topics that were identified through LDA analysis were not included in the analysis due to a lack of theoretical justification.

Table 1
Descriptive statistics.

Variable	Mean	SD	Median	Min	Max
Vendor variable					
Positive reviews (%)	87.0	28.28	97.8	0	100
Product variable					
Days selling	217	165.5	194	3	682
Price per gram	81.5	54.09	67.5	20.0	486.5
Quantity in gr	34.4	136.7	3.5	0.1	2000.0
Sales	35	163.4	1	0	4427
Transactions value(price)	1627	5520	281	0	90,000
Text variable					
Linguistic diversity	0.758	0.1533	0.770	0	1.000
Length of text	1.002	1.12	0.570	0.01	6.642
Sentiment score	0.412	0.087	0.393	0	1.000
Categorical variable					
Escrow	**n**				**%**
Yes	907				21.8
No	3253				78.2
Origin					
Worldwide	720				17.31
Asia	28				0.67
Europe	2150				51.70
North America	879				21.13
Oceania	311				7.48
South America	71				1.71
Seller ships to					
Domestic only	1758				42.26
International	2402				57.74
Topic 2					
Yes	949				77.19
No	3211				22.81
N (vendor-level)	714				
N (listing-level)	4160				

and excess zeros, which are commonly observed in sales (Shono, 2008) (see Table 1).

By applying GAM with maximum likelihood estimation and the Tweedie distribution, researchers can assess the relationship between the variables of interest and sales, taking into account non-linear effects and the specific distributional characteristics of the response variables. This modelling approach provides valuable insights into the factors that influence sales. The GAM model is preferred over polynomial regression because it avoids the need to specify the degree of the polynomial, thereby reducing the risk of under-smoothing or over-smoothing (Wood, 2006). The advantages of the GAM approach are particularly important for the darknet market, where previous studies have shown non-linear relationships between reputation and sales (Przepiorka et al., 2017) and where a target variable (sales) was left-skewed (Shono, 2008). In addition, GAM models are easier to interpret than machine learning models (Wood, 2006).

Results

The first part of Table 2 provides an overview of the fitted models. The first row indicates the dependent variable for all three models, namely 'sales', resulting from the hypothesis established in the theoretical section. 'Family' represents the use of a Tweedie distribution for modelling, while the 'Link' of 'log' indicates the transformation applied to the predicted values. The parameter 'p' defines the properties of the model distribution, with 0 representing a normal distribution, 1 a Poisson distribution, and 2 a Gamma distribution (Shono, 2008).

The first section of Table 2 describes the parametric terms of our model and presents the coefficients associated with the linear terms. The coefficients marked with asterisks indicate the corresponding p-values, while the values in parentheses represent the standard errors. The second part of Table 2 deals with the 'smooth terms'. Since each smooth term includes several coefficients, each representing a basis function, we show the column effective degrees of freedom (EDF). The EDF quantifies the complexity of the smooth term, with higher values indicating more complicated and curvilinear relationships. For example, an EDF of 1 represents a simple linear relationship, while an EDF of 2 represents a quadratic curve, and so on. Similarly, asterisks denote the significance of smooth terms. A significant EDF means that drawing a horizontal line through a 95% confidence interval is impossible. It is worth noting that a high EDF does not necessarily indicate significance. A smooth term can be linear, significant, non-linear, and non-significant (Wood, 2006). In addition, the fit of the model is assessed using two information criteria: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These criteria provide measures of model fit and complexity, with lower values indicating better model fit. AIC balances model fit and complexity, while BIC puts complex models at a greater disadvantage. Comparing AIC and BIC values between models can aid in selecting the most appropriate model (Wood, 2006).

Table 2
GAM models.

GAM models	M1	M2
Dependent variables	**Sales**	**Sales**
Family	Tweedie	Tweedie
	(p= 1.673)	(p=1.662)
Link function	log	Log
Variable name	Estimate[1]	Estimate
Intercept	1.99***	2.25***
	(0.10)	(0.36)
Escrow	−1.06***	−0.96***
	(0.07)	(0.07)
Worldwide	(Reference)	(Reference)
Asia	0.04	0.13
	(0.43)	(0.42)
Europe	0.81***	0.75***
	(0.10)	(0.10)
North America	1.04***	0.84***
	(0.11)	(0.10)
Oceania	0.76**	0.65**
	(0.24)	(0.24)
South America	1.25***	0.86**
	(0.29)	(0.27)
International ships	–0.46***	–0.33***
	(0.07)	(0.07)
Topic 2		0.48***
		(0.07)
Sentiment score		1.28***
		(0.31)
Linguistic diversity		–1.44***
		(0.34)
Length of text		0.06
		(0.04)
Smooth variable	**EDF**	**EDF**
Percentage of positive reviews	7.91***	7.96***
Days selling	7.38***	7.86***
Price per gram	8.32***	8.24***
Quantity in gr	8.62***	8.65***
n	4159	4159
Deviance explained	53.2 %	55.9 %
R-sq.(adj)	0.225	0.297
AIC	23,724	23,526
BIC	24,001	23,832
Maximum likelihood	11,900	11,800
Scale estimate	7.6625	7.3989

[1] Standard errors in parentheses; $^{***}P < .001$, $^{**}P < .01$, $^{*}P < .05$.

We initially fitted model M1 without the text analysis variables. After that, we incorporated the text predictors into the model, resulting in model M2. The additional variables introduced in M2 included Topic 2, sentiment score, linguistic diversity, and text length. The aim was to compare the performance of the models. When comparing the goodness-of-fit parameters between M1 and M2, we observed improvements with the addition of the text variable, with explained variance increasing from 53.2 % in M1 to 55.9 % in M2. Moreover, the AIC decreased from 23,724 to 23,526 and the BIC from 24,001 to 23,832 in model M2. These improvements in goodness of fit indicate that the models with the added hypothesis-based predictors offer a more concise and accurate portrayal

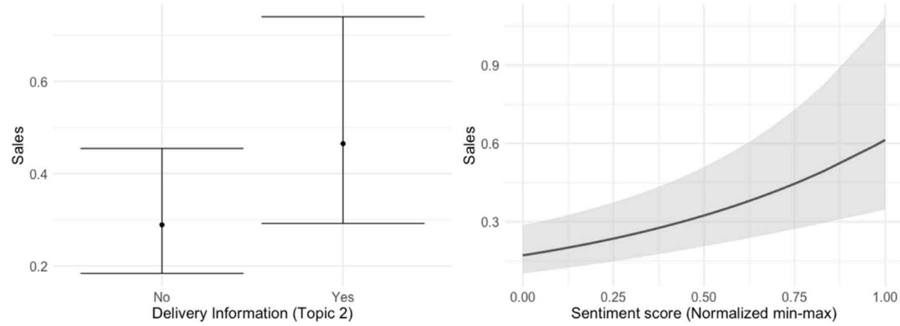

Fig. 1. Results of generalised additive models for the estimated impact of delivery information (a) and sentiment score (b) on sales
Note: In this figure, (a) represents the estimated impact of delivery information, while (b) represents the estimated impact of sentiment score on sales, as analysed through GAMs. The plot displays the predicted values and their corresponding confidence intervals, offering insights into the relationship between delivery information, sentiment score, and sales.

of the data compared to the initial models that lacked the text predictors.

By analysing the effects of the predictor variables, the application of the GAM provided empirical evidence for hypotheses 1 and 2. Model 2 indicated that sales increased by 61.6 % when listings included topic 2 (information on delivery) in their description compared to offers that did not include this information. This increase was calculated as [(exp (0.48) - 1) * 100]. See Appendix A4 for an example of a listing description that had a high probability of belonging to topic 2. As for hypothesis 1, model M2 provided empirical confirmation of the theoretical framework. The results indicated a positive and statistically significant relationship between the sentiment score (normalised) and the outcome variable (sales). Specifically, the coefficients for the sentiment score were positive in both models, with a value of 1.28 for model M2, and both were significant ($P < 0.001$), providing empirical support for hypothesis 1. This suggests that with an increase in the standardised sentiment score (ranging from 0 to 1), estimated sales also increase by 260.5 %, which is in line with the theoretical expectations described earlier in the study. See supplementary material A5 for an example of product description with high positive sentiment.

Remarkably, in both models, our analysis revealed a significant decline in sales associated with higher levels of linguistic diversity. Similarly, a decrease in sales was found to coincide with an increase in text length, although it is important to note that this correlation lacked statistical significance.

Our findings regarding the other variables in the model aligned with the existing literature. Specifically, the coefficient on listings that used escrow as a payment method was negative and significant in both models, with values of -0.96 for M2. These results are consistent with previous studies in the field (Andrei et al., 2023; Munksgaard, 2023). Regarding the origin of the listings, our analysis indicated a positive and significant coefficient for listings from Europe, North America, Oceania, and South America in both models. This suggests that sales were higher for offers that explicitly stated their origin from these regions than for those that did not, while the coefficient for Asia was positive but not statistically significant. Thus, it can be said that in the cocaine market, an explicit indication of origin increases sales. Finally, in both models, we observed that international shipments (occurring when the product's country of origin was different from its destination country) had a negative impact on sales. Indeed, the coefficient for international shipments was negative and statistically significant. More details about the smooth terms can be found in the supplementary material A6.

Discussion and conclusion

In darknet markets, the problem of social order is crucial because there is no government oversight of these hidden transactions to set quality standards and prevent opportunistic behaviour by sellers or platforms. In addition, sellers and platforms are exposed to the constant threat of law enforcement, which exacerbates the risks associated with economic transactions in this environment. One of the main challenges involved in this type of transaction is the problem of coordination among actors, as cooperation can break down due to a lack of trust and asymmetrical information. This problem becomes even more critical because, to reap the benefits of economic transactions, sellers and buyers must take several risks, including interception by law enforcement at the time of delivery and the potential loss of funds in the event of the seizure of the platform's assets or the risk of a platform exit scam. In addition, buyers may be susceptible to opportunistic behaviour by sellers.

Platforms and sellers have implemented various modalities of social influence to address the problem of social order. Existing studies have provided robust empirical evidence on the emergence of social order in the darknet, attributing it to factors such as reputation (Hardy & Norgaard, 2016; Przepiorka et al., 2017; Tzanetakis et al., 2016) and repeated interactions (Décary-Hétu & Quessy-Doré, 2017; Norbutas et al., 2020). To our knowledge, however, research has thus far ignored the influence of listing text on sales within the darknet markets. This study aims to fill this gap by exploring the impact of including descriptive text on online sales in a large darknet market. The listing description is a tool sellers can use to present their products freely and persuade buyers to purchase them. Our analysis, conducted using a GAM, revealed two main features that distinguished the listings within the dataset studied, both of which were correlated with a notable increase in sales. These distinguishing features were the provision of delivery information and the inclusion of positively oriented semantic language. How do we explain these results?

The answer lies, firstly, in the fact that the delivery phase is typically seen as the most critical step in the transaction process (Aldridge & Askew, 2017), and so providing comprehensive details about the delivery in the item description may help sellers to increase buyers' trust . This, in turn, mitigates the tendency for adverse selection and promotes effective coordination between buyers and sellers by reducing the asymmetrical information involved in these transactions. Meanwhile, the use of positive language may serve as a signal of a person's attitudes and intentions toward others (Rocklage et al., 2021). The correlation between the use of positively orientated semantic words and sales can, therefore, be explained by the increase in trust and the resulting improved coordination between the actors involved in the transactions. This mechanism aligns with the findings of Greenberg et al. (2013) and Milkman (2012), who also demonstrated in an online context that content with positive language is more likely to be successful. Therefore, although the listing description is considered to be a cheap signal (Kas et al., 2023), it ultimately serves as a modality of social influence that can strengthen trust and mitigate adverse selection (Fig. 1).

This evidence contributes to the literature both empirically and theoretically. Empirically, it illustrates the influence of listing descriptions on sales within darknet markets. Theoretically, the paper highlights that social order in the darknet marketplace emerges through a complex interplay of different social influences. That is to say, even though reputation is crucial in establishing social order on the darknet market, product descriptions also significantly facilitate coordination among actors by increasing trust.

Despite the key insights produced by this study, it should also be acknowledged that the results are subject to three major limitations. First, the cross-sectional nature of the dataset hinders the analysis of sales dynamics over time, as it does not capture the temporal aspects of the phenomenon. The volatile and ever-changing nature of the darknet market also makes it difficult to plan and conduct longitudinal data collection that would allow for a more comprehensive understanding of sales trends. Additionally, the utilisation of textual data introduces the potential for inaccuracies. Indeed, text mining techniques can be foiled by various issues associated with recognising and interpreting cryptomarket jargon, thereby reducing the precision of the analysis. Furthermore, this study is limited to a single product category. Future research efforts should aim to overcome this limitation by exploring the possibility of extending the analysis to other product categories available on the darknet market. In this way, a more comprehensive understanding of the phenomenon can be achieved, offering valuable insights into the broader dynamics and intricacies of the darknet marketplace.

CRediT authorship contribution statement

Filippo Andrei: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Giuseppe Alessandro Veltri:** Writing – review & editing, Supervision, Resources, Conceptualization.

Declaration of competing interest

The authors state that they do not have any known financial interests or personal relationships that could have potentially influenced the findings presented in this paper.

Declarations and Ethics

The authors declare that the work reported herein did not require ethics approval because it did not involve animal or human participation.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.drugpo.2024.104328.

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