Original Manuscript

Social Science Computer Review
2024, Vol. 0(0) 1–23

DOI: 10.1177/08944393241286339
journals.sagepub.com/home/ssc
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Status Spill-Over in Cryptomarket for Illegal Goods

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Abstract

Information technologies have transformed many aspects of social life, including how illegal goods are exchanged. Illegal online markets are now flourishing on various channels: the surface web (all websites accessible through a standard browser), the dark web (an encrypted internet network only accessible via anonymous browsers), and encrypted messaging applications installed on smartphones. These marketplaces take many forms, including simple web shops, chat rooms, forums, social media marketplaces, and platforms. This study focuses on the largest known darknet platform to date: AlphaBay. This cryptomarket operated from December 2014 until July 2017, when an international police operation shut it down. The dataset contains 6033 vendor profiles collected in January 2017. Using three generalized additive models (GAMs), we show that seller status positively affects sales, revenue, and sales through finalized early payment. Once sellers gain status on the platforms, they make more sales without a semi-institutionalized form of payment (e.g. escrow). On the other hand, buyers relying on status metrics as cognitive shortcuts tend to choose vendors even if they do not offer payment protection tools.

Keywords

heuristic cues, dual process theories, cryptomarket, darknet, generalized additive model

Introduction

Illicit online markets thrive across various channels, including the surface web (accessible through standard browsers), the dark web (an encrypted internet network only accessible via anonymous browsers), and encrypted messaging apps on smartphones (Martin et al., 2019). These markets facilitate the trade of a variety of goods and services, ranging from weapons to counterfeit items, with drugs being the most in-demand category.

Cryptomarkets, particularly popular with users from Europe, North America, and Oceania (Demant et al., 2018), employ cryptographic software that allows buyers and sellers to conceal

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their identities from law enforcement agencies. This is facilitated by the TOR network, which anonymizes internet traffic (Martin, 2014; Soska & Christin, 2015). Additionally, traders use virtual currencies, ensuring a high degree of anonymity (Martin, 2014).

This study's primary objective is to investigate how seller status affects sales, revenue, and sales with finalized early payment (FE) in the crypto market for illicit goods. Status, a pervasive feature of all social groups and communities, plays a crucial role in distributing resources and acting as a coordination mechanism, especially in insecure environments, as shown in existing literature (Ball et al., 2001; Podolny, 1993). This study aims to address the following research question: How does seller status influence sales, revenue, and sales with finalized early payment (FE) in the crypto market for illicit goods, and what role does it play in allocating privileges?

While previous research has extensively explored the impact of reputation systems on sales, the social mechanisms that contribute to the concentration of sales and revenue among a few sellers have been largely overlooked. This study aims to fill this gap by examining the impact of status on seller performance. Using three generalized additive models (GAMs), we show that seller status positively influences sales, revenue, and sales through early payment. Once sellers have achieved status on the platforms, they tend to make more sales without relying on semi-institutional forms of payment (e.g. escrow). Conversely, buyers who use status metrics as cognitive shortcuts often opt for sellers even in the absence of payment protection mechanisms. This empirical evidence confirms that status favours a concentration of resources and privileges.

Online Illicit Markets and Cryptomarkets

Regarding web design, cryptomarkets resemble Clearnet platforms such as eBay in that they incorporate reputation metrics, private messaging, and bidding systems. The organizational structure of cryptomarkets is similar to what economists refer to as a 'platform economy' (Rochet & Tirole, 2003). These websites offer a platform that is accessible to both buyers and sellers and charge a commission in exchange for mediating transactions and organizing information and items. The platform administration provides benefits for both parties: sellers can reach a broad audience of buyers, while buyers can compare different items before making a purchase (Tzanetakis, 2018).

The categorization system used by cryptomarkets helps buyers easily locate products they are interested in and helps sellers make their products visible to potential buyers. The hierarchical semantic categorization system generally starts with macro-categories and becomes increasingly specific with sub-categories. Vendors usually place their offers according to the categorization system created by the market administrator to make it easy for customers to find their offers. This system is quite standardized across different cryptomarkets, which reduces uncertainty and allows actors to create a recognizable socio-technical structure across different platforms. Overall, the categorization system is an important tool for information organization in the marketplace and facilitates economic transactions for both buyers and sellers (Tzanetakis, 2018).

In the context of cryptomarkets, it is common for the platform administrator to provide its sellers with two payment options: centralized through the escrow system, decentralized through finalize early payment (FE), or both, leaving the choice to the sellers. Under the escrow payment method, the seller receives payment only after the buyer has received the item and confirmed it with the platform. This gives platform administrators the power to resolve conflicts. However, several factors may make the escrow method less appealing to sellers. Firstly, selling through escrow means that payment is less certain, as the transaction amount is deposited in an escrow wallet and depends on buyer confirmation (Tzanetakis et al., 2016). Additionally, depositing funds into the platform wallet increases the risk of loss if law enforcement seizes the platform's assets (Childs et al., 2020). On the other hand, the FE payment method allows the seller to ship the goods only after receiving payment, reducing the risk of buyer disputes or the loss of funds due to platform seizure. These reasons make the FE payment method a preferred choice for sellers.

Empirical studies on illegal online markets have been conducted to understand the factors contributing to trust in these markets, characterized by asymmetrical information between sellers and buyers, the absence of regulation and standardization, and the lack of pre-purchase inspection. From a sociological perspective, several trust mechanisms have been studied in relation to illicit online markets. The first trust mechanism is trust signalling. According to Gambetta's theories, which posit that signs and signals convey information about the trustworthiness of members within a community, studies on illicit online markets have found that unlawful performance is affected by individuals' ability to send trust signals. For example, Décary-Hétu and Leppänen (2016) and Holt et al. (2013) found that specifying the type of payment mechanism, choosing the advertisement language, and selecting the type of market they operate can influence sellers' success in illicit online markets. These findings suggest that understanding the mechanisms behind trust signalling is crucial for understanding the nature of these markets. The second trust mechanism investigated is reputation. According to the evidence, studies conducted in legal online markets (e.g. Diekmann et al., 2014; Przepiorka et al., 2017) have provided ample evidence of the link between reputation and higher sales. For example, Przepiorka et al. (2017) and Hardy and Norgaard (2016a, 2016b) found that reputation plays a critical role in shaping trust when dealing with drug products in cryptomarkets. Therefore, the centrality of the reputation system has been indicated as a mechanism of trust generation (see also Tzanetakis et al., 2016; Bakken et al., 2018). These findings suggest that reputation systems are an important component of trust building in illicit online markets.

Closely linked to reputation is the mechanism of repeated exchange. The mechanism of repeated exchange is where trust builds through repeated interactions between two parties (dyadic). This allows them to learn each other's behaviour and build trust for future interactions. Reputation, on the other hand, is public and reflects the overall perception of someone's trustworthiness based on their interactions with many people. Literature on trust provides several examples that actors are more inclined to display higher trust in others with whom they have had successful exchanges in the past (Camerer & Weigelt, 1988; Barrera, 2017). This trust mechanism is also evident in online illicit markets. Commitment to a specific dealer has been documented even in illicit online markets where buyers tend to repeat exchange (Décary-Hétu & Quessy-Doré, 2017; Norbutas et al., 2020).

Other studies, adopting both sociological and criminological approaches, have examined illicit online markets by focussing on different aspects. Lusthaus (2012) highlights the importance of extra-legal governance established in the realm of cybercriminal transactions, while Munksgaard (2022), and Andrei et al. (2024) have focused on the role of escrow in producing trust. Studies in the criminology field have focused on understanding the mechanisms that lead to trust and have also delved into examining the retail and wholesale aspects of the cryptomarket by studying the market share of sellers. Earlier research has described the cryptomarket as an 'Ebay for drugs' (Barratt, 2016), where peer-to-peer dealers conduct small-scale exchanges mainly for personal use or social supply purposes. Similarly, Cristian (2013) and Martin (2014) have concluded that small quantities of illicit goods are sold in the cryptomarket, bypassing the middle distribution level. However, subsequent studies have challenged the notion that the cryptomarket is primarily a peer-to-peer market, providing evidence that most of the cryptocurrency market's revenue results from large-scale transactions (Aldridge & Askew, 2017). For instance, Demant et al. (2018) found that although most transactions were for lower prices, a significant portion of the revenue came from prices indicating business-to-business relationships on the cryptomarket. Similarly, Paquet-Clouston et al. (2018) found that competition is high on the cryptomarket, and as a result, only a few sellers succeed, while the majority of vendors do not overcome the threshold of zero sales.

Recent studies using text analyses and computational methods have investigated how offer descriptions can reduce asymmetric information and increase trust (Andrei & Veltri, 2024; Barratt et al., 2024). Overall, these results provide a detailed description of the darknet market. However, so far, there has been a lack of attempts to understand the social mechanisms that foster the concentration of sales and revenues in the hands of a few sellers.

Theoretical Frameworks

Status as a Heuristic

This work was developed based on dual-process paradigms. This paradigm distinguishes between two distinct modes of elaborating information: automatic cognition, system one (S1), and deliberate cognition, or system two (S2). System one is intuitive, emotional, fast and effortless, and operates without voluntary individual control. It is implicit, unverbalized, rapid, and automatic (D'Andrade, 1995), and it is based on a heuristic strategy that ignores part of the information to make decisions more quickly and frugally (Kahneman, 2011). System one consists of individual experiences elaborated by the automatic processing of information. Individuals tend to engage in S1 because it is far less time-consuming than S2. This behaviour can be seen when individuals fail to consider the importance of a decision (i.e. rational trade-offs) or when they cannot elaborate on the information available in each context because of cognitive limitations (Van Lange, Kruglanski, and Higgens, 2020). Furthermore, some individuals automatically adopt the heuristic approach when situations limit their cognitive capacity (Van Lange et al., 2020).

System one relies principally on heuristics, which Gigerenzer and Gaissmaier (2011, p. 454) describe as 'a strategy that ignores part of the information to make decisions more quickly, frugally, and/or accurately than more complex methods'. Social actors are more inclined to be influenced when processing information 'heuristically' because they focus only on a subset of available information on the environment to make a choice (Ibid.). For instance, when people make decisions using a heuristic, they do not consider the correlations among variables. However, this does not mean that heuristics are an inaccurate strategy since they can lead to more accurate decisions (Kahneman, 2011). In several contexts, a good heuristic can be better than a sophisticated calculation (Mousavi & Gigerenzer, 2014).

By contrast, S2 is explicit, verbalized, slow, and deliberate (D'Andrade, 1995), requiring effort to carefully process information where the individual's social experience is taking place. Psychologists have identified three factors that facilitate deliberate cognition: attention, motivation, and failure schema. According to psychological research, people tend to shift towards S2 when a problem attracts their attention (Di Maggio, 1997). Empirical findings from experimental settings report that when participants are asked to think carefully about their task, they tend to use heuristics less frequently than when the experimental setting does not require careful thinking (Abelson, 1981; Loftus et al., 1989).

When people are in a complex environment with insufficient knowledge, they rely on schemata and symbols as 'cognitive shortcuts' (Müller, 2013, p. 48) to quickly assess trustworthiness. E-commerce platforms manipulate these environments, triggering the adoption of cognitive shortcuts by providing trust-eliciting symbols and metrics. Seller metrics or rankings serve as such shortcuts for buyers to assess seller credibility and reliability.

In illegal online markets, status dynamics aim to increase trust, creating shortcuts for buyers. A person's status reflects their position in a socially recognized hierarchy, linked to access to certain resources. These hierarchies span various domains, from specific skills to broader social classifications (Ball, Grossman, and Zame, 2001). Darknet markets employ status metrics, though arbitrarily assigned by platform administrators (Holt, 2013). These metrics allow buyers to quickly assess sellers, reducing transaction uncertainty (Holt, 2013). Simultaneously, these metrics function as status indicators, establishing a seller's position within the market's social hierarchy through a top-down process (Mun et al., 2023; Washington & Zajac, 2005). While such metrics and symbols reduce uncertainty and provide reference points, they may foster a preferential attachment process. In this dynamic, wealth and interactions are distributed based on existing resources (Van de Rijt & Akin, 2020). This means those already well-off receive more than those who are not (Pollner et al., 2005). Statistically, this translates to power-law distributions, where a few dominate at the highest value, while the majority falls within the long tail (Pollner et al., 2005).

Status Dynamic in the AlphaBay Market

This study focuses on AlphaBay, the largest cryptomarket to date. This cryptomarket operated from December 2014 until July 2017, when an international police operation shut it down. According to the United States Department of The United States Department of Justice (2017), AlphaBay was like a traditional electronic commerce website in many ways. After registration on the platforms and having sent a security deposit of US$300USD to AlphaBay's wallet, vendors would be able to create a visible profile for buyers and offer goods for sale ('United States of America v. Alexandre Cazes ALPHA02', 2017). The vendors operating within the AlphaBay market utilized a hierarchical classification system established by the market administrator to categorize their products into ten macro-categories. These categories consisted of Carded Items, Counterfeit Items, Digital Products, Drugs & Chemicals, Fraud Guides & Tutorials, Jewels & Gold, Other Listings, Security & Hosting, Services Software & Malware, and Weapons.

This study focuses primarily on AlphaBay for three key reasons. Firstly, AlphaBay was one of the largest cryptocurrency marketplaces known during its operation from December 2014 to July 2017, when it was shut down through a coordinated international law enforcement action. At the time of its closure, the platform had approximately 369,000 listings of illicit goods, including illegal drugs, fraudulent services, malware, counterfeit documents, and firearms. Secondly, AlphaBay's vendor profiles provided several metrics, such as information about delivery destinations, the quantity and quality of products being sold, and pricing. Moreover, the platform offered information about vendors' feedback from previous customers and 'trust level' and 'vendor level' scores, metrics assigned to the platform. Thirdly, AlphaBay presents a unique opportunity to evaluate sellers' performance through FE payment. The market's administration empowered vendors to choose between two primary payment systems to facilitate transactions: FE payment and the escrow system. Under FE payment, buyers transferred funds directly to the seller's account before receiving the merchandise, leaving buyers without insurance against opportunistic behaviour by the seller. In contrast, under the escrow system, buyers send money to an escrow service, which releases the money and transfers it to the seller only after the buyer confirms receipt of the purchased item. The platform oversaw transactions, guaranteeing buyers that any opportunistic behaviour by the vendor could be punished (Tzanetakis et al., 2016).

In addition to escrow services, platforms often use various strategies such as seller metrics or rankings. These metrics or rankings serve as a shortcut for buyers to determine seller credibility and reliability. Using them, buyers can more quickly assess which sellers to engage with, reducing transaction uncertainty (Holt, 2013). Unlike reputation, which is usually based on anonymous feedback from buyers, status metrics for AlphaBay are arbitrarily assigned by platform administrators (Holt, 2013). Furthermore, reputation is often accompanied by written feedback describing users' experiences, but status metrics lack this context. While reputation and status both play a similar role in reducing product quality uncertainty and serve as cognitive shortcuts for vendor and product selection (Mun et al., 2023), according to Glückler and Armbrüster (2003) and Munksgaard and Tzanetakis (2022), status is a more reliable indicator than anonymous reviews provided by non-anonymous actors. This is because platforms have a greater interest than buyers in creating a trustworthy environment. Although the reputation system has been extensively studied (Diekmann et al., 2014; Hardy & Norgaard, 2016a, 2016b; Janetos & Tilly, 2017; Przepiorka et al., 2017), relatively little focus has been placed on the role of status in determining the performance of cryptomarket vendors.

Hypotheses. The transaction structure between sellers and buyers in the darknet market can be conceptualized as a form of 'trust game' involving three players, as elaborated on in game theory. The problem of trust in game theory is a three-part relationship in the form of 'A trusts B with respect to X' (Hardin, 1993, p. 56), where A is the first actor (generally called trustor) who decides to place trust or not, and B is the second actor (commonly called trustee), who is the object of that trust and decides to honour it or not, and finally, X is the content of trust relations (Rompf, 2014). The trustor, Actor A, needs to decide whether to trust the trustee, Actor B, with respect to X. If Actor A decides not to trust, the profits are zero for both, while if both decide to collaborate, they both gain. However, if the trustor places the trust but the trustee does not honour it, the trustor will gain less than zero, and the trustee will gain more than two. The trustor's strategic choice would be not to place the trust, while the trustee would be to defect. Four fundamental elements characterize the trust relationship described. The first element is related to the vulnerability of the trustor. The trustor becomes 'objectively' vulnerable when he decides to pass over certain resources' control to the trustee (Rompf, 2014). Vulnerability implies that a stake is included in the interaction. The stake could be a material or immaterial resource; what matters is that actors involved in the trust relationship have something to lose or something to gain (Nooteboom, 2006). Furthermore, what makes the relationship of trust even more vulnerable is that the result of trust cannot be immediately observed (Luhmann, 2018). As observed by Coleman (1994), there is a lag between when the trustor places the trust and when the trustee decides to honour it. The trustee may decide not to honour that trust, but the trustor will only know when he has already passed control of resources to the trustee.

The markets on the dark web have a few things in common with trust games. One key similarity is the vulnerability of the buyer (trustor). In a dark web market, the buyer becomes vulnerable by taking the first step of the transaction, similar to the trust game where the trustor (buyer) hands over resources (money) before knowing whether the trustee (seller) will fulfil its obligation (delivery of the product). There is also a delayed confirmation in both dark web transactions and trust games. Similar to the trust game, the buyer only finds out after the purchase whether the seller (trustee) has fulfilled its obligation. There is a delay between payment and receipt of the product, leaving the buyer in the dark about the seller's intentions. In addition, both parties have an interest in the outcome of transactions on the dark web. The buyer has an interest in receiving the product, while the seller has an interest in receiving the payment. This stakes environment reinforces the similarities with the trust game, as the interests of the parties are closely linked.

Studies conducted in laboratory settings show that when a third-party rates a trustee, cooperation among actors increases (Boero, Bravo, Castellani, & Squazzoni, 2009; 2017). Similarly, AlphaBay Market uses various strategies, such as seller metrics or rankings, to help buyers assess seller credibility and reliability. Among these, status metrics, which are arbitrarily assigned by the platform administrators (Holt, 2013), are commonly used in illegal online markets. When faced with uncertainty about seller reliability and product quality, and unwilling or unable to investigate thoroughly, buyers may rely on status as a cognitive shortcut for selecting sellers and products. However, the preferential attachment process suggests that status dynamics can concentrate resources in the hands of a few. By enabling privileges, status affects resource distribution within the market. Additionally, in high-uncertainty contexts, individuals or information with higher status are generally perceived as more trustworthy (Sammut & Bauer, 2021). Based on these points, we propose the following hypotheses:

> **H1:** Sellers with higher status will have a greater number of sales than sellers with lower status.

However, market share can be influenced by factors beyond sales volume. For example, a vendor might gain a significant market share through a single high-value sale (Paquet-Clouston et al., 2018). Market share, especially in terms of revenue, serves as an indicator of relative dominance in a market compared to others (Hindriks & Hindriks, 2013). Therefore, to analyse status dynamics, it's necessary to consider not only the number of sales but also market share in terms of revenue, which represents the share of total market revenue.

> **H2:** Sellers with higher status will generate more revenue than sellers with lower status.

In the previous paragraph, we discussed sellers' options: escrow and finalized early payment (FE). Under FE, a delay exists, giving sellers an advantage. This advantage comes from receiving payment before shipping, bypassing platform protection services. By choosing FE, sellers can mitigate potential disagreements or conflicts with buyers. Conversely, escrow agreements carry an increased risk for sellers, as disputes are arbitrated by the platform (Moeller et al., 2017). Since FE offers reduced risk of platform-mediated disputes, it's assumed that high-status sellers will leverage their status to conduct transactions via FE payment.

> **H3:** Sellers with higher status scores are likely to have more completed sales through the finalize early payment (FE) system than sellers with lower status.

Data and Methods

Data

We used a dataset containing 114,385 items, 6033 vendors, and 1,270,000 reviews collected by McKenna and Goode (2017) on the AlphaBay cryptomarket between 26 January 2017 and 28 January 2017. According to the data scraping protocol provided by McKenna and Goode (2017), most of the listings posted on the AlphaBay platform were included, even if the respective items were not purchased. However, the scraping was partially incomplete: 1636 TOR pages could not be downloaded, resulting in approximately 700 missing listings. The missing data represent only 0.01% of all listings. Thus, they are unlikely to affect our findings. We extracted the following vendor-level data from the TOR pages: nickname, number of listings, reputation scores, and lifespan as a vendor on the platform (see Figure A1 in the Appendix). Moreover, we extracted the following listing-level data: product description, number of sales per listing, origin and destinations of the listed goods, payment method, transaction feedback, and comments left by the buyers.

Variables

The unit of analysis in this study is the seller's profile. Three dependent variables were utilized: (Model 1) the ratio of sales per seller to total market sales, (Model 2) the ratio of revenue per seller to total market revenue, and (Model 3) the ratio of sales made through finalize early payment (FE) per seller to total market sales made through (FE). By comparing each measure with the total market, the study can evaluate a seller's relative performance compared to all other sellers in the market (Hindriks & Hindriks, 2013; Paquet-Clouston et al., 2018). In contrast to other studies (Christin, 2013; Demant et al., 2018; Soska & Christin, 2015), we estimated sales using the number of transactions provided by AlphaMarket instead of the number of feedbacks left by buyers. We did this for two main reasons. Firstly, Alpha Market provides the number of sales for each offer, unlike other platforms. Secondly, since not all buyers leave feedback after a transaction, we consider the platform's measure to be more reliable.

Our main explanatory variables were the status class, a nominal variable consisting of seven categories generated through latent profile analysis (LPA) (see section 3.3.1 for more details). We conducted an LPA based on three vendor attributes that we presumed were relevant in determining the latent status profile of the sellers: vendor level, trust level, and vendor lifespan. Vendor level and trust are attributes provided by the platform administration based on parameters that administrators do not always disclose. These variable-level attributes have already been used as status indicators in past research to investigate premium pricing in cryptomarkets for illegal drugs (Munksgaard & Tzanetakis, 2022). We added the vendor lifespan variable since seniority could be considered a signal of the seller's expertise. LPA was considered a better option because it allows the use of all three variables without requiring multiple interactions among them (Zyphur, 2009).

In addition, we included several other variables in our analysis. One variable was the number of offers per seller, and the proportion of FE (finalize early) offers per seller. This variable was created by dividing the number of direct payment offers by the total number of offers per seller. Another variable was the average feedback_rating_1_to_1, which was calculated by taking the average of the reviews received by each seller. The reviews on AlphaBay market could be positive (+1), neutral (0), or negative (−1). The average price of the offers per seller was also included in the analysis. We also collected the seller's origin data and generated dummy variables for the 11 product macro-categories.

Model Estimations

Latent Profile Analysis: Identification and Description of the Status Profile. The main explanatory variable vendor status was generated through an LPA, a model-based probabilistic clustering approach that allows the identification of types or groups of units that have different configural profiles of personal and/or environmental attributes. The profiles that emerged during the analysis have also been denominated as classes, groups, or clusters in past work (Spurk et al., 2020; Vermunt & Magidson, 2002). In its results, an LPA provides a latent categorical variable, its value indicating which profile an individual belongs to with a certain degree of probability. Latent variable models offer three main advantages. Firstly, this model allows for the creation of a parsimonious typology of sellers based on data (Costa, 2013). Secondly, the LPA enables easy exploration of the effect of multiple variables on an outcome, avoiding complex interactions in regression models. Lastly, LPA has the potential to develop and expand the theoretical understanding of the existence of different status configurations of seller profiles.

We used the 'tidyLPA' R package (Rosenberg et al., 2019) to conduct the Latent Profile Analysis (LPA). Table 1 displays the statistical criteria utilized to evaluate and select the LPA-generated model based on two ordinal variables (trust level and vendor level) and one continuous variable (seller lifespan). As the number of groups increased, the log-likelihood value decreased, suggesting that it did not offer a solution. However, the BIC (Bayesian Information Criterion) and SSA-BIC (Sample Size Adjusted Bayesian Information Criterion) decreased until they reached 39,004 and 38,908, respectively, for models with seven groups, after which both values increased again. We also noted that the p-value for the bootstrapped likelihood ratio test remained significant

Table 1. Descriptive Statistics.

Variable	Mean	SD	Median	Min	Max
Ratio of sales per seller to total market	0.0	0.01	0.0	0.00	0.032
Ratio of sales made through FE per seller to total market sales made through FE	0.00	0.0018	0.0	0	0.091
Ratio of revenue per seller to total market revenue	0.00	0.0016	0.0	0	0.091
Number of offers per sellers	19.25	38.17	8	1.00	411.00
Offers proportion by FE per sellers	0.07	0.25	0.0	0.00	1.00
Average feedback_rating_1_to_1 per sellers	0.97	0.49	0.97	−1-0	+1.0
Offers average price per sellers	628.9	35,64.4	133.92	0	100,000
Variable used in latent profile analysis					
Trust level	4.3	1.2	4	1	10
Vendor level	2.2	2	1	1	10
Vendor's age (day)	306.3	207.9	285	3	772
Status class					
Class 1		2380	40.74		
Class 2		608	10.41		
Class 3		643	11.01		
Class 4		652	11.16		
Class 5		716	12.26		
Class 6		472	8.08		
Class 7		371	6.35		
Sellers's origin					
Worldwide		1,757	29.89		
Africa		23	0.39		
Asia		126	2.14		
Europe		1,640	27.90		
North America		1,872	31.85		
Oceania		429	7.30		
South America		31	0.53		
Drug chemicals offers					
No		1,469	24.99		
Yes		4,409	75.01		
Carded items offers					
No		5,740	97.65		
Yes		138	2.35		
Counterfeit items offers					
No		5,570	94.76		
Yes		308	5.24		
Digital products offers					
No		5,376	91.46		
Yes		502	8.54		
Fraud offers					
No		4,388	74.65		
Yes		1,490	25.35		
Jewels gold offers					
No		5,826	5,826		
Yes		52	52		

(continued)

Table 1. (continued)

Variable	Mean	SD	Median	Min	Max
Other listings offers					
No	5,471		93,08		
Yes	407		6,92		
Security hosting offers					
No	5,765		98.08		
Yes	113		1.92		
Services offers					
No	5,424		92.28		
Yes	454		7.72		
Software malware offers					
No	5,662		96.33		
Yes	216		3.67		
Weapons offers					
No	5,747		97.77		
Yes	131		2.23		

for models ranging from two to seven groups. Consequently, we adopted a seven-group solution that provided a model with the lowest BIC and SSA-BIC values and a significant value for the bootstrapped likelihood ratio test (Table 2). The entropy value (0.81) indicates that sellers are assigned to the correct latent group with an optimal level of certainty (note that 0.80 is considered the optimal threshold value [Jung et al., 2008]). Additionally, no group of small size was observed in this model; all profiles contained at least 6% of the total vendors (refer to Appendix 1 for more details).

Figure 1 illustrates the group of the 7-class model based on the mean of standardized score factors, with negative scores reflecting a low expression and positive scores reflecting a high expression of the factor. Figure 1 illustrates the profile of the 7-group model based on the mean of standardized score factors, where negative scores indicate low expression and positive scores indicate high expression of a factor. The largest group of sellers ($n = 2382$, 42.19%) was classified into the first class, indicating that at the time of data collection, a significant portion of vendors had a low status level on the AlphaBay market. The second group and fourth profile can be defined as medium-status vendors, as they have positive values in all indicators, and they represent 19.13% of the sellers. The third profile is the most anomalous, as it exhibits a higher level of seniority in the market but low values on the vendor and trust level indicators. One possible explanation is that this group includes sellers who had been re-registered in the market but were never very active. However, it is small in size ($n = 645$, or 11.42%). The fifth group is a small group ($n = 516$ or 9.14%), which has no seniority in the market and has a negative value in the vendor-level indicators but a positive value in the trust level. The sixth group was small ($n = 472$, 8.36%) and was characterized by a high level of trust and seniority but with a low vendor level. The seventh group can be defined as the 'elite', as they are the smallest group ($n = 371$, 6.10%) in the market with the highest values in all factors. According to this classification, we expect that Class 7, with the higher status, will perform better in terms of sales (sales by FE payment) and revenue, as elaborated in the theoretical section.

GAM Model. Generalized additive model (GAM) maximum likelihood estimation and Tweedie distribution have been used to study the relationship between status class, the number of sales per

Table 2. Statistical Fit Indices for Different Group Solutions.

Profile	LL	BIC	SSA-BIC	Entropy	BLRT_p
2	−22,472	45,032	45,000	0.960	0.00990
3	−21,877	43,877	43,832	0.836	0.00990
4	−21,877	43,910	43,853	0.650	0.0198
5	−21,596	43,384	43,314	0.745	0.00990
6	−21,596	43,418	43,336	0.625	0.00990
7	−19,371	39,004	38,908	0.813	0.00990
8	−19,371	39,039	38,930	0.720	0.673
9	−19,370	39,072	38,952	0.648	0.0891
10	−19,370	39,108	38,974	0.638	0.950

Note: LL = log likelihood; BIC = Bayesian Information Criterion; SSA-BIC = sample size adjusted Bayesian Information Criterion; SABIC = sample size-adjusted Bayesian Information Criterion (Sclove, 1987); BLRT = *p*-value: *p*-value for the bootstrapped likelihood ratio test; Entropy = A measure of classification uncertainty, reverse-coded so that 1 reflects complete certainty of classification and 0 reflects complete uncertainty (see Celeux and Soromenho, 1996).

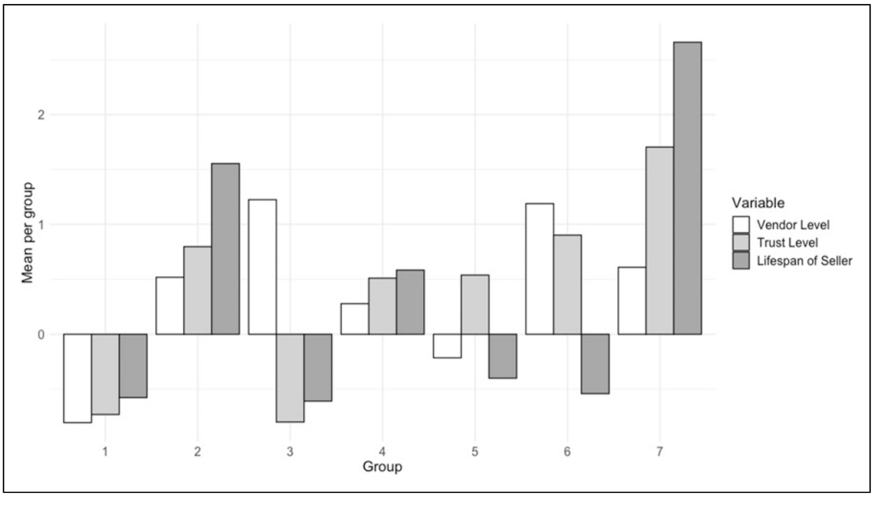

Figure 1. Results of the latent profile analyses. The grouped bar plot depicts the average values of three scaled variables in different classes identified by latent profile analyses. Each bar corresponds to a specific variable (vendor level, trust level, and lifespan of seller) within the respective class.

vendor, revenue per seller, and FE payment. The GAM model explains the dependent variable as an additive combination of parametric and non-parametric functions of the explanatory variable. This model offers two main advantages over ordinary linear regression. First, by the functions generated by non-parametric functions that can take on a large variety of shapes, GAM allows uncovering non-linear relations that optimally adjust the outcome to the predictors and that can condition such relations on covariates. Finally, the GAM model allows residual distribution to follow other than the normality assumption by choosing among different families (Hastie, 2017). This model has been preferred as an alternative to polynomial regression because it is not necessary to specify the degree of the polynomial, thereby reducing the risk of both under- and over-smoothness. By relying on smooth functions of covariates, which penalize unnecessary complexity (Wood, 2006), the GAM model avoids both over-smoothness and under-smoothness.

Flexible smooths are created from many smaller functions called basis functions. Each smooth is the sum of a number of basic functions, and each basis function is multiplied by a coefficient, each of which is a parameter in the model. The smoothness of the function is summarized by degrees of freedom. The advantages of this approach are extremely important in the darknet market, where previous studies have shown nonlinear relationships between reputation and sales (Przepiorka et al., 2017). In addition, as our target variable is skewed to the left, the Tweedie-GAM model handles dependent variable with many zero values (Shono, 2008).

Results. The first part of Table 3 describes the models that we fitted. The first line indicates the dependent variable of the three models according to the hypothesis elaborated in the theoretical section: M1 (ratio of sales per seller to total market sales), M2 (ratio of revenue per seller to total market revenue), and M3 (ratio of sales made through FE per seller to total market sales made through FE). The 'Family' component indicates that the model assumes a Tweedie distribution of our errors, and the 'Link' of the 'log' indicates that the model does transform the predictions. Parameter p defines the details of the model distribution (consider that when $p = 0$, it is a normal distribution; if $p = 1$, it is a Poisson distribution; and if $p = 2$, it is a gamma distribution) (Hastie, 2017). The first section of Table 3 describes the parametric terms of our model; specifically, it provides the coefficients of the linear terms in the models. Asterisks next to the coefficients indicate the p-values, while values in parentheses indicate standard errors (Wood, 2006). The second part of Table 3 covers 'smooth terms'. Smooth coefficients are not shown because each smooth has several coefficients – one for each basis function. Instead, the column shows 'EDF', which provides the effective degrees of freedom (EDF). This value specifies the complexity of the smooth. An EDF with a higher value describes a wigglier curve. For instance, an EDF of 1 is equivalent to a straight line, whereas an EDF of 2 is equivalent to a quadratic curve and so on. Even in this case, the asterisk indicates the significance of smooth terms. A significant EDF means drawing a horizontal line through a 95% confidence interval is impossible. Note that a high EDF does not mean significance. A smooth may be linear and significant or non-linear and non-significant (Hastie, 2017). The last line of the table indicates the proportion of deviance explained, which is considered a more appropriate measure of goodness of fit for non-Gaussian models (Wood, 2006).

Table 3 outlines the application of three distinct generalized additive models (GAMs) in this study, namely, the ratio of sales per seller to total market sales (M1), the ratio of revenue per seller to total market revenue (M2), and the ratio of sales made with finalize early payment (FE) per seller to total market sales made with FE (M3). Our analysis of the results reveals that status classes 2, 4, and 7 (which exhibit positive values across all status parameters, as presented in Image 1) display a statistically significant positive coefficient, which lends empirical support to the hypotheses under investigation.

According to the M1 model, the ratio of sales to total market sales is significantly higher for sellers classified in Class 2 than for those in Class 1, with a factor of 5.4 (exp 1.68). Likewise, for sellers classified in Class 4, the model coefficient of 0.96 suggests that this group's predicted ratio of sales to total market sales is 2.60 times higher (exp 0.96) than for sellers in Class 1. Notably, the coefficient estimate for Class 7 (the elite vendor) is 2.52, which implies that this group's ratio of sales to total market sales is considerably higher, specifically 12.40 times higher (exp 2.52), than for sellers in Class 1. The analysis produced an interesting finding when examining the variable 'offers proportion by FE', which represents the proportion of offers made with finalize early payment (FE) per seller divided by the total number of offers per seller. The coefficient for this variable was positive and significant, measuring 1.58 (0.46 exp). This implies that when sellers offer their products with FE options, the ratio of sales to total market sales tends to increase. The analysis revealed a third significant finding: despite drugs being the primary category of sales in

Table 3. GAM models.

GAM Models	M1	M2	M3
Dependent variables	Ratio of sales per seller to total market sales	Ratio of revenue per seller to total market revenue	Ratio of sales made with FE per seller to total market sales with FE
Family	Tweedie (p =1.765)	Tweedie (p =1.804)	Tweedie (p = 1.496)
Link function	log	log	log
Variable name	Estimate	Estimate	Estimate
(Intercept)	−9.96*** (0.06)	−10.98*** (0.07)	−16.40*** (0.35)
Class 2	1.68*** (0.06)	1.10*** (0.08)	5.04*** (0.33)
Class 3	−0.40*** (0.07)	−0.41*** (0.08)	1.96*** (0.39)
Class 4	0.96*** (0.06)	1.07*** (0.07)	3.88*** (0.33)
Class 5	−0.01 (0.06)	0.77*** (0.06)	2.13*** (0.39)
Class 6	0.08 (0.07)	0.68*** (0.08)	3.03*** (0.40)
Class 7	2.52*** (0.07)	1.61*** (0.10)	5.24*** (0.35)
Offers proportion by FE per sellers	0.46*** (0.06)	0.06 (0.08)	-
Offers average price per sellers	0.00 (0.00)	0.00*** (0.00)	0.00 (0.00)
Number of offers per sellers	-	-	0.00 (0.00)
Drugs chemicals (Yes)	−1.20** (0.06)	−0.38*** (0.07)	1.38** (0.23)
Carded items (Yes)	−0.03 (0.12)	0.60*** (0.14)	−1.58** (0.59)
Counterfeit items (Yes)	0.17* (0.07)	−0.26** (0.09)	0.61* (0.30)
Digital products (Yes)	0.45*** (0.07)	−0.90*** (0.09)	0.14 (0.28)
Fraud (Yes)	−0.14 (0.05)	0.00 (0.06)	−0.03 (0.16)
Jewels gold (Yes)	0.21 (0.17)	−0.11 (0.22)	1.31* (0.57)
Other listings (Yes)	−0.15* (0.07)	−0.19 (0.08)	−0.24 (0.22)
Security hosting (Yes)	0.12 (0.13)	0.58 (0.16)	−0.17 (0.58)
Services (Yes)	−0.47 (0.07)	−0.05 (0.08)	0.11 (0.24)
Software malware (Yes)	0.21* (0.10)	−0.99 (0.13)	−1.09 (0.49)
Weapons (Yes)	−0.54*** (0.13)	0.34 (0.13)	−2.68** (0.98)
Africa	0.18 (0.26)	−0.39 (0.31)	0.60 (0.84)
Asia	0.53*** (0.11)	−0.02(0.13)	0.36 (0.17)
Europe	−0.16** (0.05)	−0.50 (0.06)	0.25 (0.17)
North America	−0.28*** (0.05)	−0.01 (0.06)	−0.07 (0.18)
Oceania	−0.48*** (0.07)	0.13 (0.08)	0.34 (0.23)
South America	−0.15 (0.27)	0.34 (0.28)	−3252.72*** (410.04)
Smooth variable	EDF	EDF	EDF

(continued)

Table 3. (continued)

GAM Models	M1	M2	M3
Dependent variables	Ratio of sales per seller to total market sales	Ratio of revenue per seller to total market revenue	Ratio of sales made with FE per seller to total market sales with FE
Family	Tweedie (p =1.765)	Tweedie (p =1.804)	Tweedie (p = 1.496)
Link function	log	log	log
Variable name	Estimate	Estimate	Estimate
Total sales by vendor	-	8.88***	8.59***
Number of offers per sellers	13.41***	8.41***	-
Avg seller feedback rating (1+1)	8.78***	8.46***	4.81***
N	5,846	5,846	5,846
Deviance explained	70%	82%	80.6%

Notes: Standard error in parentheses; (***$P < 0.001$; **$P < 0.01$; *$P < 0.05$).

the market, sellers who offer drugs and chemicals exhibit a lower ratio of sales to total market sales than those who do not offer them (with a coefficient of −1.20 exp). This result can be attributed to the intense competition within the drug market, making it difficult for many sellers to generate sales. Lastly, it is noteworthy that in Europe, North America, and Oceania – geographical areas where there is a higher number of sellers – the coefficient is negative and significant, respectively (−0.16 exp for Europe, −0.28 exp for North America, and −0.48 exp for Oceania). This suggests that the ratio of sales to total market sales per seller is lower in highly competitive markets in these geographical areas.

The analysis of smooth terms in Model 1 reveals a non-linear relationship between the number of offers per seller and the average seller feedback rating, with a 99% confidence interval. Figure 2 presents the plots of the smooth terms, which indicate that the number of offers per seller displays a highly irregular trend with three distinct peaks: the first over 100, the second over 200, and the third at approximately 400. Despite this irregularity, the ratio of sales to total market sales generally increases with an increase in the number of offers, reaching its highest peak at 200 offers. It is important to note, however, that the number of vendors with over 100 sales is limited. Consequently, confidence intervals above this threshold tend to widen, making the observed trends less reliable.

The effect of reputation on sales appears consistent with previous studies in the literature (Diekmann et al., 2014; Hardy & Norgaard, 2016a, 2016b; Janetos & Tilly, 2017; Przepiorka et al., 2017). Sellers with a negative average reputation score make fewer sales, while as reputation increases, sales increase considerably. However, when sellers reach a reputation score of 0.8, sales per seller begin to decline. This effect is reasonable because sellers increase the chance of receiving negative reviews as sales increase. It is also important to consider that sellers who have only made one sale and received a single positive review are assigned a reputation value of one, by reducing the association. Another complementary explanation arises from the fact that sellers seek to maximize their profits when they achieve a favourable

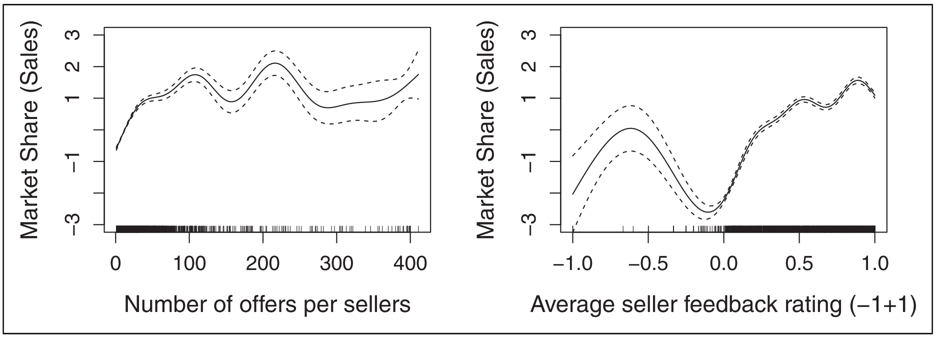

Figure 2. Results of generalised additive models for estimated impact of number of offers per sellers and average seller feedback rating (-1+1) on ratio of sales per seller to total market sales.

reputation score and therefore occasionally and strategically act opportunistically. This is underpinned by the jargon of the market community, which characterizes this behaviour with the term 'selective scammer' (Espinosa, 2019). Finally, the confidence intervals for sellers with low reputation scores are very wide, as few dealers have negative average reputation scores.

Our findings in Model 2 are consistent with those of Model 1. In particular, we observe that sellers in the highest status classes (classes 2, 4, and 7) exhibit higher, positive, and statistically significant coefficients. Specifically, the coefficients for classes 2 and 4 are estimated to be 1.10 and 1.07, respectively. This indicates that the ratio of revenue to total market revenue for those sellers belonging to classes 2 and 4 is 3 and 2.92 higher, respectively, than that of Class 1. Furthermore, we note that sellers belonging to Class 7 (the elite sellers) exhibit the highest coefficient, with a value of 1.61(exp). This implies that the ratio of revenue to total market revenue for Class 7 sellers is significantly higher than that of Class 1, with an increase of approximately 5 times the revenue earned by Class 1 sellers.

In line with Model 1, where the ratio of sales per seller to total market sales was the dependent variable, it was also observed in Model 2 that sellers offering drugs may exhibit a lower revenue ratio to total market revenue. This could be attributed to the intense competition prevalent in this specific market. Furthermore, the coefficient for sellers offering counterfeit items and digital products (both popular categories on the AlphaBay market) was significantly negative, indicating that such sellers encounter difficulties in generating revenue. Notably, in Model 1, it was found that counterfeit items have a positive and significant coefficient. This discrepancy can be attributed to the lower prices of counterfeit items, which may result in high sales volume but lower revenue for sellers in this category. With respect to the impact of nationality on revenue, the analysis reveals that there is no significant effect on revenue.

Model 2 exhibits three non-linear relationships, the first of which is depicted in Plot 2a. It illustrates the relation between the number of sales and the revenue ratio to total market revenue per seller. The plot shows a significant positive relationship, indicating that as the number of sales increases, the ratio of revenue to total market revenue per seller increases markedly. This relationship is, however, characterized by a nonlinear pattern, as the ratio peaks around 1800 sales before experiencing a subsequent decline. It is noteworthy that the confidence interval beyond this point widens considerably, reflecting a decrease in the number of cases with a higher number of sales, which could account for the irregular pattern of the relationship beyond the second peak (Plot 2b) depicts the relationship between the average feedback score received by sellers ranging from −1 to 1, and the ratio of revenue to total market revenue per seller. The results reveal a positive relation between reputation score and revenue ratio to total market revenue per seller. As the reputation score increases, there is a marked increase in the ratio of revenue to total market revenue per seller. Conversely, for sellers with a negative reputation score, there is a negative correlation between the reputation score and the ratio of revenue to total market revenue per seller. This finding is in line with prior research that has demonstrated the importance of reputation in online marketplaces, where buyers rely on reputation signals to evaluate the trustworthiness of sellers and the quality of their goods and services (Diekmann et al., 2014; Hardy & Norgaard, 2016a, 2016b; Janetos & Tilly, 2017). The results suggest that maintaining a positive reputation is crucial for sellers to achieve higher revenue ratios, while a negative reputation can have a detrimental effect on revenue ratios.

Finally, Plot 2c reveals the unsteady relationship between the number of offers and the ratio of revenue to total market revenue per seller. This relationship is characterized by multiple peaks and irregularities. Initially, as the number of offers increases (Figure 3) the ratio of revenue to total market revenue per seller increases rapidly. Then, it drops, reaching a second peak at around 100 offers. However, the confidence interval becomes wider, and the relationship becomes more complex, showing that an increase in offers does not always lead to an increase in revenue per seller.

The latest model (M3) reflects the impact of direct sales without the involvement of intermediary platforms. In this case, buyers send the payment directly to the sellers before receiving the product. As hypothesized in the theoretical section, the ratio of sales made with FE (i.e. without the involvement of intermediary platforms) per seller to total market sales with FE is higher for sellers belonging to the higher status. Specifically, Class 2 and Class 4 have 154.50 (5.04 exp) and 48.42 (3.88 exp) higher sales than Class 1, respectively. In contrast, the coefficient for the elite class (Class 7) is significantly higher (5.24 exp), meaning that sellers belonging to Class 7 have a ratio that is 188.70 times higher than Class 1.

In contrast to the findings of models 1 and 2, the results of Model 3 indicate a statistically significant positive coefficient for sellers offering drugs and chemicals. Specifically, the coefficient is estimated to be 1.38 (exp), suggesting that sellers in this category have a ratio of sales made with FE per seller to total market sales with FE that is 3.97 times higher than that of sellers belonging to Class 1. These results are consistent with Munksagaard's (2022) findings, which

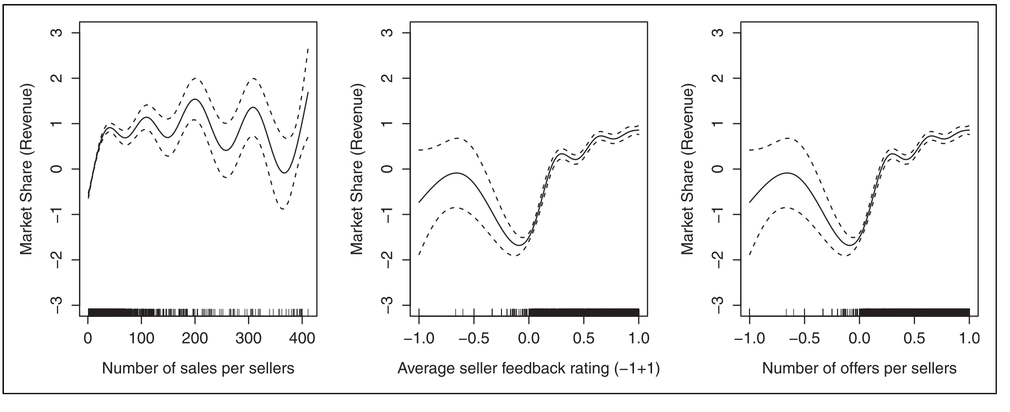

Figure 3. Results of generalised additive models for estimated impact of number of sales per sellers, average seller feedback rating (-1+1) and number of offers per sellers (c) on ratio of revenue per seller to total market revenue.

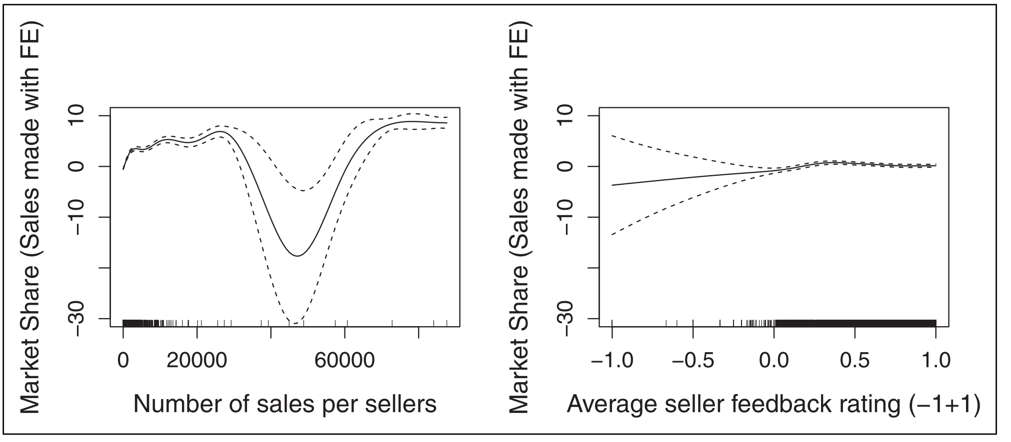

Figure 4. Results of generalised additive models for estimated impact of number of sales per sellers and average seller feedback rating (-1+1) ratio of sales made with finalize early payment (FE) per seller to total market sales made with FE.

showed that escrow negatively affects drug sales. This unexpected result is explained by the fact that dark web drug markets are embedded in a reciprocity and community environment characterized by trustful exchanges (Przepiorka et al., 2017). With respect to the impact of nationality ratio of sales made with FE per seller to total market sales with FE, the analysis reveals that, aside from sellers from South America who have a significant coefficient, there is no significant effect of nationality on the ratio of sales made with FE per seller to total market sales with FE. However, the limited number of cases from South America yields a high standard error (410.04), which calls for caution in interpreting the coefficient estimate.

The non-linear relationship in Model 3 reveals that the ratio of sales made with FE per seller to total market sales with FE increases significantly with an increase in the number of sales, as shown in Plot 3a. However, this relationship is characterized by irregular undulations. After reaching its first peak at 4000 sales, there is a significant drop before the second peak is achieved at 8000 sales. It is important to note that the confidence interval beyond the threshold of 1000 sales is wide, indicating the scarcity of sellers who achieve such high sales volumes. The unexpected drop observed in the ratio of sales made with FE per seller to total market sales with FE could be explained by a few sellers with a lower ratio of sales made with FE per seller to total market sales with FE but still make a lot of sales (Figure 4). In contrast to the non-linear relationship observed in Plot 3a, the relationship between a seller's reputation score and the ratio of sales made with FE per seller to total market sales with FE appears to be more regular. The confidence interval for sellers with negative reputation scores is notably high, likely due to the limited number of such cases. As the reputation score increases, the confidence interval becomes smaller, and the ratio of sales made with FE per seller to total market sales with FE. However, beyond a certain point, this relationship experiences a slight decrease, while the confidence interval remains stable.

Discussion and Conclusion

This research sheds light on the importance of seller status and its relationship with performance in online marketplaces. Different from the various studies conducted on darknet platforms, which focus on the effect of reputation on sales (Diekmann et al., 2014; Hardy & Norgaard, 2016a, 2016b; Janetos & Tilly, 2017; Przepiorka et al., 2017), this paper studied how sellers' status affects the ratio of sales per seller to total market sales, ratio of revenue per seller to total market revenue, and ratio of sales made with FE per seller to total market sales with FE in one of the largest cryptomarkets that ever existed, AlphaBay market. We used a large dataset containing 6083 sellers' profiles to test the hypothesis that status generates sellers' success in the cryptomarket for illegal goods. We created status variables through an LPA, including trust level, vendor level, and vendor lifespan, which classified sellers into seven status categories (see Image 1). Our empirical investigation, utilizing three general additive models, reveals that sellers belonging to the higher status class exhibit a statistically significant positive impact not only on the ratio of sales per seller to total market sales and the ratio of revenue per seller to total market revenue but also on the ratio of sales made with FE per seller to total market sales with FE.

Based on the heuristic-systematic model from the literature of dual process theories, this work finds support for certain cognitive shortcuts implemented by metrics that can influence purchasing decisions in the context of the dark web market. This study contributes to the literature in two ways. First, different from precedent, which argues that the reputation produced by an anonymous network facilitates seller success, we show that the status score attributed by the platform's administrators generated sellers' success in an anonymous, unregulated market. Second, we show that higher-status sellers make sales even overcoming the protection of platforms dealing directly with buyers through the method of FE payment. These results suggest that status may work as a cognitive shortcut in the darknet market. If on the one hand, status provides symbols and metrics that allow buyers to assess trustworthiness rapidly. On the other hand, status enables privileges for sellers who sell their products, avoiding interaction with third-party guarantors. There are three main implications of the results. First, the metrics guaranteed by third parties, who have an encompassed interest (such as darknet platforms), favour the emergence of trust in uncertain settings and asymmetric information, such as darknet markets. Second, such metrics, fostering direct dealing between sellers and buyers, could reduce the importance of the party in the market. Finally, the status metric could favour the sales of a few sellers penalizing newcomers in the market. According to Paquet-Clouston et al. (2018), the cryptomarket is characterized by intense competition, leading to a small number of successful sellers and a large proportion of unsuccessful vendors who are unable to generate any sales. This phenomenon may be attributed to the metric status system, which affords preferential treatment to established vendors who have been recognized as trustworthy by the platform while imposing disadvantages on new entrants to the market.

These results have two primary limitations. The first limitation relates to the cross-sectional nature of the dataset, which hinders the analysis of the evolutionary dynamics of seller status on sales and revenue. It is only possible to measure market share at the specific time when the data was collected. Due to the instability of cryptomarket, planning and implementing systematic longitudinal data collection is challenging. The second limitation is the inability to gather data from buyers. Most darknet platforms do not provide buyer data, making it difficult to collect or obtain data that includes such information.

However, these results have implications for law enforcement intervention on the darknet and for policymakers who regulate the platform economy. The use of status metrics by e-commerce platforms concentrates trust among a select group of sellers, leading to increased sales and revenue for them. This promotes a business-oriented approach for sellers rather than a peer-to-peer orientation. As a result, new organizations that capitalize on the benefits of darknet retail may emerge. Future research should aim to understand whether blocking the activities of the largest sellers, instead of focussing on shutting down darknet platforms, constitutes a more effective policy in this environment. Additionally, future research should investigate how the concentration of sales among a select group of sellers, facilitated by platform metrics, can impede the entry of new sellers into the market.

Appendix

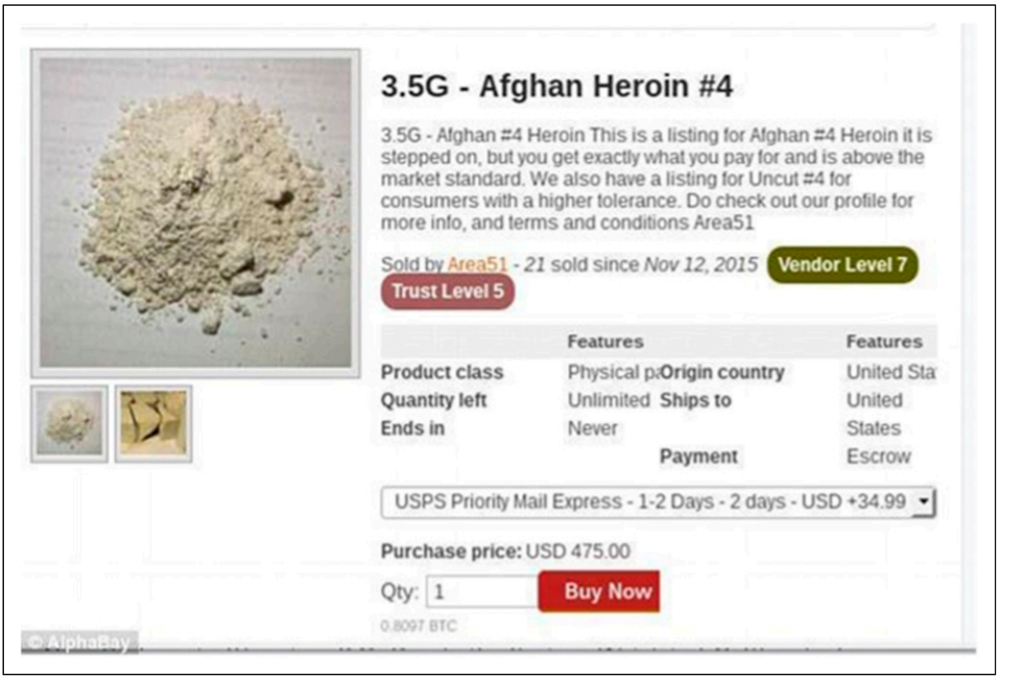

Figure A1. Example of offers on darknet market.

Author's Contributions

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

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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