The Pennsylvania State University

The J. Jeffrey and Ann Marie Fox Graduate School

"RAIN DROP, DROP TOP, PUTTING THESE POUNDS IN YOUR MAILBOX": AN EXAMINATION OF REPUTATION SYSTEMS AND PRICE ON ALPHABAY

A Thesis in

Criminology

by

Ella Taylor

Submitted in Partial Fulfillment

Of the Requirements

for the Degree of

Master of Arts

May 2026

The thesis of Ella Taylor was reviewed and approved by the following:

Holly Nguyen
Associate Professor of Sociology, Criminology, and Public Policy
Thesis Advisor

Riley Tucker
Assistant Professor of Criminology

Daniel DellaPosta
Associate Professor of Sociology and Social Data Analytics

Michelle Frisco
Professor of Sociology and Demography
Head of the Department of Sociology and Criminology

ABSTRACT

The reputation-price premium has been well-established in literature on online illicit marketplaces (Przepiórka et al., 2017; Espinosa, 2019; Munksgaard & Tzanetakis, 2022). However, there are gaps in the current literature surrounding whether price premiums operate uniformly across products and across reputation signals. This thesis examines associations between ratings and consumer feedback and price using data from the AlphaBay marketplace. Additionally, this thesis will determine if there are differences in the monetary values assigned to ratings for a variety of drug (e.g., stimulants, cannabis, and opioids) and non-drug products (e.g., counterfeit items, fraud products, and weapons) available on AlphaBay. Using signaling theory and the rational choice perspective, hypotheses are drawn regarding expected relationships. Signaling theory posits that credible signals of reputation are used to decrease information asymmetry (Spence, 1973; Connelly et al., 2011), and the rational choice perspective argues that these signals are only as effective in their pricing power as their ability to reduce risks for consumers (Albonetti, 1986; Klepper & Nagin, 1986; Pogarsky et al., 2018). The analytic strategy estimates ordinary least squares regression models to determine associations between reputations (ratings and reviews) and price. Equality of coefficients tests will determine if there are significant differences in how ratings are translated into economic value across products. By examining these relationships, inferences can be made about marketplace dynamics, specifically for price formation and consumer decision-making. The findings suggest a positive association between ratings and price for nearly all products, reinforcing prior literature that has found that reputable vendors can charge a price premium. Equality of coefficients tests show that certain products are significantly different in their rating-price relationship, suggesting that price premiums do not operate uniformly across all products. Finally, findings from the review-price relationship display fewer products commanding price premiums, suggesting that the monetary values assigned to vendor reputations are not consistent between ratings and reviews. These findings yield important implications for theory and enforcement. First, findings expand signal theory application to apply to environments of extreme uncertainty. Second, results suggest that the rational choice perspective is applicable to illicit online marketplaces. Third, implications for enforcement include transitioning from supply-side interventions to demand-side enforcement, disrupting reputations that are intended to reduce risk for consumers. Future research should consider longitudinal studies of vendors and the operationalization of perceived risk as a measure.

Table of Contents

LIST OF TABLES

ACKNOWLEDGEMENTS

I would like to thank my thesis advisor, Holly Nguyen, for her continued support of my research and overall guidance during this process. I will be forever grateful for her unwavering support and willingness to explore a new topic of research with me. I am also grateful for the direction and enthusiasm from my research advisor, Riley Tucker. I also want to thank Daniel DellaPosta for his assistance with my methodology and insights into economics literature. In addition, I want to acknowledge my family and partner for supporting me throughout this process. I could not have done this without their belief in me as a scholar. Finally, I want to thank my friends in the Department of Sociology and Criminology for always lifting my spirits and celebrating all of my accomplishments. The community we have here is truly special.

Chapter 1: Introduction

Online illicit marketplaces have become an emerging avenue to sell varying types of illegal goods and services including a variety of drugs, fraud services, and counterfeit items. Opposed to traditional street markets, online illicit markets function under anonymity and uncertainty, pushing users to seek out trustworthy transactions through the use of reputation systems like ratings and reviews. The current study examines under what conditions these reputations may translate into the pricing strategies of the goods and services offered. Prior research on reputation and price has consistently found that vendors with better reputations tend to charge higher prices for the drug products they offer, suggesting that reputation plays a role in price formation (Przepiórka et al., 2017; Espinosa, 2019; Munksgaard & Tzanetakis, 2022). However, drugs are merely one type of commodity found in online illicit marketplaces and whether this reputation-price relationship operates uniformly across varying types of goods and services is unknown. Due to a variation in perceived and actual product risk, general uncertainty, and delivery methods across products, it is important to explore if there are certain conditions under which reputation and price differ from previous findings.

The existing literature argues drug products sold by vendors who have a favorable reputation have consistently higher prices, otherwise known as a price premium, closely mirrors findings on the rating-price relationship for licit online marketplaces. Research conducted on the topic of price premiums on online illicit markets has largely focused on drugs and relies strictly on consumer ratings as an indicator of vendor reputation. Consequently, little is known about whether price premiums for products from highly reputable sellers are generalizable across product categories, or whether other measures of reputation, such as consumer feedback reviews, operate in a similar fashion.

The lack of research into non-drug products is a significant gap in the existing literature given that online illicit marketplaces hold an extremely diverse portfolio of other goods and services like bank account information, fake identification, and weapons to name a few. Non-drug products introduce different risks associated with the buying and selling of these products compared to certain health and law enforcement risks seen in the drug market. Some non-drug listings are available via online delivery, which could subject a consumer to potential malware and viruses, a risk those involved in the drug trade may not have. These different risks introduced with each category of product suggests that reputation systems may function differently across product types, rather than being a uniform pricing mechanism across listings.

Examining how reputation shapes pricing for both drug and non-drug products impacts policy because certain pressures from law enforcement, like increased postal surveillance and interception of packages may negatively impact consumers and vendors. This tactic may influence vendor reputation through creating more negative ratings and reviews from packages that were left undelivered and result in the subsequent arrests of individuals either buying or selling the product. Additionally, law enforcement could infiltrate entire marketplaces' reputation systems, disrupting the reputations vendors use to set their price premiums and reduce consumer risk, introducing more uncertainty to the marketplace as a whole in an attempt to reduce the demand for these products. Therefore, the typical supply-side interventions that target entire marketplaces (Décary-Hétu & Giommoni, 2017) may not be an effective intervention due to the unique impacts whole site takedowns have on specific products and vendors.

The current study seeks to evaluate if the price premiums associated with favorable vendor ratings found in prior literature (Przepiórka et al., 2017; Espinosa, 2019; Munksgaard & Tzanetakis, 2022) are generalizable to drug and non-drug products for vendors who hold a perfect rating on the AlphaBay marketplace. Furthermore, this study will evaluate if these rating-price relationships are significantly different between products, signaling that perhaps the monetization of price through ratings is not uniform across products with differing risk profiles. Finally, numerical representations of consumer reviews are analyzed for their association with price to determine if the reputation signal of reviews produces similar price premiums to ratings.

According to the rational choice perspective, consumers are assumed to weigh the costs and benefits before purchasing a product. On these online illicit marketplaces, this decision calculus also involves incorporating perceived risk, whether a delivery will be successful, and inferring product quality. The signaling theory framework furthers how sellers utilize reputation systems to inform buyers of credibility, reducing information asymmetry between the two parties. If the reputation of a vendor acts as a trustworthy signal, the price of the product would then reflect both their reputation as well as the associated risks with making said transaction. Appropriately, the current paper conjectures that reputation is not a uniform pricing mechanism based solely on reputation, but rather in tandem with product-specific risks. By comparing ratings and consumer reviews across both drug and non-drug listings, this study evaluates if reputation signals can translate into pricing power on the AlphaBay marketplace.

Data from the AlphaBay marketplace is used to answer two key research questions: 1) Are reputations related to price; 2) Are the relationships between ratings and price different across product types? AlphaBay uses a common reputation system across all products, allowing for reliable product comparisons with distinct risk factors by holding these marketplace features constant. Product categories for analysis include drugs, fraud, counterfeit items, weapons, and other available goods and services. The total sample from the AlphaBay data across all product categories is 43,208 unique listings to investigate the rating-price relationship, and 41,423 listings to explore the consumer feedback reviews and price relationship. The statistical methods used will be ordinary least squares regressions (OLS), equality of coefficients tests, and a Valence Aware Dictionary and sEntiment Reasoner (VADER). Findings suggest that price premiums are present for nearly every product category, and there are significant differences between certain products, highlighting that the economic value of trust conveyed through ratings is not uniform across products. A potential reason for this includes the variety of risks associated with each product, that could influence consumer decision-making and the formation of price for these products. Results also show that price premiums appear less frequently when consumer feedback reviews are the reputation signal that are assigned monetary value compared to ratings, suggesting that not only is the economic value assigned to reputation signals variable between products, but also inconsistent between reputation systems

This thesis proceeds as follows: first, the dark web and AlphaBay will be described. Second, signaling theory and the rational choice perspective will be introduced and connected to the broader research agenda. Third, to provide context for online illicit markets, a comparison of street and online drug markets along with online illicit markets and online licit markets will provide an overview of the structural and operational differences between these markets, highlighting how important reputation systems are for online illicit marketplaces. Fourth, an overview of perceived risks of purchasing a variety of products is reviewed to offer an explanation for why products might differ in how much monetary value ratings are given for specific goods and services. Fifth, the data and analytic strategy of the study is described, and results will be presented. Lastly, implications of the findings, study limitations, and avenues for future research will be discussed.

Chapter 2: Literature Review

The Dark Web & AlphaBay

The dark web provides a unique opportunity to study how ratings and reviews relate to prices. There is tremendous growth in sales on online marketplaces as more illegal transactions are moving to these online illicit marketplaces (Moeller & Sandberg, 2019). Therefore, it is crucial to study how these markets operate and what variables shape their operation. There are a variety of products on these dark web marketplaces, offering a unique setting where someone can purchase pounds of cannabis and counterfeit designer goods from the same marketplace. Prior research suggests that online marketplaces are not only used for personal consumption, rather certain higher-priced drug and larger quantity listings were found to be intended for resale (Aldridge & Décary-Hétu, 2014), suggesting that online marketplaces can serve as an intermediary in the illicit market supply chain. In addition to drug dealers purchasing drugs for resale, illicit drug manufacturers were also found to be purchasing precursor chemicals to make their own illicit drugs (Aldridge & Décary-Hétu, 2014). Martin (2014) similarly observed that the Silk Road was not only seen as a site to purchase drugs for personal use but acted as a sort of "middleman" between vendors and drug dealers. The lack of a physical "middleman" seen in the street drug market can then streamline drug distribution and enhance efficiency (Tzanetakis et al., 2016). This expansive role of illicit marketplaces underpins the importance of studying how these markets operate.

The internet exists in three layers: the surface or clear web, deep web, and dark web. A typical web search on a search engine such as Google is publicly available and easy to access all fall under the category of the surface or clear web (Ngo et al., 2023). Anything that is restricted access by way of passwords or a paywall constitutes the deep web (Ngo et al., 2023). The dark web, however, is part of the deep web that requires specialized software, such as The Onion Router (Tor) to access (Zambiasi, 2022).

Tor originated in the 1990s as a tool made by the United States government to have protected communication about American intelligence (Ngo et al., 2023). By 2004, the government released Tor to the public, allowing for anyone to access the browser legally (Ngo et al., 2023). The concealing of IP addresses, data delaying by way of network nodes, and layered encryption is what makes Tor a reliable browser for those seeking anonymity (Ngo et al., 2023). While Tor is useful for intelligence communication and allowing individuals in highly censored countries access various websites and communicate safely without government oversight, it also gave way to what we know today as dark web marketplaces.

The first modern dark web marketplace, the Silk Road, illustrated how the features offered with the Tor browser could be used to operate an illicit market online. The Silk Road's interface appeared to resemble that of a licit e-commerce website, complete with listings, photos, prices, and ratings, however, its products included cannabis, methamphetamines, along with heroin. Beginning in February 2011, it is estimated that the Silk Road generated approximately $14.4 million in the middle of 2012, but jumped to $89.7 million before the United States FBI seized the site in October of 2013 (Aldridge & Décary-Hétu, 2014). Following the seizure of the Silk Road, many other marketplaces emerged including AlphaBay, following a similar market organization and yielding many of the same structural features.

AlphaBay was one of the largest online illicit marketplaces on the dark web (Andrei & Veltri, 2025). It operated between December 2014 and July 2017, until it was seized by authorities on July 4th, 2017 (Espinosa, 2019; Andrei & Veltri, 2024; Andrei & Veltri, 2025). Being the largest marketplace at the time, there is a wide variety of products and listings available for analysis using this marketplace. AlphaBay differed from more specialized markets and single-vendor sites because of its diverse variety of listings, offering both drug and non-drug products.

As Martin (2014) describes, an ideal online illicit market is

characterized using cryptocurrency, postal service delivery for physical goods, access via Tor, anonymity provided by digital encryption, and third-party hosting and administration. Providing vendors with a space to advertise and sell various goods and services anonymously hinders law enforcement's ability to expose users' real identities (Aldridge & Décary-Hétu, 2014; Zambiasi, 2022). The emergence of the dark web has pivotally shaped the global drug trade, especially by vendors' ability to ship almost any good worldwide (Aldridge & Décary-Hétu, 2014). There are a wide variety of goods and services available on the dark web, especially for drugs (Barratt & Aldridge, 2016). On AlphaBay for instance, listings include LSD, methamphetamines, and even weight-loss drugs, alongside counterfeit jewelry, bank account information, guns, and more.

Perhaps even more than online marketplaces such as Amazon or eBay, dark web markets rely heavily on reputation systems, such as ratings and customer reviews, to establish trust among these anonymous buyers and sellers (Espinosa, 2019). In the absence of face-to-face interactions and no legal enforcement, buyer ratings and reviews serve as some of the sole pieces of information consumers hold to estimate vendor credibility and product quality.

Theoretical Framework: Signaling Theory and Rational Choice Theory

Online illicit marketplaces, while they lack legal protections and the identity of sellers and consumers, still rely on trust, pricing strategies, and transactions. Signaling theory (Spence, 1973) posits that information asymmetry between two parties can be lessened by conveying credible, costly signals. This signal then functions to reassure the signal receiver that this interaction and subsequent transaction will be successful. Thus, signals can come in the form of ratings and consumer reviews, which signal trustworthiness and reliability. The payoff for the signal is that sellers can charge a higher premium for their products. Therefore, signaling theory provides insight into how information is conveyed. The rational choice perspective, on the other hand, can be used to understand the mechanisms through which buyers use signals. If reputation functions as a credible signal, vendors should be able to convert trust into pricing power, but only when buyers perceive that trust meaningfully reduces uncertainty about risks.

Importantly, using these theories outside of a typical, regulated marketplace broadens their scope of use to extremely uncertain environments. Examining the reputation-price relationship through the lens of the rational choice perspective and signaling theory allows inferences to be drawn regarding how trust through reputation can be monetized differently across products and across reputation signals (ratings and reviews).

Signaling Theory

Signaling theory, was first introduced by Spence (1973) in the field of labor economics to explain how educational credentials signal that an employee will be productive in their given job, because education credentials are hard to fake. Therefore, signaling theory describes how two parties can convey information to reduce information asymmetry (Spence, 1973). Information asymmetry occurs when one individual knows private information that could aid the other individual in making a well-informed decision (Connelly et al., 2011). When one individual knows more than the other, like the quality of a product on the dark web and a vendor's intentions, positive outcomes for the other individual, such as the potential buyer on the dark web, becomes uncertain.

To mitigate this uncertainty in decision-making, signalers who know the private information about the good or service that is not available to the receiver, send cues to the receiver (the individual who does not know the private information) (Connelly et al., 2011). In order for this cue, or signal, to be credible, Spence (1973) argues it must be hard to fake. For example, a review written by a past customer would be a credible signal because it was not posted by the vendor themself.

Tests of signaling theory reveal that its scope reaches between licit and illicit marketplaces, reinforcing its use as part of the theoretical framework in the current study. For licit markets, Mavlanova and colleagues (2012) explore the use of signals for a sample of 120 online pharmacies. They collect this sample from directories of pharmacies using both "recommended" and "not recommended" pharmacies to conduct a content analysis investigating high-cost signals, low-cost signals, and ease of verification of these signals (Mavlanova et al., 2012). From this analysis, they found support for their hypotheses that compared to high-quality sellers, low-quality sellers displayed fewer high-cost signals, fewer signals that were easy to verify, and generally fewer signals (Mavlanova et al., 2012). These results display how high-quality sellers build a reputation to gain and maintain customers, like how vendors on the dark web use ratings and reviews to generate business.

Andrei and Veltri (2025) employ signaling theory to explain how costly signals that are difficult to fake can reduce fraud on online illicit marketplaces. Using reviews from AlphaBay analyzed through a unique AFINN sentiment analysis, results show that reputations of vendors are costly signals that reduce the prevalence of fraud when coupled with an escrow system (Andrei & Veltri, 2025). Framed through signaling theory, the authors describe that the reduction in fraud is minimized through purchasing from individuals with better reputations since reputations are hard to build and easy to lose, meaning reputations keep the market in order (Andrei & Veltri, 2025). Illustrating how signaling theory can be utilized as a theoretical framework in both licit and illicit online marketplaces shows that its scope is vast, allowing for it to be applied to information asymmetry in marketplaces that operate outside of the traditional legal framework.

Signaling theory, in the context of online illicit marketplaces, explains how reputation systems serve as mechanisms of trust. Specifically, since on an online marketplace, information asymmetry manifests because buyers of a product cannot judge the product quality in person (Mavlanova et al., 2012). In online licit marketplaces, many products can be tested before making a purchase online (e.g., testing makeup at a store and then purchasing the same product online). If a good or service from a seller cannot be tested in person, buyers from traditional licit online marketplaces typically can send items back and receive a refund. On the dark web however, the opportunity to test a product and return a product if it is not satisfactory is quite low. Instead, vendors use their reputations through ratings and reviews to signal credibility and trust in the market, so consumers will be more confident in purchasing their product.

Connelly and colleagues (2025) in their meta-analysis of signaling theory, proposed four conditions when applying the theory. First, a clear description of components of the signal, who the signaler is, and who the receiver is (Connelly et al., 2025). For the current study, ratings and reviews act as costly signals to build trust in an anonymous, uncertain environment. Vendors then are the signalers, attempting to build up their reputations through ratings and reviews to minimize uncertainty for transactions and therefore, earn the ability to command a price premium. This leaves consumers as the receivers of these costly signals that reduce information asymmetry and uncertainty. Second, one of the most missed aspects of utilizing signaling theory is clarifying what the unobservable quality of the signaler that the signal is attempting to communicate is (Connelly et al., 2025). In the case of online illicit markets, this is trust. Vendors are actively trying to signal that they are a trustworthy individual to conduct business with through their reputation. Third, the signal should align with the unobservable construct (Connelly et al., 2025). As mentioned above, trust as the unobservable construct is strengthened by the signaler through their favorable ratings and reviews, therefore, allowing the receiver (consumer) to make an informed decision about their purchase by mitigating uncertainties around the various risks associated with each type of product in addition to allowing vendors to change a price premium for their highly rated product. Finally, an explanation of costs for generating the signal or false signaling (Connelly et al., 2025). One potential cost for generating a reliable signal would be the time it takes to generate a favorable reputation on these marketplaces because of the required consistency of completing successful transactions. Additionally, if vendors have negative reputations, uncertainty is heightened, and vendors will not be able to charge a price premium. As noted by Tzanetakis and colleagues (2016), certain marketplaces will provide information if a vendor is under investigation for scamming, which also serves to mitigate risk through a marketplace level signal. On these online illicit marketplaces, vendor reputations, typically through ratings and reviews, are the only source of information a buyer has to make educated purchasing decisions. Therefore, because trust and reputations are built by consumers, vendors have the ability to implement a price premium as a reward but also as an additional signal of trust and product quality.

Rational Choice Perspective

While signaling theory provides insight into what constitutes as key signals in online marketplaces, the rational choice perspective elucidates how buyers use or respond to these signals. This means that signaling theory alone does not specify when signals carry greater or lesser economic value because the value of a signal depends on how much uncertainty it resolves for the receiver. Reputation systems, like ratings and reviews, are crucial pieces of information that help buyers evaluate vendor trustworthiness and product quality in both licit and illicit online marketplaces. This decision-making process aligns with the rational choice perspective, which posits that under bounded rationality, where despite not being possession of all the necessary information about the costs and benefits of a decision, individuals attempt to do their best with the information available to them to make informed decisions (Gül, 2009). These individuals then act within the context of their environment to weigh the perceived costs and benefits before taking an action (Simon, 1957). Anonymity and uncertainty define online illicit markets, and reputation systems act as crucial signals that facilitate transactions in the absence of legal enforcement.

The rational choice perspective is a general theory of human behavior that posits that individuals are "utility maximizers", which is the proposition that individuals seek to maximize pleasure and minimize pain (Bentham, 1781). The amount of utility an individual receives from an action depends on rewards, costs, and risks associated with the decision to engage in criminal or deviant behavior (Thomas and Vogel, 2019). Central to this school of thought is that crime can be prevented if risks are certain, proportional, and swift (Beccaria, 1764; Nagin, 2013). Thus, signals of trustworthiness reduce uncertainty in online marketplaces, which is especially important because there is anonymity between sellers and buyers, lack of legal channels of recourse, and a multitude of risks.

However, in heterogenous marketplaces, there are heterogenous risks. Risks associated with purchase vary by product and can include legal consequences, health risks, and potential scams. For example, drugs that are widely perceived as "high-risk" like heroin and cocaine, might require stronger reputation signals and price premiums to adequately reduce uncertainty compared to "low risk" substances like cannabis. Thus, reputation and signals should translate into larger price premiums when the risks are higher, given the consequences of uncertainty are more severe.

Research in criminology shows that perceived certainty plays an important role in decision making (Albonetti, 1986; Klepper & Nagin, 1986; Pogarsky et al., 2018). Decision making is influenced by an individual's attempt to avoid uncertainties (Albonetti, 1986). Empirically, Klepper and Nagin (1989) found that perceived certainty of punishment influenced individuals' decisions to offend. This finding is consequential for understanding the rational choice perspective, by noting that the perceived certainty of risks influences decision making. Additionally, Pogarsky and colleagues (2018) argue that offender expected utility decreases as certainty for punishment increases. In other words, the benefit of committing an offense is lessened when offenders are more certain they will face consequences. The rational choice perspective is especially useful because it provides a general framework in understanding the relationship for how information on reputation and price can be used to reduce uncertainty regarding a product sold in online marketplaces.

Childs and colleagues (2020) argue that the lack of information for illicit drug markets creates more uncertainty and subsequently greater risk. This risk from perceived uncertainty about the transaction is then assumed to influence consumer decision-making. Specifically for online markets where there is a lack of social embeddedness, consumers must rely on feedback from previous buyers to reduce uncertainty (Childs et al., 2020). Finally, once these vendors have obtained a favorable rating through continued reduction in uncertainties, they have the ability to charge a price premium.

In arguing how street drug dealers decide which customers to rip-off, Jacques and colleagues (2014) point to perceived uncertainties of an illicit drug transaction. They review the different risks associated with swindling a variety of different customer types such as first-time, uninformed, and substance dependent customers. Through qualitative interviews, they determined that first-time buyers are riskier to rip-off because of the uncertainties surrounding their true identities and their true intentions (Jacques et al., 2014). Uninformed customers are seen to be great targets for drug dealers to upcharge, because they do not know what the fair price of the drug is to begin with (Jacques et al., 2014). This then tips the cost-benefit analysis in the favor of the dealer to rip them off, because there are hardly risks associated with doing so. While this study examines street drug dealers, it provides a good example of how decisions can be influenced by perceived uncertainties regarding risks.

Indeed, while scholars argue that rational choice perspective is a general theory (Loughran et al., 2016), it may be moderated by context, or in this case, product type. Varying products hold a variety of risks, which may, in turn, influence the perceived certainty of a successful transaction. Drug risks may include health risks like products laced with lethal amounts of fentanyl or enforcement risks such as shipment tracking and arrest for possessing a certain drug. Non-drug items hold some of the similar risks such as legal consequences, but some products only available digitally may contain software that could potentially corrupt a consumer's device. So, according to rational choice, we would expect that vendors can translate trust and reputation into a price premium, but these premiums may be significantly different between products due to their different risk profiles.

Together, signaling theory and the rational choice perspective explain how reputation becomes economically meaningful in online illicit marketplaces. Signaling theory describes how vendors convey otherwise unobservable qualities (trust and reliability) through ratings and consumer feedback, reducing information asymmetry in anonymous markets. The rational choice perspective explains how buyers incorporate these signals into cost-benefit calculations under uncertainty, weighing price against perceived risks and inferred product quality. Importantly, the extent to which reputation translates into pricing power should depend on how much risk a signal mitigates. Where perceived risks are higher or consequences of failure are more severe (such as overdoses), credible signals of trust should carry greater economic value, enabling vendors to command larger price premiums. Conversely, when potential risks are lower, reputation may play less of a role in pricing. This framework suggests that reputation is not a uniform pricing mechanism across all products, but instead operates conditionally, shaped by product-specific risks.

Structural Differences between Offline and Online Drug Markets

As prior research highlights, there are a few structural differences between how street and online markets shape trust, reputation, and pricing (Martin, 2014; Tzanetakis et al., 2016). While offline and online markets are interconnected (Aldridge & Décary-Hétu, 2014; Martin, 2014; Barratt & Aldridge, 2016), there are structural differences in how reputation is formed and monetized. The street market typically involves dealers and consumers meeting face-to-face to make a transaction which may result in physical altercations, whereas these dark web marketplaces have no physical contact. Additionally, the dark web marketplaces employ third-party administrators to aid in settling disputes and monitor transactions for successful delivery. Trust in street drug markets is reciprocal between buyers and sellers, whereas for online marketplaces, trust is conveyed mainly from vendor to consumer. Through comparing street and online drug markets, structural differences become apparent, explaining how online marketplaces navigate uncertainties that could impact decision-making and price formation.

Violence and Conflict Mediation

A key distinction between these markets involves how certain risks are handled within the markets. Literature consistently shows that there is a lessened risk of physical violence when operating on the dark web compared to the street market (Tzanetakis et al., 2016; Martin et al., 2020; Zambiasi, 2022), since these transactions do not occur face-to-face. While conflict may be handled using physical violence in the street drug market, online drug markets have different mechanisms for conflict mediation. One mechanism is the presence of site administrators on online markets, allowing for a third-party individual to be present to mediate sales and settle disputes (Tzanetakis et al., 2016; Munksgaard & Tzanetakis, 2022). The mediation of sales is done through an escrow system, which withholds payments from vendors until buyers have confirmed delivery (Ladegaard, 2020). On the contrary, there is no mediation of sales by an actor outside of the transaction in the traditional street market. Lacking a mediator, the actors in street drug markets are susceptible to robbery, both sellers and buyers alike (Jacques et al., 2014; Childs et al., 2020). So, by not interacting face-to-face and being able to conceal their identities (Martin et al., 2020), individuals on online marketplaces are less likely to be victims of the physical violence associated with the street drug market. By implementing systems that aid in the mediation of marketplace transactions and conflict, the uncertainty associated with unsuccessful transactions and violence can be reduced. Through lessening the perceived uncertainties surrounding violent behaviors and potential monetary loss, the cost-benefit calculation of a consumer may shift to other perceived risk that can be mitigated through vendor reputation.

Delivery

Another key difference between markets is the mode of delivery. Street drug market interactions occur face-to-face either in open-air or sometimes in a dealer's residence (Martin et al., 2020). Street market dealers are concerned when making a product exchange about the individual they are conducting business with being an undercover law enforcement agent (Jacques et al., 2014; Martin et al., 2020). This delivery risk may be heightened when dealers are interacting with first-time customers (Jacques et al., 2014). So, while dealers can use technology to set up meetings with buyers (Martin, 2020), the delivery occurs with both parties physically present for the transaction.

Virtual dealing relies on the postal system for distribution for many products, since there are physical packages of drugs and other products being shipped from all over the globe (Tzanetakis et al., 2016). However, when shipping drugs or other illegal goods there are certain drawbacks. Décary-Hétu and colleagues (2016) found that shipping internationally was related to lower ratings, smaller shipment sizes, and the perceived effectiveness of law enforcement. Vendors with higher ratings may not consider shipping internationally due to the risks such as consumers claiming they never received their package or interception by law enforcement at customs (Décary-Hétu et al., 2016). Interception may be less likely if the package is smaller, because the packages might not be inspected or are less likely to be identified by dogs or X-rays (Décary-Hétu et al., 2016). Finally, the perceived effectiveness of law enforcement impacts whether a vendor is willing to ship internationally because if a vendor does not perceive their package will be intercepted, or if it is unable to be traced back to them, the perceived risk of arrest goes down. Therefore, vendors shipping from origins with stricter inspections of packages may not choose to ship internationally in order to keep their reputations favorable, allowing them to safely charge higher prices for their products without the risk of arrest weighing too heavily on their decision to sell a certain product.

In addition to using the postal service for physical packages, certain goods are only available digitally. Product categories in the current study such as digital products, guides and tutorials, and software and security are only transferrable from device to device. Therefore, there are no delivery risks associated with physical shipping for these products, but other risks such as corrupt files and financial loss may influence purchases of digitally delivered goods and services, and subsequently, how much monetary value can be placed on a favorable vendor reputation. Thus, while engaging in discreet deliveries is pertinent in both markets, the mechanisms of distribution display unique vulnerabilities that overall impact both reputations and pricing strategies.

Trust Formation and Reputation

Street markets rely on both the buyer and seller establishing trust so that risks involving law enforcement detection and the possibility of imprisonment are reduced (Tzanetakis et al., 2016). Dealers interviewed by Martin and colleagues (2020) note that the majority of the time when buyers are arrested, they are more than willing to snitch on their dealers. Therefore, reciprocal trust for the street drug market is paramount. For buyers, they remain cautious when establishing trust for elements of the transactions such as product quality and fair pricing (Tzanetakis et al., 2016). In contrast, the online market is structured for sellers to attempt to convey trust to potential buyers through ratings and reviews. This key difference of vendors not being equally weighted in terms of trust formation makes vendor reputation the key indicator of product quality, vendor reliability, delivery success, and product concealment that can influence consumer decision-making through lowering risks but also can allow vendors to charge premiums for their products without consumers feeling conned.

To build or maintain a favorable reputation on these online illicit marketplaces, vendors engage in trust-signaling behaviors such as sending extra product to the buyer to signal that they want to do business again (Tzanetakis et al., 2016). Additionally, quick replies from vendors, short delivery times, and successful product concealment can also be seen as favorable by buyers and translate into higher ratings (Tzanetakis et al., 2016). It is then based on their reputations that consumers can judge how trustworthy a vendor is and decide which vendor to make a purchase from while minimizing uncertainties (Przepiórka et al., 2017).

Trust formation on the dark web, through the ability of vendors to set price premiums, is perhaps more salient than in street drug markets. Price premiums are less frequent in traditional street drug markets (Childs et al., 2020), perhaps because an upcharge in price may be associated with consumers being swindled (Jacques et al., 2014). However, online, the ability to charge more for a product is a reward from having a favorable reputation (Przepiórka et al., 2017). Since the brunt of trust formation is given to the vendor on online illicit marketplaces, reputation may play a larger role in consumer decision-making because buyers are less concerned with establishing trust with a vendor and more concerned with the various risks associated with the purchase. This enables sellers to leverage trust as a form of economic capital, increasing the reputation price premium.

In sum, the differences between offline and online drug markets fundamentally shape how risks are mitigated and managed, trust is built, and price is formed. Whereas street markets rely on the social aspect of face-to-face interactions and referrals of trust from other buyers to the sellers, online illicit marketplaces utilize escrow systems, administrator mediation, and structured site-wide metrics of reputation to reduce uncertainty. These structural differences for dark web marketplaces limit the presence of physical violence, shift the role of trust building to the vendors, and therefore, raise reputation to the primary signal of product quality and vendor reliability. This creates a marketplace where trust can be monetized, allowing highly reputable vendors to charge price premiums. Importantly, the size of these premiums is unlikely to be uniform because products involving higher perceived risk (legal, delivery, financial loss, etc.), may shape how much economic value is placed on reputation. As a result, reputation is expected to be associated with price increases but expected to vary in magnitude across product categories with varying risks.

The Reputation Systems in Licit and Illicit Online Marketplaces

Studying a variety of online licit marketplaces' reputation systems is important because it has been suggested that these markets function similarly to their online illicit counterparts (Georgoulias et al., 2021; Ladegaard, 2020) in terms of reputation systems (Haynie & Duxbury, 2024). Ratings are used in both licit and illicit online marketplaces to evaluate a vendor's trustworthiness and infer product quality. Comparing ratings in online markets allows consumers to act under economic rationality when deciding which vendor to purchase from. While similarly priced items might appear as equally feasible options, consumers often rely on ratings and consumer feedback reviews to distinguish between products. These ratings and reviews are especially important for users of these dark web marketplaces because these reputation signals help mitigate the potential risks associated with purchases. Consulting these ratings and reviews before considering price, consumers can determine whether they are willing to pay a price premium for more favorably rated products. Ratings and consumer reviews then remain a crucial aspect for both seller success and consumer decision-making in both licit and illicit online marketplaces, despite the varying levels of legality these marketplaces operate within. While prior research has investigated higher ratings and the outcome of price premiums, less attention has been focused on how these premiums may vary across products depending on risk.

Licit Online Marketplaces

Research on licit online marketplaces provides a baseline for understanding how a seller's reputation impacts pricing strategies. Licit online marketplaces include traditional online markets such as Amazon or AirBnb where sellers set a fixed price for their product, and buyers decide whether to purchase or find a comparable alternative product. Licit markets also include auction sites such as eBay, where consumers bid competitively for a product. In both licit marketplace formats, ratings are the focal source of information for consumers regarding both product quality and the trustworthiness of the seller (Bruce et al., 2004; Ackerman et al., 2024; Sunda, 2024).

It has been well-established that there is a price premium for higher-rated goods, a finding that has since been replicated across conventional online markets and auction sites (Resnick et al., 2000; Bruce et al., 2004; Diekmann et al., 2014; Thompson & Haynes, 2017; Li, Wang, & Wu, 2020; Ma et al., 2021). Higher ratings are not only associated with higher prices, but also to a higher volume of sales (Resnick, 2000; Thompson & Haynes, 2017). Resnick and colleagues (2000) also argue that price premiums promote higher quality products because sellers are incentivized to maintain this high rating. Several studies and their findings will be highlighted to further understanding into online licit marketplace dynamics regarding price premiums from seller reputations.

Thompson and Haynes (2017) explore price premiums through the use of a price comparison website for digital cameras. Measuring price as a discount on the manufacturer's recommended selling price (MRSP), a regression analysis finds that the number of seller stars has a negative impact on the discount on the MRSP (Thompson & Haynes, 2017). This result means that sellers with better ratings sell at a less discounted price than those with a lower rating. Controlling for the different camera models within the analysis highlights how more expensive models show smaller discounts than cheaper models (Thompson & Haynes, 2017). While this conclusion was drawn from their single model, a study by Bruce and colleagues (2004) explores what occurs with price premiums when goods are parsed out into different categories and analyzed separately.

Bruce and colleagues (2004) attempt to navigate the question of price premiums for online goods using data from eBay auctions. The items they selected to analyze were laptops, PCs, Shrek DVDs, and Harry Potter books. Through a regression analysis of all items, results show that there is a price premium for Shrek DVDs and Harry Potter books, but not for laptops and PCs (Bruce et al., 2004). Both the DVDs and books were the cheaper items, which Bruce and colleagues (2004) argue that higher ratings may matter more for lower priced items. Similar findings from Thompson and Haynes (2017) and Bruce and colleagues (2004) suggest that on licit online marketplaces, both auction and traditional, there are price premiums for higher rated goods, however, there are inconsistencies between products. The finding that price premiums can vary and are not uniform across products is an insight that becomes especially relevant in marketplaces where goods and services vary substantially in terms of risk.

An especially relevant study by Diekmann and colleagues (2014) explored the reputation-price relationship for an online, anonymous, German marketplace selling mobile phones and DVDs. Their findings revealed that sellers with higher ratings do in fact have more sales and increased prices across both products (Diekmann et al., 2014). Additionally, it was also found that negative ratings had a larger impact on prices and sales (Diekmann et al., 2014). These findings align with the broad consensus from licit marketplace literature that reputation systems influence buyer behavior along with seller pricing strategies. Since both licit and illicit marketplaces appear to use reputation systems similarly (Ladegaard, 2020), it may be assumed that there might be differences in price premiums for a variety of products on the dark web, similar to findings from licit marketplaces (Bruce et al., 2004; Thompson & Haynes, 2017).

Illicit Online Marketplaces

Contrary to legal online markets, online illicit marketplaces operate under higher levels of risk due to the anonymous and uncertain environment on the dark web. Certain risks like legal consequences of possessing or transporting a product, or health risks for taking drugs that could be laced with lethal doses of fentanyl, the risks surrounding these dark web marketplaces are numerous. These risks make reputation systems paramount for consumer decision making and seller success. These reputation systems including vendor ratings, consumer feedback reviews, “vendor level”, and “trust level” are all available on AlphaBay for consumers to see. Buyers who have previously purchased from a vendor can leave ratings and review of their experience with the vendor and the sale as a whole (Georgoulias et al., 2021). The level of trust expressed through previous buyers then serves as a proxy for determining product quality (Zambiasi, 2022; Haynie & Duxbury, 2024), making ratings and consumer feedback a crucial decision-making tool for the buyer (Goonetilleke, 2023; Ladegaard, 2020). Through these reputation systems, buyers can increase their confidence that their purchase will be satisfactory and delivered successfully to them (Georgoulias et al., 2021).

Pricing strategy for vendors operating on online illicit marketplaces has been well-documented in the dark web literature. Munksgaard and Tzanetakis (2022) claim drug pricing hinges on a variety of aspects and identify several key factors. First, the legal risk of selling drugs impacts the price (Munksgaard & Tzanetakis, 2022), presumably due to a weighing of the risks such as law enforcement interventions and possible arrest against the benefit of monetary gain. Second, a drug's legal classification can also factor into pricing (Munksgaard & Tzanetakis, 2022). Third, geographic factors might influence pricing such as a vendor's distance from their buyer (domestic or international), and which borders these drugs might cross due to importation risk (Munksgaard & Tzanetakis, 2022). Fourth, vendors and buyers experience information asymmetry about product quality, influencing the decision to set price premiums based on reputation (Munksgaard & Tzanetakis, 2022). Finally, advanced payment options (finalizing early) along with bulk discounts may impact pricing (Aldridge & Décary-Hétu, 2014; Munksgaard & Tzanetakis, 2022). While all of these risk factors play respectable roles in influencing vendor pricing, reputation alone remains a consistently studied influence across the literature, and the role of how risk may impact the economic value of reputation is largely unstudied.

Several studies have explored this rating-price relationship, all yielding similar results. Przepiórka and colleagues (2017), using data from Silk Road 1.0 with a subset of drugs including weed, hash, methamphetamines, MDMA, heroin, cocaine, and ketamine, found that vendors with better reputations are able to sell their products at a higher price compared to vendors with negative or no reputation history. Their study also found that negative ratings have a larger impact on prices than positive ratings (Przepiórka et al., 2017), similar to findings from Diekmann and colleagues (2014). However, pooling a variety of drugs, all with different perceived health risks and legal consequences, hinders knowledge of how price premiums may be dependent on both product-specific risk and reputation.

Similarly, Espinosa (2019), using data from the Hansa market, found support for a price premium citing that vendors with better reputations charge significantly higher prices for weed, hash and ecstasy. They found that a 10% higher reputation was associated with a 0.32%, 0.35%, and 0.61% increase in price for weed, hash, and ecstasy respectively. Espinosa (2019) also found that more negative feedback was related to lower prices, with a 10% lower reputation being associated with a 0.84% and 1.1% decrease in pricing for weed and ecstasy. Again, while separating the drugs to explore the reputation-price relationship adds nuance for investigating differences in products through consumer decisions and vendor pricing, their reasoning for these differences in price fluctuation is simply diversity from vendors (Espinosa, 2019). The current study argues that this diversity from vendors may come from the risks associated with selling certain products and how these risks can be reduced through implementing price premiums. So, while Espinosa (2019) offers an explanation for the visual differences between the reputation-price relationship for weed, hash, and ecstasy, they did not test this analytically to see if these are true significant differences, and they did not offer discussion for if risks play a role in these apparent differences.

Finally, Munksgard and Tzanetakis (2022) used both the Silk Road 3.1 and the Empire market and found evidence for a price premium per weight for cocaine on the Silk Road 3.1 and heroin on the Empire market using a fixed effects approach. Munksgaard and Tzanetakis (2022) also explored this relationship between both markets for cannabis as well, however, the results were not significant lending to the idea that perhaps price premiums are not consistent across products. The reasoning for these inconsistencies, according to Munksgaard and Tzanetakis (2022), falls to drug enforcement and policies as well as risks for various subclasses of the drugs explored. With different levels of legality and risk associated with the drugs surveyed, there may be different scales at which reputation influences the pricing strategies. Drugs that are often considered “high-risk” such as heroin and cocaine displayed price premiums for higher rated products, while a drug typically perceived as less risky, cannabis, was not shown to have higher prices for higher rated goods. Therefore, the current study extends the prior literature by analytically testing whether price premiums act uniformly across products, or if there are other factors, such as perceived risks, that may play a role in how much economic value can be assigned to a favorable reputation. These perceived risks may be reduced through vendor reputation, allowing highly rated vendors to charge higher prices for their products.

Differential Perceived Uncertainties across Products

The current study conceptualizes risk and uncertainty in illicit online transactions. Knight (1921) argued that risks and uncertainty are concepts that are mutually exclusive. Those believing this interpretation often claim that risk involves having a defined probability of possible outcomes, whereas uncertainty is not knowing the probability (LeRoy & Singell, 1987). However, LeRoy & Singell (1987) argue that this interpretation of Knight's (1921) original piece is faulty, and that individuals can develop subjective probabilities of outcomes for uncertainties, and that objective probabilities of risks should be thought of as "publicly verifiable", which is more abstract than its interpretation by some. LeRoy and Singell (1987) concluded that Knight's (1921) central theme was not as targeted at probability calculating as originally taken by some scholars, but it still serves as a valuable piece for exploring information asymmetry. Therefore, the current study uses the perception of risk and uncertainty together, because there is still room for consumers and vendors alike to assign subjective probabilities to outcomes as well as determine "publicly verifiable" outcomes of transactions from personal experience, forum chats, and consumer reviews. Since there is room for interpretation of risks versus uncertainties, the current study utilizes both definitions when discussing events that have somewhat unknown, but inferable outcomes for both vendors and consumers.

Ratings and reviews serve as credible signals of vendor trustworthiness and expected product quality, but these signals influence the decision-making process to purchase products in the context of the differential uncertainty surrounding the transaction. Both drug and non-drug products hold unique uncertainties associated with perceptions of risk regarding law enforcement detection, scams, and health-related risks. These risk factors, distinct to each product, operate to influence the purchasing decision of consumers and the implementation of a price premium.

Law Enforcement Detection

Users of online illicit marketplaces, although anonymous, still face law enforcement detection risks. While users are instructed to not use their own addresses for shipping and to use false identities for shipping (Martin, 2014), there are other ways that law enforcement can impact actors on these marketplaces. Operation Onymous was a law enforcement effort across 16 countries aimed to shut down the following marketplaces: Agora, Silk Road 2, Evolution, Andromeda, Bluesky, Cloud-Nine, and Hydra. This international take-down of these marketplaces led to the arrest of 17 individuals and seizures of drugs, precious metals, cash, and $1.7 million USD in Bitcoin (Décary-Hétu & Giommoni, 2017). Operation Onymous left participants of these markets noting a reduction in supply and certain vendors retired from vending altogether (Décary-Hétu & Giommoni, 2017). However, its effects were short-lived with many vendors simply transitioning to other sites, a subsequent increase of sales on these remaining sites, and stronger security measures were established for successor sites (Décary-Hétu & Giommoni, 2017). So, while the threat of another marketplace-wide shutdown looms in some minds, there are more individual law enforcement risks that may also influence decision-making.

Vendors and consumers must find ways to elude law enforcement detection during delivery for physical goods (Tzanetakis et al., 2016) because products from the dark web are traveling through the postal service either domestically or internationally. Since there is a possibility that the package will be inspected or intercepted by law enforcement (Martin, 2014; Tzanetakis et al., 2016), consumers must weigh this risk in the context of their local law. The penalties for possessing and vending certain drugs might hold different penalties and may vary on weight and purity. So, vendors must weigh the risks of their products being intercepted and potentially traced back to them. Additionally, if the transaction involves and escrow system to ensure buyers receive their product and the product is intercepted, vendors experience a financial loss. These risks associated with law enforcement detection may propel vendors to apply a price premium for taking on these risks (Childs et al., 2020). On the contrary, buyers weigh a similar risk of their order being inspected and potentially traced to them, along with the risk of financial loss if their product does not arrive because it was intercepted and they decided to finalize their payments early, meaning their product is not insured by the escrow system.

Non-drug goods vary in terms of delivery because some goods, like software and e-books are not physical packages, and therefore, do not travel through the postal service. However, they may hold other delivery risks such as corrupted files or malware. Other products such as weapons may carry more of a detection risk and potential consequence than the aforementioned goods, yet this is still variable based on location of the vendor and consumer. Due to the specific risks associated with each product in terms of delivery risk and legal consequences, price premiums are assumed to vary between products.

Scams

Despite employing an escrow system to aid in reducing scams (Andrei & Veltri, 2025) as well as some marketplaces posting if a vendor is currently being investigated for scamming (Tzanetakis et al., 2016), there are still risks that involve scams. Both exit scams and scams resulting from finalizing early are risks that might increase uncertainty around transactions for all types of products. An exit scam occurs when a marketplace suddenly shuts down without warning, and the admins profit from all the funds that were held in escrow (Zambiasi, 2022). This type of risk, similar to a full marketplace shutdown by law enforcement, impacts everyone using the marketplace, not just the consumer. However, because this is a macro-level risk, it might not influence decision-making as much as an individual level risk, like finalizing early.

Finalizing early means that funds are not held by the marketplace in escrow but rather go straight to the vendor without confirmation of delivery (Tzanetakis et al., 2016; Zambiasi, 2022). The drawback of finalizing early is the potential of receiving a fraudulent product or not receiving a product at all. Andrei and Veltri (2025) argue that the use of an escrow system, opposed to finalizing early is inversely associated with vendor scams. Particularly scams involving financial loss such as a misuse of finalizing early may play a role in how the rating-price relationship differs between products. If a consumer is purchasing a cheaper product, they might weigh the risk of a scam like this less so than if they were purchasing an expensive product. The risk of scamming is prevalent on the dark web and risk of financial loss could impact and individual's decision to purchase a product, hence why vendor reputations are crucial signals of reliability that are intended to alleviate these uncertainties.

Health Risks

Certain products come with physical health risks while others do not. Health risks are arguably one of the most important factors associated with uncertainty in purchasing on illicit online marketplaces – and the most salient in terms of valuation of positive reputations. Drug products, like heroin and cocaine, have the potential to be laced with other substances particularly to reduce the cost for the vendor (Behrman, 2008). Nolan and colleagues find that increases in drug overdoses were attributed to a larger presence of non-pharmaceutical fentanyl for drugs such as heroin and cocaine, therefore, solidifying the central theme of the current study that vendors who can mitigate risks (like laced products) have the ability to charge larger price premiums for their products. Weapons (firearms and explosives particularly) also carry health risks such as equipment designs that could result in death or injury if mishandled (Lee & Nolte, 2000). These varying risk factors could dictate decision-making and pricing strategies.

A case study by Lee and Nolte (2000) revealed that two men were fatally shot by the same Ruger Blackhawk revolver after unintentional discharges, one of which was due to the design of the firearm. The first death was due to mishandling the firearm in combination with a slip that occurred when decoking that caused the firearm to discharge, striking and killing one man in the abdomen (Lee & Nolte, 2000). The second death, a family member of the individual who was killed in the first incident, occurred when the same firearm was dropped and discharged (Lee & Nolte, 2000). This death was partially due to the design of the firearm, raising an important health risk consideration for weapons available for purchase. Therefore, these elevated health risks increase uncertainty surrounding weapon purchases, increasing consumers reliance on reputation systems to evaluate safety and reliability. As a result, the rating-price relationship may differ for weapons relative to less risky product categories.

While most drugs pose health risks, certain drugs consistently are perceived as high-risk, while others remain at the lower bound of perceived harmfulness. According to the "Key Substance Use and Mental Health Indicators in the United States" report by the Substance Abuse and Mental Health Services Administration (2021), when asked questions about perceived harms of certain drugs, individuals reported cocaine and heroin as the riskiest, whereas cannabis was viewed as the least risky. Similarly, the Monitoring the Future Study Annual Report from 2024 (Miech et al., 2025) found methamphetamines and heroin were perceived to have the greatest risk of harm from experimental use, and heroin and cocaine perceived as the greatest risk of harm when used regularly. Both for experimental and regular use, cannabis was the drug with the lowest perceived risk of harm (Miech et al., 2025).

Empirical studies exploring perceived drug risk use assessments of harm for multiple substances, guided by both public and expert perceptions. Taylor (2012) asked clinical experts from Scotland to score substances on a scale from 0 ("no risk") to 4 ("extreme risk"), finding that the riskiest drugs were heroin, cocaine, and methamphetamines (Taylor, 2012). Cannabis, LSD, and ecstasy were found to be among the least risky drugs, with cannabis as the least risky (Taylor, 2012). Similarly, Bonnett and colleagues (2020) surveyed physicians in Germany to rate substances on their perceived risks. The overall consensus highlights cocaine, methamphetamines, and heroin as the riskiest drugs, and cannabis and LSD in the lower risk category (Bonnett et al., 2020).

Given that certain drugs are generally perceived as riskier than others, it is expected that the rating-price relationship would be the strongest for the riskiest drugs. While prior literature on dark web marketplaces has examined the reputation-price relationship on drugs, no study has examined this *across* drug types. In terms of the reputation-price relationship, while products are expected to display a price premium if the vendor has a favorable rating, health risks may influence each product differently, because reputation might matter more for vendors dealing products of a considerable health risk.

Chapter 3: The Current Study

The current study examines the relationship between reputation and price and if there are significant difference between the rating-price relationship across product types using data from the AlphaBay marketplace. Specifically, I investigate whether ratings and consumer reviews are related to price, and whether the price premiums shown in the rating and price relationship are significantly different between products. Using an ordinary least squares (OLS) regression, the impacts of ratings and reviews on price is estimated for a variety of drug and non-drug products available on AlphaBay. Then, coefficients from the rating-price relationship will be tested for significant differences using an equality of coefficients test (Paternoster et al., 1998) for cannabis, stimulants, opioids, counterfeit items, fraud, and weapons. These product categories were selected due to the variety of perceived risks associated with the purchase goods, because prior literature claims that perceived uncertainty about risk influences decision-making (Klepper & Nagin, 1986). The different risks associated with each of these products ranges from delivery and law enforcement intervention to health risks. The results provide important implications for understanding how risk is mitigated through reputation signals, and how much monetary value can be assigned to reputation.

Based on prior literature, there are a few expectations of the results. First, I expect to see a positive association between rating and price, highlighting the appearance of price premiums for higher rated goods. Prior literature suggests that a favorable reputation signaled through ratings is related to the implementation of a price premium for certain drug products (Przepiórka et al., 2017; Espinosa, 2019; Munksgaard & Tzanetakis, 2022). Additionally, because these online illicit marketplaces are argued to function similarly to their online licit counterparts (Georgoulias et al., 2021; Ladegaard, 2020) in terms of reputation systems (Haynie & Duxbury, 2024), and licit online marketplaces have been found to display price premiums (Resnick et al., 2000; Bruce et al., 2004; Diekmann et al., 2014; Thompson & Haynes, 2017; Li, Wang, & Wu, 2020; Ma et al., 2021), favorable reputations on AlphaBay are expected to display price premiums as well. Second, due to different risk profiles of both drug and non-drug products, I expect to see significant differences in how reputation is monetized across products because individuals attempt to minimize uncertainties when making decisions (Albonetti, 1986) and these reputation signals are intended to reduce uncertainties. Through this reasoning, I expect products that carry more risk, like stimulants and weapons, to have a significantly stronger rating-price relationship from a less risky product such as cannabis. The results of these analyses have important implications for the scope of application of both the rational choice perspective and signaling theory, as well as broader policy implications for how law enforcement can use these results to better inform intervention.

Through the theoretical frameworks of signaling theory and the rational choice perspective, coupled with prior literature on how dark web marketplaces monetize ratings and the risks associated with transactions for a variety of products, the hypotheses of the current study are as follows:

H1: Both drug and non-drug products will display a positive association between ratings and price.

H2: Drugs with higher risk profiles will be significantly higher in their rating-price relationship compared to drugs with lower risk profiles.

H3: There will be significant differences between the rating-price relationship between drug products and non-drug products of varying risk profiles.

H4: Both drug and non-drug products will display a positive association between reviews (average sentiment scores) and price.

Chapter 4: Data and Methodology

Data

The current study utilizes data scraped from the AlphaBay marketplace by McKenna and Goode (2017). The web scrape of AlphaBay produced screen mirrors of the website with listings, that then were coded into a .csv file for use. The data were downloaded from an online collection known as the Darknet Market Achieves (Gwern et al., 2017). These data are all publicly available and collected for research purposes.

The AlphaBay data contains 114,385 individual product listings. Listings on AlphaBay are the unit of analysis for the following analyses. The original data included information about the 6,033 sellers, however, the publicly available data does not include which vendors listed a specific product. In addition to the large 114,385 listing data frame, there is a separate frame that includes 1,270,000 reviews for certain listing. Data frame refers to the original, raw data in its .csv format. Some of the feedback does not include comments, and those will not be used in the current study.

The collection period for this data spans between January 26 to 28, 2017. Although the data includes all listings regardless of if the listing is associated with a purchase, those listings with no purchase history are excluded from the current study since a listing without a valid rating backed by prior consumer experience would result in inaccurate estimations. McKenna and Goode (2017) also report that in the process of web scraping AlphaBay, about 700 listings were inaccessible. These 700 listings account for approximately 0.01% of the total listings, and therefore, should not have large impacts on the results.

The products on AlphaBay were originally categorized by McKenna and Goode (2017) in the raw data and were then edited to into the final product categories used in the current study. Each listing in the raw data has a label for “category1”, “category2”, and “category3”, and upon inspection, these categories appeared to go from most broad, down to specific products in some cases (e.g., category1: drugs & chemicals, category2: cannabis, category3: buds and flower). The original raw data was first split to reflect each "category1" denotation for each listing. After the split, the categories included carded items, counterfeit items, digital products, drugs and chemicals, fraud, guides and tutorials, other, security and hosting, software and malware, and weapons. The original "other" category was dropped from the final sample because it mainly includes custom listings and cannot be described accurately in terms of risk profile for interpretation of a reputation-price relationship. Drugs and chemicals held 76,747 listings, making it the largest category after the initial split.

Following the split, each product category is further examined for the "category2" distinction to better understand the products within each broader category. After examination, certain products that appear to fit better into another product category are moved. Products were left in their original categories unless the author felt it did not reflect the broader title of the category. Many products include an "other" subcategory that is untouched because many of the products within this subcategory reflect the broad title of the final product category.

Product Categories

Carded Items. Clothing is removed from carded items and added to counterfeit items since counterfeit items also includes this subcategory. Carded items, in its final form, includes subcategories of digital, other, electronic, and appliance distinctions. The total number of observations after splitting is 1,028 listings.

Counterfeit Items. Counterfeit items remain untouched after the addition of clothing form carded items. It includes money, electronics, fake IDs, jewelry, other, and clothing. The total number of observations after splitting is 3,373 listings.

Digital Products. Fraud software and legit software are removed from digital products. Digital products, in its final form, includes e-books, game keys, and other. The total number of observations after splitting is 6,254 listings.

Fraud. The original fraud category remains untouched with a total number of observations of 12,888 listings. This category includes accounts and bank drops, other, CVV and cards, dumps, and personal info and scams.

Guides and Tutorials. The original guides and tutorials category remains untouched with a total number of observations being 5,612 listings. This category includes security and anonymity, other, fraud, social engineering, hacking, and drugs. This category is largely digital products, so these subcategories reflect the larger product category.

Software and Security. This category includes a combination of the original security and hosting and software and security categories from the initial split, along with fraud software and legit software from the original digital products category. The total number of observations after splitting is 2,433 listings.

Weapons. Weapons remain untouched and include hand weapons, ammunition, explosives, pistols, and long-range guns. The total number of observations is 1,085 listings.

All drug products in the current study come from the “category2” distinction, drugs and chemicals. The original “category2” separations for drugs and chemicals include prescription, stimulants, cannabis, benzodiazepines, opioids, paraphernalia, weight loss, ecstasy, dissociatives, psychedelics, other, tobacco, and steroids. Other and paraphernalia are dropped altogether because a consistent drug weight measurement cannot be obtained from these categories. Tobacco was also dropped because it only contains 297 listings.

Benzodiazepines. Only research chemicals are dropped from this category, and the total number of observations after the initial split includes 5,358 listings. The subcategories include pills, powder, and other.

Body Modification. The original categories of steroids and weight loss drugs are combined to create the body modification category due to less observations in both the steroid and weight loss categories. The original sample includes 4,081 listings.

Cannabis. The cannabis product category remains untouched. It includes buds and flowers, concentrates, synthetic, edibles, topicals and others, other, hash, shake, prerolls, and seeds with a total number of observations after splitting of 23,116 listings.

Dissociatives. This category is left unaltered, and includes GHB, ketamine, MXE, and other. The total number of observations is 1,661 listings after the initial split.

Ecstasy. This category remains untouched and includes MDA, MDMA, methylone and BK, pills, and other, for total number of observations, following the split, of 10,856 listings.

Opioids. Opioids remain untouched with a total number of observations of 6,673 listings after splitting which include fentanyl and research chemicals, heroin, other, and pills. Research chemicals are included in this product because they are not distinct from fentanyl in the original "category3" distinction from McKenna and Goode (2017), and therefore, cannot be separated.

Prescription. This category includes the "Adderall and Vyvanse" category from stimulants with a total number of observations of 5,247 listings after the split, and its subcategories are prescription drugs and Adderall and Vyvanse.

Psychedelics. Research chemicals were the only subcategory dropped from this category originally, however, many categories were extremely small and were dropped in subsequent editing. The original subcategories within psychedelics includes 2C-B, DMA/DOX, DMT, LSA, LSD, mescaline, NBOME, schrooms, and other. The total number of observations includes 5,645 listings after splitting.

Stimulants. 2-FA is dropped from stimulants due to its presence skewing the price variable extremely far to the left. After this edit, research chemicals and Adderall and Vyvanse are also dropped, leaving 2-FA, cocaine, crack, meth, other, pressed pills, and speed as the final subcategories. The total number of observations following the initial split includes 11,448 listings.

Recall that the hypotheses associated across products are as follows:

H1: Both drug and non-drug products will display a positive association between ratings and price.

H2: Drugs with higher risk profiles will be significantly higher in their rating-price relationship compared to drugs with lower risk profiles.

H3: There will be significant differences between the rating-price relationship between drug products and non-drug products of varying risk profiles.

H4: Both drug and non-drug products will display a positive association between reviews (average sentiment scores) and price.

Variables

Dependent Variable: Price. The dependent variable used in this study is price in its logged form. The original price variable is examined for each product category, and outliers are identified at the 99th percentile. Those observations are then removed from the total number of listing observations. A total of 1,052 outliers are dropped across product categories. Additionally, any listing that displayed a price as $0 is also removed. The total amount of listings dropped due to having a price listed as $0 is 4,111 listings from the total sample across all product categories. Fraud has the largest number of prices that are $0 at 1,526 listings. Price is logged to prevent skewness and now appears more normally distributed. Price, in its logged form, allows for interpretations of the ordinary least squares regression models to be in percentages.

Independent Variables: Two focal independent variables are analyzed in the current study. Both rating and reviews are analyzed separately to investigate if reputation signals function similarly at the macro level in their ability to generate price premiums across product type.

Rating. The first focal independent variable that will be regressed on price to determine the rating-price relationship for each product is rating. Vendor ratings are originally coded on a continuous scale from -1 to 1. Ratings that appear as negative numbers represent vendors who have received negative ratings from consumers who have purchased their product. Positive ratings encompass those ratings from consumers after a satisfactory transaction, where the buyer has given them a positive rating. Any rating that is 0 is a neutral rating. AlphaBay's rating system was moderated by site administrators and allowed vendors to remove negative ratings but not positive ratings (van Waardenberg, 2021). Perhaps due to this, the ratings are overwhelmingly positive for this marketplace, which is expected as it is stated in prior literature (Haynie & Duxbury, 2024). After examination of each product category of interest and their ratings, rating will be treated as a binary variable with 1 representing a perfect rating and 0 representing all other ratings.

It is important to note though that these ratings are assumed to be at the vendor level. With that being said, the data does not provide the vendor name for each listing, so it is not possible to determine if there are multiple listings from the same vendor. If there are listings from the same vendor within a product, this could potentially weigh this vendor's rating higher than if each listing was from a unique vendor. The lack of vendor ID knowledge for ratings impacts the validity of the rating measure, because it is unclear if these ratings are from unique vendors, or if there are multiple listings from the same vendor with the same ratings.

When observations of ratings occur more than once for the same vendor, correlated errors occur due to these unobserved vendor-level factors. Treating these clustered observations as independent, the standard errors are underestimated and estimates of significance may be overinflated. However, the point estimates will remain the same as if the vendors were clustered for their ratings. While this is a limitation of the study, it is still important to explore this rating-price relationship using the AlphaBay marketplace because it has not yet been explored in this context.

Average Sentiment Scores. Average sentiment scores is the second focal independent variable this study will explore, regressing it on price to determine if there are price premiums associated with the numerical version of consumer reviews. A Valence Aware Dictionary and sEntiment Reasoner (VADER) lexicon analysis is used to quantify consumer reviews.

A lexicon analysis is a subset of a sentiment analysis approach that determines the attitudes of a piece of text (Bonta et al., 2019). The lexicon approach draws from a large, set list of words, and categorizes them as positive or negative (Hutto & Gilbert, 2014; Bonta et al., 2019). Additionally, not only is the text assigned positively or negatively, but the VADER approach determines the strength of the sentiment that is expressed in the text (Hutto & Gilbert, 2014). The lexicon available for the VADER has been shown to be one of the best lexicons to evaluate social media posts (Bonta et al., 2019). On the dark web, slang and profanity are used extensively in item descriptions as well as reviews, so the VADER method appears to be the best sentiment analysis approach for this study. Furthermore, according to Bonta and colleagues

(2019) and Hutto and Gilbert (2014), VADER is argued to be the “gold standard” for lexicon approaches and has also been evaluated and its quality has also been verified by humans.

To implement the VADER approach to quantify reviews, the original data frames are merged on item number with the “feedback” .csv provided by McKenna and Goode (2017) with the original AlphaBay data. After merging, the VADER sentiment scores are assigned to each row with a comment and then averaged on item number to evaluate the single listing’s sentiment score. This allows for single items with consumer reviews to be treated as one singular listing. This combats a similar issue to the rating variable, where there may by an overinflation of significance due to treating clustered variables as independent. By averaging sentiment scores on item number, a more accurate analysis can be made without overestimating significance from correlated errors.

Control Variables

Various controls are included in the analyses. Controls are included due to prior literature and market-specific features that could influence the reputation-price relationship. The controls for each product category hinge on their own makeup of products. The controls used for drug products include whether the listing ships strictly domestically, a ratio of the total sales and feedback each listing has received, the sum of the vendor levels, and the weight of the product in either grams or milligrams that were both logged. Non-drug products vary in their controls including only domestic shipping, sales-feedback ratio, vendor levels, and if the product is shipped as a physical package.

Domestic Shipping. Décary-Hétu and colleagues (2016) found that if a vendor is willing to ship internationally, they tend to have lower ratings and typically sell smaller packages, so a control for listings only shipped domestically is used. The domestic shipping control is coded as a dichotomous variable with 1 denoting that the listing only ships domestically, and 0 representing listings that ship either strictly internationally or domestic and international. Some product categories such as digital products, guides and tutorials, and software and security consist of mainly, if not all, products that are digital, and therefore do not use the domestic shipping control.

Sales per Feedback. The ratio between sales and feedback control is created by taking the "sold" column for each listing and dividing it by the "feedback" column for each listing. This measure is created to evaluate the proportion of the number of sales the listing had and the number of feedback the vendor received. This variable accounts for diversity in a vendors' ability to convert reputation into sales volume, allowing for an isolation of the association between vendor reputation and prices. Prior research has shown that vendor reputations positively impact sales (Przepriórka et al., 2017; Andrei & Veltri, 2024 2). Including the ratio of sales and feedback adjusts for differences between listings for how frequently a consumer leaves feedback relative to the actual number of sales the listing has received, providing an accurate measurement representative of marketplace activity. Therefore, a larger sales-feedback ratio means that a vendor receives more sales than feedback.

Before creating this variable, every listing that has no sales as well as no feedback is dropped from the total sample because without having any sales, the listing cannot be rated or have consumer feedback reviews. A total of 39, 922 listings are removed for having no sales and no feedback.

Vendor Levels. Vendor profiles contain several different types of ratings. In addition to the standard rating variable, there are two ratings given to vendors on AlphaBay by site administrators (Andrei & Veltri, 2025), vendor level and trust level. The sum of the vendor levels refers to both levels summed together. Both levels are on a scale from 0 to 10, and together the summed control variable becomes a range from 0-20. This control is included in each model for every product category. Controlling for these vendor levels that are similar to ratings and reviews allows the analyses to account for differences in vendor reputation determined by the vendor level and trust level beyond the generic rating variable.

Drug Weight. For drug products, the total weights for each listing are obtained in order to control for bulk purchases. Previous literature highlights that certain listings are intended for resale by street dealers and therefore, may appear in higher quantities at a more discounted price than drugs intended for individual consumption (Aldridge & Décary-Hétu, 2014; Munksgaard & Tzanetakis, 2022). Many listings in the product description of the listing include a weight for each drug product. After creating a new column, coding techniques isolate specific weights and place them into a new weight column. Each product is examined to ensure accuracy in the code and additions are made if the original code did not place the weight into the new weight column. Each product includes weight in either grams or milligrams to reflect the majority of listings' original unit of weight. A histogram reveals skewness, and all weights are logged in their final form for estimation. Each listing that does not include a valid weight is dropped from the total observations, because product weight can influence the reputation-price relationship as price comparisons without quantity information may conflate reputation effects with differences in product weight. In total, 26,092 observations were dropped due to lacking a weight.

Physical Package. The final control, specifically for the products categories, carded items and fraud, is whether the product is delivered as a physical package. This control is important to use because part of the risk associated with selling items on the dark web is that the products must go through the postal service (Martin, 2014; Tzanetakis et al., 2016). If intercepted, a vendor could risk being exposed or lose revenue if they used an escrow system. Buyers can also be at risk when receiving a physical package if they use their own name and/or address, and that package is intercepted by authorities.

Analytic Plan

The analyses will proceed in three stages. Frist, to test the hypothesis that both drug and non-drug products will display a positive association between ratings and price (hypothesis 1), an ordinary least squares (OLS) regression will be used. While price premiums for highly rated goods are well documented in dark web literature for drugs (Przepiórka et al., 2017; Espinosa, 2019; Munksgaard & Tzanetakis, 2022), it is important to establish that this relationship is observed in the current data. I estimate a model for each of the product categories to test for the appearance of price premiums.

An ordinary least squares regression models the relationship between slopes and the various outcome variables, holding all other control variables constant (Fox, 2016). The formula to complete a multivariate, OLS regression can be seen below:

$$Y_i = b_0 + b_1 X_1 + \dots + b_k X_k + \varepsilon_i$$

The formula can be interpreted as follows. First, b_0 represents the intercept of the slope, or the predicted value of Y when X is zero. Then, b_1 represents the number of units change in Y for a unit change in X_1, and X_1 is the value of the independent variable. This same structure holds for all other variables in the regression. Finally, ε_i represents the random error, or how far observations deviate from the regression line. Altogether, Y_i is the predicted dependent variable values based on the independent variable's values.

Before executing an OLS regression, there are several assumptions that must be met: linearity, independence, normality, constant error variance (homoskedasticity), and multicollinearity. The linearity assumption states that the model cannot be accurate if the independent variables and dependent variables do not form a linear relationship (Fox, 2016). If the error terms in the model are determined to be uncorrelated with each other, the independence assumption is met (Fox, 2016). Normality is determined by checking if in the regression, the distribution of the errors following the normal distribution shape (Fox, 2016). Homoskedasticity occurs when there is consistent variation of the dependent variable in the model (Fox, 2016). Finally, when independent variables share a similar linear relationship, the model is unable to establish the effects of each separate variable, the multicollinearity assumption has not been met (Fox, 2016).

While ideally every assumption of an OLS regression model will be met to draw accurate conclusions from the model, there are limitations for the current study. One focal independent variable, ratings, are given per listing. This, however, introduces a violation of the independence assumption of correlated error terms because there may be several listings put forth by the same vendor. When this occurs, the ratings remain the same across each listing, so it is not possible to parse out if there are certain listings within the same data frame that come from the same vendor, and therefore, have the same rating. Each listing is treated as if it were a unique listing with a unique rating due to data limitations. The AlphaBay data does not include names of specific vendors, so this study is not able to cluster these vendors together. Despite this limitation, an OLS regression is appropriate given the data is cross-sectional.

Second, after examining the rating-price relationship for each product category, an equality of coefficients test (Paternoster et al., 1998) is be used to test hypotheses 2 and 3, testing for significant differences in the rating-price relationship. An equality of coefficients test uses the regression coefficients as well as the standard errors to determine if there is enough evidence to reject the null hypothesis that $\beta_1 = \beta_2$ (Paternoster et al., 1998). The complete formula can be seen here:

$$z = \frac{\beta_1 - \beta_2}{\sqrt{SE\beta_1^2 + SE\beta_2^2}}$$

Therefore, if the z-score calculated from the above equation is outside of the standard -1.96 to 1.96 threshold to obtain a p-value less than 0.05, the coefficients for the rating-price relationship of each pairwise comparison of product categories are significantly different.

Lastly, for the final hypothesis that both drug and non-drug products will display a positive association between reviews and price, a VADER lexicon analysis is used to quantify consumer feedback review into numerical values representing how positive or negative they are, and these values (averaged by item number) are then estimated using an OLS regression. The "vader" library available in RStudio is used to complete the sentiment analysis prior to the model estimation of average sentiment scores and price. The lexicon used for VADER was developed by Hutto and Gilbert (2014) and is publicly available through the "vader" package to view. Additionally, certain characters are used to amplify the sentiment such as "!". The original scores for each piece of text available in the lexicon are assigned a score and then compounded to output a score between -1 and 1. Once these scores are compounded and averaged on item number, they are used as the independent variable in an OLS regression.

Chapter 5: Results

Descriptive Statistics

Table 1 presents the binary rating variable. As noted, these are ratings for each unique listing, and not vendor. There are a substantial number of "perfect ratings" for each product category, which is a phenomenon documented by Haynie and Duxbury (2024) as a common occurrence for dark web marketplaces. Cannabis has the largest number of observations with 11,414 total listings, and weapons have the smallest with 428 listings used for analysis. The product category with the largest proportion of perfect vendor ratings is carded items and the smallest is dissocaitves.

Table 1. Descriptive Statistics for Binary Ratings

Product Category	Not Perfect Rating	Perfect Rating	Proportion of Perfect Ratings	Total
Benzodiazepines	451	1939	0.81	2390
Body Modification	138	1049	0.88	1187
Cannabis	2296	9118	0.80	11414
Dissociatives	185	454	0.71	639
Ecstasy	935	3064	0.77	3999
Opioids	632	2808	0.82	3440
Prescription	348	2258	0.87	2606
Psychedelics	587	2121	0.78	2708
Stimulants	1351	3557	0.72	4908
Carded Items	46	471	0.91	517
Counterfeit Items	232	922	0.80	1154
Digital Products	226	1129	0.83	1355
Fraud	1052	3492	0.77	4544
Guides and Tutorials	371	920	0.71	1291
Software and Security	190	458	0.73	628
Weapons	52	376	0.88	428

Table 2 reflects the price descriptive statistics for listings in each product category. The mean total prices for each listing for drug products on AlphaBay are mostly higher than the non-drug products, an observation consistent with the literature that shows that there are drug products available on these marketplaces listed as higher quantities and are often intended for resale (Aldridge & Décary-Hétu, 2014; Munksgaard & Tzanetakis, 2022). The minimum prices for each of these products are all quite low, possibly indicating a sample product or a potential scam. However, these low prices are included in the study because the true intention of the listing is unknown. Median drug prices are also substantially lower than the means, suggesting that while there are certain products on AlphaBay intended for resale, there are still drugs offered in smaller quantities at lower prices. There is also quite a bit of variation and skewness among prices, so prices for analyses are logged. Additional descriptive statistics for all variables included in the rating-price relationship are available in the appendix (Appendix-1.1-1.6).

Table 2. Descriptive Statistics for Price for Rating and Price

Data Frame	Mean	Median	Min	Max	SD	N
Benzodiazepines	323.96	64.81	0.01	11250	988.73	2390
Body Modification	62.58	44.83	3.5	903.52	74.8	1187
Cannabis	298.01	91.42	0.01	6250	597.28	11414
Dissociatives	394.27	100	0.14	15000	1144.12	639
Ecstasy	388.97	105	0.01	13268.42	917.63	3999
Opioids	290.91	93.93	0.01	12000	799.97	3440
Prescription	87.99	39	0.25	4800	164.46	2606
Psychedelics	180.49	64.66	0.01	7542	422.93	2708
Stimulants	395.21	125	0.01	19100	974.10	4908
Carded Items	251.93	150	0.01	2000	307.6	517
Counterfeit Items	170.56	75	0.31	2352.37	264.08	1154
Digital Products	17.04	9.95	0.01	641.32	51.25	1355

Fraud	119.29	28.62	0.01	2990	261.21	4544
Guides and Tutorials	31.79	5	0.1	700	86.02	1291
Software and Security	31.46	5.71	0.01	1500	107.63	648
Weapons	497.06	63.5	1	6000	994.17	428

Table 3 explores the average sentiment scores across products. As shown through the total listings included some observations from the rating-price descriptives are excluded in this model. There are a total of 2,318 missing average sentiment scores from the data above in tables 1 and 2. The exclusion occurred due to certain items not having corresponding consumer reviews. If no review was present after matching item numbers from the listings data with the feedback data, those listings were dropped. Looking at the mean average sentiment scores, there appears to be more variation than ratings, however, these average sentiment scores derived from consumer reviews are overwhelmingly positive, similar to ratings.

Table 3. Descriptive Statistics for Average Sentiment Scores for Consumer Feedback and Price

Data Frame	Mean	Median	Min	Max	SD	N
Benzodiazepines	0.473	0.496	-0.852	0.965	0.242	2314
Body Modification	0.461	0.471	-0.735	0.972	0.227	1112
Cannabis	0.492	0.521	-0.972	0.993	0.257	11414
Dissociatives	0.456	0.490	-0.861	0.963	0.263	619
Ecstasy	0.478	0.509	-0.94	0.993	0.261	3891
Opioids	0.522	0.550	-0.926	0.988	0.245	3342
Prescription	0.503	0.520	-0.861	0.993	0.227	2487
Psychedelics	0.504	0.521	-0.978	0.968	0.218	2627
Stimulants	0.476	0.499	-0.961	0.99	0.250	4753
Carded Items	0.408	0.44	-0.778	0.966	0.318	457
Counterfeit Items	0.468	0.503	-0.855	0.973	0.295	1057
Digital Products	0.424	0.459	-0.858	0.954	0.253	1355
Fraud	0.391	0.44	-0.943	0.98	0.311	3952

Guides and Tutorials	0.366	0.411	-0.967	0.959	0.288	1086
Software and Security	0.404	0.438	-0.889	0.974	0.285	559
Weapons	0.455	0.478	-0.855	0.966	0.302	398

Table 4 displays descriptive statistics for prices that are included in the average sentiment score and price model. These prices closely mirror prices seen on table 2. This is to be expected because the price variable was untouched, and each product category did not lose many observations. Additional control variable descriptive statistics can be seen in the appendix (Appendix-2.1-2.6).

Table 4. Descriptive Statistics for Price for Consumer Feedback and Price

Data Frame	Mean	Median	Min	Max	SD	N
Benzodiazepines	318.534	64.805	0.01	11250	972.116	2314
Body Modification	61.492	44.48	3.5	903.52	70.675	1112
Cannabis	294.964	90.75	0.01	6250	591.743	11414
Dissociatives	387.001	100	0.14	15000	1118.268	619
Ecstasy	389.582	105	0.01	13268.42	922.348	3891
Opioids	290.826	94.34	0.01	12000	805.355	3342
Prescription	87.427	38.04	0.25	4800	165.181	2487
Psychedelics	180.004	64.19	0.01	7542	424.336	2627
Stimulants	394.033	125	0.01	19100	977.837	4753
Carded Items	250.761	180	0.01	2000	296.081	457
Counterfeit Items	171.227	79	0.99	2352.37	266.846	1057
Digital Products	17.241	9.95	0.01	641.32	51.431	1355
Fraud	121.649	29.99	0.01	2990	267.313	3952
Guides and Tutorials	33.823	5	0.1	700	88.740	1086
Software and Security	31.501	5.99	0.01	1500	109.874	559
Weapons	506.423	68.375	1	6000	989.436	398

Rating and Price OLS Regression Models

Table 5. OLS Regressions estimating the Association Between Rating and Price for Drug Products

	Benzodiazepines (N = 2390)	**Body Modification (N = 1187)**	**Cannabis (N = 11414)**	**Dissociatives (N = 639)**	**Ecstasy (N = 3999)**	**Opioids (N = 3440)**	**Prescription (N = 2606)**	**Psychedelics (N = 2708)**	**Stimulants (N = 4908)**
Perfect Vendor	0.221***	0.022	0.267***	0.168*	0.235***	0.356***	0.175*	0.491***	0.515***
Rating	(0.054)	(0.065)	(0.019)	(0.070)	(0.031)	(0.054)	(0.072)	(0.061)	(0.034)
Domestic	0.336***	0.153***	0.244***	0.468***	0.580***	0.226***	0.131**	-0.013	0.357***
Shipping	(0.043)	(0.041)	(0.015)	(0.066)	(0.026)	(0.042)	(0.050)	(0.050)	(0.030)
	0.039***	0.009	0.047***	0.040***	0.029***	0.040***	-0.014*	0.106***	0.093***
Vendor Levels	(0.006)	(0.007)	(0.002)	(0.009)	(0.003)	(0.006)	(0.007)	(0.008)	(0.004)
Sales-Feedback	-0.007	-0.021	-0.039***	-0.018	-0.020***	-0.030*	-0.054**	-0.069**	-0.062***
Ratio	(0.008)	(0.017)	(0.005)	(0.011)	(0.005)	(0.013)	(0.018)	(0.021)	(0.008)
Weight in mg	0.537***	0.053***			0.712***	0.278***	0.194***		
(log)	(0.009)	(0.009)			(0.007)	(0.007)	(0.010)		
Weight in grams			0.583***	0.655***				0.102***	0.417***
(log)			(0.004)	(0.018)				(0.006)	(0.008)
	0.695***	3.348***	2.586***	3.190***	-2.183***	2.095***	2.628***	3.162***	3.093***
(Intercept)	(0.094)	(0.124)	(0.029)	(0.115)	(0.072)	(0.095)	(0.122)	(0.112)	(0.054)

*p<0.05, **p<0.01, ***p<0.001

The regression analysis in table 5 reveals that compared to vendors with imperfect ratings, vendors who possess a perfect rating have higher prices for all drug products other than body modification substances. Compared to those without a perfect rating, listings for benzodiazepines from vendors with a perfect rating have a 22.1% ($p < 0.001$) higher price, controlling for if the vendor is shipping domestically, their vendor level, the ratio of sales to feedback, and logged drug weight in milligrams. Ecstasy, opioid, and prescription drug vendors with perfect ratings are seen to have a 23.5% ($p < 0.001$), 35.6% ($p < 0.001$), 17.5% ($p < 0.05$) higher prices respectively than those without perfect ratings, holding the same variables constant as benzodiazepines. Cannabis, dissociative, psychedelic, and stimulant drug vendors also have a positive rating-price relationship with price increases of 26.7% ($p < 0.001$), 16.8% ($p < 0.05$), 49.1% ($p < 0.001$) and 51.5% ($p < 0.001$) respectively if they have perfect ratings compared to those without, also holding constant shipping domestically, their vendor level, the ratio of sales to feedback, and logged drug weight in grams.

In terms of controls, all significant domestic shipping coefficients suggest that vendors who ship only domestically implement a price premium. This result is expected because prior literature form Décary-Hétu and colleagues (2016) finds that international shipping is associated with lower vendor ratings. These lower vendor ratings therefore do not translate into higher prices because vendors are unable to convert their reputation into pricing power. The weight variables display a positive association in their logged form with logged price. However, the interpretation of the two logged variables is different than for other measures that are not logged. For example, a 1% increase in milligrams for benzodiazepines is related to a 0.537% increase in price, holding all other variables constant. Conceptually, because all coefficients for this relationship are under 1%, we are seeing a bulk discount for larger weights. This result is consistent with prior literature that states that individuals are purchasing a variety of weights of drugs, since some consumers are purchasing for resale in the street market, and these larger quantities often result in a bulk discount (Aldridge & Décary-Hétu, 2014; Munksgaard & Tzanetakis, 2022).

These regression results indicate price premiums for perfectly rated drug products for nearly all drug categories. This aligns with the half of first hypothesis that price premiums will be present for products on AlphaBay based on their ratings. Through these analyses, vendors are shown to implement price premiums to increase consumer certainty about product quality and a successful transaction. This result was expected based on the rational choice perspective and signaling theory, which suggests that under situations of uncertainty, buyers attempt to maximize their utility from a transaction by limiting these uncertainties by using reputation to indicate quality and vendor reliability. The price premium serves also as an indicator of trust and quality but can only be implemented if the vendor has the reputation to back it.

Table 6. OLS Regression estimating the Association Between Rating and Price for Non-Drug Products

	Carded Items (N = 517)	**Counterfeit Items (N = 1154)**	**Digital Products (N = 1355)**	**Fraud (N = 4544)**	**Guides and Tutorials (N = 1291)**	**Software and Security (N = 648)**	**Weapons (N = 428)**
Perfect Vendor	0.926***	0.707***	0.419***	0.855***	0.283**	0.624***	0.877**
Rating	(0.219)	(0.104)	(0.077)	(0.061)	(0.087)	(0.118)	(0.257)
Domestic	-0.769	-0.083		0.047			-0.613*
Shipping	(0.456)	(0.156)		(0.219)			(0.240)
Vendor	0.228***	0.003	0.015	0.010	0.063***	0.105***	-0.375***
Levels	(0.026)	(0.015)	(0.009)	(0.010)	(0.016)	(0.024)	(0.041)
Sales-Feedback	-0.044***	-0.025***	-0.001*	-0.003***	-0.000	-0.003**	0.019
Ratio	(0.011)	(0.004)	(0.000)	(0.001)	(0.000)	(0.001)	(0.026)

Physical	1.926***			1.827***			
Package	(0.160)			(0.087)			
	0.247	3.749***	1.518***	2.410***	1.325***	0.799**	6.556***
(Intercept)	(0.303)	(0.158)	(0.114)	(0.103)	(0.164)	(0.239)	(0.428)

*p<0.05, **p<0.01, ***p<0.001

The regression analysis in table 6 reveals that compared to vendors with imperfect ratings, vendors who possess a perfect rating display higher prices for all non-drug products. Compared to those without a perfect rating, listings for carded items and fraud from vendors with a perfect rating have a 92.6% ($p < 0.001$) and 85.5% ($p < 0.001$) price markup, holding domestic shipping, their vendor level, the ratio of sales to feedback, and if the product is shipped in a physical package constant. Additionally, there appears to be higher prices for perfect-rated vendors of digital products, guides and tutorials, and software and security products compared to those without perfect ratings. For digital products, a 41.9% ($p < 0.001$) premium is observed, guides and tutorials highlight a 28.3% ($p < 0.01$) increase, and software and security products show a 62.4% markup, while holding vendor levels and the ratio of sales to the number of feedback constant. Finally, a 70.7% price increase is observed for counterfeit items and an 87.7% markup for price is seen for weapons for perfectly rated vendors compared to imperfect-rated vendors, holding domestic shipping, vendor levels, and the ratio of sales to feedback constant. Results illustrating price premiums for all non-drug products highlights how similar licit marketplaces and illicit marketplaces are in seller's abilities to set price premiums.

In terms of control variables, results differ from the drug products. If a vendor ships domestically is only significantly associated with price for weapons, and this association is negative, suggesting that only shipping purely domestically is related to lower prices for weapons products. This may be due to the risks, mainly legal, that can occur for shipping weapons. The lower prices for domestic weapons may reflect a vendor pricing strategy that is aimed more at-risk reduction, rather than using their reputation to implement a price premium. If a weapon does not have to cross a boarder to arrive at its destination, vendors may perceive this delivery as lower risk, and therefore, offer a discount to those buyers who purchase domestically. The physical package variable is unique to carded items and fraud within the non-drug category. Results suggest that if a vendor ships a physical package rather than a digital good, prices are expected to increase by 192.6% ($p < 0.001$) and 182.7% ($p < 0.001$) for carded items and fraud products respectively, holding all other variables constant. This suggests that physical goods themselves may have higher prices than digital good, perhaps due to the delivery risks associated with shipping physical packages.

These results from tables 5 and 6 support hypothesis one, with the exception of body modification drugs. All products that display price premiums, both drug and non-drug alike have distinct risk profiles that may also impact how influential a perfect rating is. So, while a test of the rational choice perspective and signaling theory broaden the scope of their theoretical applications to extremely uncertain marketplaces, one other component of decision-making still looms, risk. To examine the potential impacts of perceived risk from uncertainty, equality of coefficients tests for a select group of products will be examined.

Equality of Coefficients Test

Table 7. Equality of Coefficients Test for Drug Products

Comparison	z	p-value
Opioids vs. Cannabis	-1.57	0.116
Stimulants vs Cannabis	-6.33	0.000***
Opioids vs. Stimulants	-2.5	0.013*

*p<0.05, **p<0.01, ***p<0.001

Table 7 explores the differences between the rating-price relationship between opioids and cannabis, stimulants and cannabis, and opioids and stimulants. Tables Appendix-4.1 and Appendix-4.2 displays the rest of the pairwise comparisons but for the main presentation, three drugs were selected based on their prevalence and perceived risks for both health and legal consequences. While there are many legal consequences around the world regarding these illicit drugs, in the context of the United States, cannabis is legal to purchase for recreational and medicinal use in many states. Due to this, it may be considered less risky than both stimulants and opioids for law enforcement detection consequences. Additionally, cannabis was consistently perceived to be the lowest risk drug health wise, whereas stimulants and opioids were viewed as the riskiest.

Results indicate that there is a significant difference between the rating-price relationship for stimulants and cannabis. This result is to be expected due to their different risk profiles. The uncertainty around purchasing cannabis can be lowered through product descriptions noting different strains or photographs of the product that are intended to reduce uncertainty about product quality. Stimulants though have more uncertainties surrounding overdose and laced products, and therefore, show a significantly higher price premium than cannabis.

A comparison of opioids and cannabis does not reveal a significant difference. Potential reasoning for this may be that individuals purchasing opioids may be dependent, and willing to stick to their original choice of vendor out of habit. Jacques and colleagues (2014) argue that substance dependent individuals are easier to rip off on the street drug market because they are willing to pay any amount for the drug they are dependent on and therefore are less likely to conflict with their dealer. Additionally, heroin ranked as the highest drug for dependence for both psychological and physical dependence (Nutt et al., 2007). So, while there are still risk factors that are similar for both stimulants and opioids, opioid purchasers on the dark web may be clouded by their dependence and not factor in the high risks associated with use, because their focus is to obtain the drug while not focusing on risk.

Finally, results highlight a significant difference between the rating-price relationship for stimulants and opioids. As highlighted above, substance dependent individuals may not factor risk preferences into their decision-making to purchase a drug, since their utility maximization is concerned with just obtaining the drug. So, while there are risks associated with the purchase of opioids that could influence decision-making for some, these risks do not appear to function as strongly as they might for consumers of stimulants. The amount of risk a perfectly rated vendor can mitigate for opioid consumers is less of a concern, therefore, the monetary value assigned to these perfect reputations is less than that for stimulants.

Overall, the significant difference in the rating-price relationship for stimulants and cannabis and stimulants and opioids suggests that while there are apparent price premiums for these perfectly rated products, the different risk profiles between the drugs allow for reputation to monetized more for stimulants. In contrast, the insignificant difference between the relationship between ratings and price for opioids and cannabis suggests that perhaps not only risks are influencing decision-making, but rather dependence and addiction are driving the purchase of opioids, allowing for the price premiums to be more similar to a lower risk drug, like cannabis. In sum, the findings provide mixed support for hypothesis 2.

Table 8. Equality of Coefficients Test for Drug and Non-Drug Products

Product	**Comparison**	**z**	**p-value**
Opioids vs.	Counterfeit Items	-3.01	0.003**
	Fraud	-6.13	0.000***
	Weapons	-1.99	0.047*
Stimulants vs.	Counterfeit Items	-1.76	0.078

	Fraud	-4.85	0.000***
	Weapons	-1.4	0.162
Cannabis vs.	Counterfeit Items	-4.18	0.000***
	Fraud	-9.18	0.000***
	Weapons	-2.37	0.018*

*p<0.05, **p<0.01, ***p<0.001

Table 8 displays the equality of coefficients tests for the same drugs examined in table 7 (cannabis, opioids, and stimulants), comparing their rating-price relationship to a select group of non-drug products, all with distinct risks. Again, due to presentability, three non-drug items are included in the main tables and all comparisons can be found in Appendix-4.1 and 4.2. Counterfeit items are significantly different from opioids and cannabis, presumably because of the wide variety of products within the counterfeit items category that also vary in risk profiles themselves. Counterfeit items include clothing, jewelry, electronics, fake identifications, and money. The majority of this product category is made up of fake identification and money, both of which may carry harsh penalties if the package is intercepted by law enforcement. Therefore, while clothing, jewelry, and electronics may be less risky to purchase and sell, most of the goods in this category are quite risky to deliver and come with legal consequences, hence why counterfeit items display significantly larger price premiums when compared to cannabis and opioids, but not stimulants.

The relationship between reputation and price for fraud products which include accounts, credit cards, and personal information are significantly smaller than the relationship between reputation and price for all three drug products. A vendor with a perfect rating is associated with an 85.5% markup in price for fraud products, compared to the largest markup for drug products being stimulants at 51.5%. Therefore, reputation carries more economic value for fraud than all drug products. This suggests that the risks associated with fraud products, such as law enforcement detection through the use of a stolen credit card or the financial loss from being scammed and receiving false products (e.g., fake credit card numbers), can be largely mitigated by a vendor having a favorable rating.

Finally, weapons, in their rating-price relationship, are significantly different from cannabis and opioids, but not stimulants. Since weapons and stimulants both carry high risks for health and perceived legal repercussions for delivery, it is expected they would monetize trust through perfect ratings similarly, and therefore, the equality of coefficients test would be unable to the reject the null that $\beta_1 = \beta_2$ for these two products. Findings from table 7 finds that cannabis and opioids are not significantly different in their rating and price relationship, suggesting that these drugs may operate similarly in their monetization of reputation. This result then expects that weapons will have significantly higher price premiums when compared to both opioids and cannabis, which is confirmed in table 8.

In sum, price premiums are not uniform across all products, indicating that there are other factors, including risks, that influence decision-making and pricing strategies. Two out of three comparisons yielded significant differences for drug products, offering partial support for hypothesis 2 that hypothesized drug products with higher risks profiles with the purchase of each would be significantly different in terms of the rating-price relationship compared to low risk drugs. Hypothesis 3 that there will be significant difference between drug and non-drug products all with different risk profiles will be significantly different in their rating-price relationship is also partially supported with seven out of nine comparisons displaying significant differences. In total, nine out of twelve comparisons for significant differences in the rating and price relationship highlights how risk impacts decision-making, and that reputation is not a consistent pricing influence alone.

Average Sentiment Scores and Price OLS Regression

Table 9. OLS Regression estimating the Association Between Average Sentiment Score and Price for Drug Products

	Benzodiazepines (N = 2314)	**Body Modification (N = 1112)**	**Cannabis (N = 11414)**	**Dissociatives (N = 619)**	**Ecstasy (N = 3891)**	**Opioids (N = 3342)**	**Prescription (N = 2487)**	**Psychedelics (N = 2627)**	**Stimulants (N = 4753)**
Average Sentiment	-0.139	0.147	-0.042	-0.224	0.166***	0.259**	0.467***	0.304**	0.237***
Scores	(0.088)	(0.092)	(0.030)	(0.121)	(0.050)	(0.085)	(0.108)	(0.116)	(0.062)
	0.352***	0.183***	0.263***	0.478***	0.589***	0.242***	0.122*	0.010	0.393***
Domestic Shipping	(0.043)	(0.042)	(0.016)	(0.068)	(0.027)	(0.042)	(0.051)	(0.052)	(0.032)
Vendor	0.036***	0.010	0.043***	0.037***	0.024***	0.033***		0.094***	0.077***
Levels	(0.006)	(0.007)	(0.002)	(0.009)	(0.003)	(0.006)	-0.015* (0.007)	(0.008)	(0.004)
Sales-Feedback	-0.008	-0.021	-0.040***	-0.019	-0.020***	-0.027*		-0.081***	-0.058***
Ratio	(0.008)	(0.018)	(0.005)	(0.011)	(0.005)	(0.013)	-0.041* (0.019)	(0.022)	(0.008)
	0.542***	0.052***			0.718***	0.280***	0.199***		
Weight in mg (log)	(0.009)	(0.009)			(0.007)	(0.008)	(0.010)		
			0.587***	0.663***				0.105***	0.431***
Weight in grams (log)			(0.004)	(0.018)				(0.006)	(0.008)
	0.923***	3.282***	2.840***	3.412***	-2.087***	2.289***	2.494***	3.517***	3.463***
(Intercept)	(0.093)	(0.115)	(0.029)	(0.108)	(0.074)	(0.093)	(0.117)	(0.111)	(0.054)

*p<0.05, **p<0.01, ***p<0.001

Table 9 shows the relationship between average sentiment scores and price for drug products. An increase in average sentiment scores is associated with a 16.6% ($p < 0.001$), 25.9% ($p < 0.01$), and 46.7% ($p < 0.001$) increase in price for ecstasy, opioids, and prescription drugs respectively, holding domestic shipping, vendor level, the ratio of sales to feedback, and logged drug weight in milligrams constant. Additionally, an increase in average sentiment scores is related to a 30.4% ($p < 0.01$) and 23.7% ($p < 0.001$) markup in price for psychedelics and stimulants, controlling for domestic shipping, vendor level, the ratio of sales to feedback, and logged drug weight in grams. Benzodiazepines, body modification drugs, cannabis, and dissociatives all did not have a significant relationship between average sentiment scores and price.

These results differ from the rating-price relationship for drug products in a couple of ways. First, there are less significant results for the review-price relationship than for the rating-price relationship. In the relationship between reviews and price, benzodiazepines, cannabis, and dissociatives are all not significant, even though they displayed a positive association with ratings and price in table 5. Second, the relationships between reviews and price are different than the rating-price relationships for certain drug products that are significant for both relationships. Opioids, psychedelics, and stimulants all display lower price premiums for the review and price relationship, whereas ecstasy and prescription drugs show stronger relationships for the review-price relationship. These differences may suggest that not only does pricing power through reputation differ between products, but it might also differ between the type of reputation signal.

Control variables for the review and price relationship for drug products yield similar results to the rating-price relationship. Domestic shipping is positively related to price for all products except for psychedelics. All weight variables are also positively related to price in the review-price relationship, consistent with findings from the rating-price relationship.

Table 10. OLS Regression estimating the Association Between Average Sentiment Score and Price for Non-Drug Products

	Carded Items (N = 457)	Counterfeit Items (N = 1057)	Digital Products (N = 1355)	Fraud (N = 3952)	Guides and Tutorials (N = 1086)	Software and Security (N = 559)	Weapons (N = 398)
Average							
Sentiment	-0.307	0.839***	-0.209	0.405***	0.585***	0.202	0.480
Scores	(0.205)	(0.146)	(0.127)	(0.091)	(0.152)	(0.207)	(0.285)
Domestic	-0.760			0.017			-0.504*
Shipping	(0.501)	-0.161 (0.161)		(0.227)			(0.253)
Vendor	0.236***	0.007	0.016	-0.002	0.050**	0.080**	-0.412***
Levels	(0.029)	(0.015)	(0.010)	(0.010)	(0.018)	(0.027)	(0.042)
Sales-Feedback	-0.054***	-0.041***	-0.001*	-0.003***	-0.000	-0.002	0.015
Ratio	(0.011)	(0.008)	(0.000)	(0.001)	(0.000)	(0.001)	(0.026)
Physical	1.938***			1.896***			
Package	(0.172)			(0.094)			
	1.180***	3.937***	1.954***	3.019***	1.455***	1.336***	7.417***
(Intercept)	(0.274)	(0.163)	(0.118)	(0.102)	(0.176)	(0.248)	(0.365)

*p<0.05, **p<0.01, ***p<0.001

Table 10 shows the relationship between average sentiment scores and price for all non-drug products. As average sentiment score increases, there is an 83.9% ($p < 0.001$), 40.5% ($p < 0.001$), and 58.5% ($p < 0.001$) price increase for counterfeit items, fraud, and guides and tutorials respectively, holding all other variables constant. Carded items, digital products, software and security, and weapons reviews are all not associated with prices.

Compared to the rating-price relationship, results for the association between reviews and price for non-drug products vary greatly. First, every product in the rating-price relationship model displayed a positive, significant association. However, only three out seven products display price premiums for favorable reviews in the current model. Additionally, products like carded items, software and security, and weapons that all displayed high markups for perfect ratings, now show that reviews are not associated with price at all. Second, similar to drug products in the review-price relationship, certain products display weaker or stronger relationships for reviews and price compared to ratings and price. Counterfeit items and guides and tutorials display a stronger review-price relationship than rating-price, while fraud displays a weaker relationship.

In terms of controls, directionality for significant results similarly mirror the rating-price relationship. However, domestic shipping only yields one significant result for weapons. The domestic shipping for weapons was negatively related to price in the rating-price relationship and is also negatively related in this model. Physical packages for carded and items and fraud are still strongly positively related to price in the current model, as they were in the rating-price relationship.

These regression results indicate the appearance of price premiums for certain drug. This result partially supports hypothesis 4 that price premiums will be present for products on AlphaBay based on their reviews. Five out the nine drug products displayed an apparent price premium for goods with more positive reviews. While results are not as strong for the review-price relationship when compared to the rating-price relationship, findings suggest that reputation through reviews can be monetized for certain products into a price premium.

In sum, support is found for the first hypothesis that there are price premiums for the overwhelming majority highly rated goods on AlphaBay. Hypothesis 2a is partially supported given the significant difference found in the rating-price relationship between stimulants and cannabis, but insignificant for opioids and cannabis. Hypothesis 2b is generally supported showing seven significant differences between drug and non-drug products for the rating-price relationship out of nine total comparisons. Finally, hypothesis 3 is partially supported, with ten out of sixteen products displaying a price premium that manifests through positive consumer reviews.

Chapter 6: Discussion and Conclusion

Discussion

The current study examined the relationship between vendor reputation and pricing across drug and non-drug product categories on the AlphaBay marketplace. Guided by signaling theory and the rational choice perspective, the analyses investigated whether numeric ratings and written consumer reviews function as signals capable of generating price premiums, and if the premiums associated with perfect ratings varied across product type. The findings demonstrate that vendor ratings are strongly and consistently associated with higher prices across nearly all product categories, indicating that reputation functions as a form of economic capital that has the ability to be monetized under conditions of uncertainty. Additionally, results suggest that the monetization of reputation through ratings does not operate uniformly across product types with different risk profiles. In contrast, consumer reviews displayed more inconsistent relationships with price, indicating that different forms of reputation capture distinct aspects of trust and decision-making.

Together, these results provide evidence that online illicit marketplace pricing is influenced by the strategic use of reputation in the form of signals to manage informational asymmetries, risk, and uncertainty. Through examining how reputation-based price premiums are variable across products characterized by various levels of risk, this study extends prior research by demonstrating that the economic value assigned to trust is contingent on structural features of risk associated with the transaction. These findings offer important theoretical contributions to signaling and the rational choice perspective, while also providing insights into the market governance, structure, and vulnerabilities of online illicit marketplaces.

Reputation as Pricing Power Under Uncertainty

Crucially, the findings indicate that price premiums from reputation are present for nearly every product category. This central role of reputation enables online illicit marketplaces to function efficiently despite large amounts of information asymmetry and perceived uncertainties. These rating-price results mirror findings from prior literature that demonstrated favorable reputations allow vendors to charge higher prices for drugs (Przepiórka et al., 2017; Espinosa, 2019; Munksgaard & Tzanetakis, 2022). In the current study, all drug products, except for body modification drugs, displayed significant price premiums for perfectly rated vendors. Non-drug products all showed price premiums when vendors held perfect ratings, compared to those without a perfect rating.

Prior literature has studied reputation in a variety of ways. Przepiórka and colleagues use the number of five-star and non-five-star ratings to measure vendor reputation, whereas other studies use indicators of positive and negative seller reputations (Espinosa, 2019; Munksgaard & Tzanetakis, 2022). The current study, while also exploring ratings, examined consumer reviews as well. While seller reputation, in the form of ratings, has been shown to be related to higher prices when ratings are high, no study has examined these consumer reviews as it relates to product price. Findings of this study suggest that consumer reviews, when quantified and averaged on item number, yield different results than ratings in terms of eliciting a price premium. This difference extends prior literature by offering a new measure of vendor reputation and illustrating how these reputation signals appear visually different when regressed on price. This opens opportunities for future research to dig deeper into how to quantify these reviews, and why vendors may assign different monetary values to reviews compared to ratings.

One interesting finding related to reputation and pricing power comes from the control variable of vendor level. The vendor levels measure, that captures both the vendor level and trust level assigned to a vendor by the site administrators (Andrei and Veltri, 2025), yields directionally different results for certain products. These vendor levels are significant and positively related to price for many products, suggesting that these levels function similarly to ratings and reviews in their ability to convey vendor reliability through administrator scoring. However, both prescription drugs and weapons for both reputation-price relationships display negative associations with vendor level and price. This suggests that perhaps the vendor level and trust level assignments by administrators are not widely perceived as a useful tool to reduce uncertainties for these products. This extends signaling theory by noting that perhaps for certain goods, even though vendor levels are assumed to be credible signals of reputation given by site administrators, the degree to which these reputation signals can be monetized is product specific.

The current study additionally extends prior literature by highlighting that price premiums are not only present for many drug products, but for non-drug products as well, and differ in magnitude between types of reputation signals. Prior literature examining this rating-price relationship has explored drug products both together in a heterogenous category (Przepiórka et al., 2017) and separately (Espinosa, 2019; Munksgaard & Tzanetakis, 2022) all of which found price premiums using their respective drug categorizations. However, neither Espinosa (2019) or Munksgaard and Tzanetakis (2022) examined whether reputation influenced prices differently, despite results suggesting that reputation operates inconsistently across drug product type. While they tested the effect of ratings on price, both studies lacked analytical estimations to determine if different products significantly differed in their rating-price relationships. The current study analytically tests these relationships to extend prior literature, highlighting that there are significant differences between drug products as well as drug and non-drug products. So, while price premiums appear to be a generalizable pattern across marketplaces and products, these premiums varying across product categories.

Reputation Variability in Pricing Power Across Products

Important theoretical framing by the rational choice perspective suggests that signals of reputation are only as effective as their ability to mitigate uncertainties related to perceived risks in terms of their pricing power. The rational choice perspective posits that individuals attempt to maximize utility (Bentham, 1781) through the weighing of costs, benefits, and risk associated with decisions (Thomas & Vogel, 2019). Since perceived uncertainties influence decision-making (Albonetti, 1986; Klepper & Nagin, 1986; Pogarsky et al., 2018), signals of favorable reputation can aid in lessening these uncertainties surrounding risk, but the monetary value reputation carries are dependent on how much perceived uncertainty from risk it can reduce. Therefore, consistent with the current study's findings, price premiums vary across products depending on the risks related to certain products. Specifically, the drug product category of stimulants, that is widely regarded as high-risk, especially in terms of health risk (Taylor, 2012; Bonnett et al., 2020; Substance Abuse and Mental Health Services Administration, 2021; Miech et al., 2025), when compared to both opioids and cannabis, displays a significantly higher price premium.

Stimulants such as cocaine and methamphetamines can carry high legal penalties, elevated health risks, and variability in purity from potential adulterants. These features may intensify consumer uncertainty and increase perception of risk and therefore increase the monetary value ratings carry. Under these conditions, consumers may be more likely to rely heavily on vendor ratings as a tool to minimize uncertainty, allowing vendors with perfect ratings to command higher price premiums. Cannabis, by contrast, is generally perceived as lower risk (Taylor, 2012; Bonnett et al., 2020; Substance Abuse and Mental Health Services Administration, 2021; Miech et al., 2025) in terms of legal penalties and health risks, particularly due to the reduced stigma and legalization surrounding cannabis use. These findings have important implications for understanding how vendors view perceived uncertainties and decide how high or low to set their prices. Vendors for products within the stimulants category may decide to set higher price premiums for their riskier products compared to cannabis vendors, because consumers are willing to pay more for the reduction of perceived risks vendors communicate through their perfect ratings. Since the uncertainties surrounding the perceived risk for cannabis is perceived to be lower than stimulants, vendors of cannabis products then cannot utilize their perfect reputation as much in terms of setting price premiums, because the consequences for both consumers and vendors for transacting are considerably less than those for stimulants.

Interestingly, even though opioids are widely regarded as "high risk" (Taylor, 2012; Bonnett et al., 2020; Substance Abuse and Mental Health Services Administration, 2021; Miech et al., 2025), they were found to be significantly different from stimulants for the rating and price relationship. While opioids carry similar risks in terms of overdose and legal consequences to stimulants, the dependence on the drug may factor more into the purchasing decisions, lowering the perception of risk for buyers. Consumers who are substance dependent might prioritize immediate availability and affordability over vendor credibility, reducing the economic impact of reputational signals. Therefore, opioids may not see as much economic value assigned to higher rated vendors.

A study by Olmstead and colleagues (2016) reveals that the price elasticity of demand for heroin is around -0.8 from a sample of regular heroin users. Price elasticity of demand refers to how much the quantity demanded changes in response to the price changing. This finding suggests that heroin users reduce consumption proportionally less in response to price increases compared to more elastic goods, which reflects the influence of dependence on consumer choice. However, inelastic demand does not necessarily imply that dependent users are willing to pay higher prices for perfectly rated vendors, but instead, dependence may constrain users' financial resources and increase urgency of obtaining the drug, encouraging them to seek cheaper options to sustain continued substance use. Supporting this interpretation of the findings, Jacques and colleagues (2014) argue substance dependent individuals are prime targets for drug dealers to swindle, because they are more concerned with acquiring the drugs rather than the price. Consistent with this interpretation, heroin has been identified as one of the most dependence-producing substances both psychologically and physically (Nutt et al., 2007). Taken together, these findings suggest that opioid-dependent consumers may be less responsive to reputational signals and more motivated by price and availability, which could explain why opioids in the current study exhibited lower price premiums from ratings despite their high-risk profile.

Another key finding of the current study is that non-drug products, specifically fraud products, counterfeit items, and weapons, display larger price premiums than drug products, and these premiums, in some cases, are significantly larger than the subset of drug products examined. Specifically, fraud products, which include personal information and scams along with credit cards and bank information, may have a vastly different risk profile than drug products. While around half of the listings within this product category do not ship physically, which minimizes the risk of concealment and law enforcement detection through package inspection as a risk, certain physically available goods may carry significant penalties. Evading law enforcement is still a significant risk for individuals purchasing fraud products like credit cards and personal information. Detection risk may be heightened if these cards and personal information are used either at a store or to obtain a loan at the bank. Additionally, the risk of a scam from obtaining a fake product may also factor into risk-reward calculation, and ultimately the implementation of price premiums. Due to these different risks associated with fraud products, results suggest that for the rating and price relationship, the economic value assigned to perfectly rated vendors of fraud products are higher than drug products. Overall, this result suggests that vendors of non-drug goods, specifically for counterfeit items, fraud, and weapons might assume that they can place more monetary value on these products for their higher ratings, because their higher ratings may reduce the perceived risks and uncertainties for buyers.

Reputation System Differences

The current study find that price premiums are more apparent when rating is the reputation signal and less when consumer reviews are analyzed. These findings underscore that signals can function differently in terms of pricing power depending on the type of reputation signal. Ratings on dark web marketplaces function as standardized, interpretable signals that facilitate quick and easy comparisons across vendors. Their visibility makes ratings well-suited tools for decision-making, where buyers are presented with hundreds, if not thousands of options. By contrast, consumer reviews that are written by former customers of a particular vendor and provide a more in-depth explanation of individual's experience with the vendor and transaction overall. Additional information regarding shipping concealment and product quality, to name a few, can be expanded on within a review. These expansions may offer more information than ratings since they are intended to discuss the details of a transaction but may not be used by consumers as an initial tool to narrow down listings that appear to reduce risks. Moreover, van Waardenberg (2021) notes that due to the ability for vendors to remove negative rating but are unable to remove positive ones on AlphaBay, the numerical ratings may be inflated, but the reviews may be more negative. Consumers then may leave more positive ratings and then a review detailing their true experience with a vendor.

A correlation between ratings and average sentiment scores yielded an average correlation across all products of 0.38, suggesting that these two reputation signals are not highly correlated with each other. The highest observed correlation was between ratings and reviews for the software and security product category at 0.57, and the lowest, at 0.17, body modification drugs. The result of this correlation then may partially aid in explaining the inconsistencies when observing the rating and price relationship alongside the review and price relationship.

Consumers of certain products may use reviews more than ratings when determining which vendors are reducing risks most effectively. For example, ecstasy, prescription drugs, counterfeit items, and guides and tutorials all displayed visually higher, positive relationships between reviews and price opposed to ratings and price. Consumers of these products may use these consumer reviews more to reduce perceived uncertainties, rather than simply looking for vendors with perfect ratings, and vendors then might assign more monetary value to reviews rather than ratings. However, fraud products, opioids, psychedelics, and stimulants all displayed a higher relationship for the rating-price relationship compared to the review-price relationship. This finding suggests that ratings are the primary signal that vendors are able to monetize within this product category. These results suggest that not only is the monetary value of a rating different between products of certain risk profiles, allowing vendors to charge higher prices, but the economic value of reputation in a broad sense is variable in which reputation signal can command a larger price premium.

Since consumer reviews are not standardized like ratings, vendors may not assign as much economic value to reviews not only because they are not in a standardized form, but because reviews have the potential to put consumers into information overload. Prior literature suggests that when consumers receive too much information, there can be consequences (Jacoby, 1984). Too much information in the context of online illicit marketplaces may manifest in the form of consumer feedback reviews. Consumers can already view the ratings, vendor level, and trust level easily when viewing products. However, weighing these in addition to written review may overload their decision-making process. Jacoby (1984) however, argues that consumers typically stop before they become overloaded with information, and buyers typically look for small amounts of information available to them. Therefore, if some consumers stop before getting to the reviews for certain products, vendors might not assign as much monetary value to these reviews since consumers may not read them as frequently to efficiently make purchasing decision, meaning the reviews might not serve as effectively to reduce perceived risks as ratings can for certain products.

Lastly, the VADER method used to assign sentiment scores to each review could impact the model estimations and be partially responsible for the visual differences between the reputation-price relationships. Sentiment analyses come in varying forms, and the most basic form is sentiment categorization (Khoo & Johnkhan, 2018). The categorization approach involves putting pieces of text into either a positive or negative category (Khoo & Johnkhan, 2018). The two approaches within this type of sentiment analysis are lexicon and machine-learning (Khoo & Johnkhan, 2018). Machine-learning, due to its ability to be easily customizable is a favorable option for sentiment analysis, but it is also time consuming and requires knowledge of how to develop to classifier (Khoo & Johnkhan, 2018). A lexicon-based approach, used in the current study also holds some benefits and limitations for use. The lexicon approach, pulling from a set list of text that has already been assigned a score, is less time consuming than the machine-learning approach (Hutto & Gilbert, 2014), but since words can have multiple meaning and text is context dependent, issues may arise when working with this type of approach (Khoo & Johnkhan, 2018). Several of these limitations for the lexicon-based approach are addressed below.

For this study, a face validity check of the VADER sentiment analysis for each product category was done to determine how well the analysis fared with the AlphaBay comments. Each product category was examined by looking at the ten lowest and ten highest sentiment scores to judge how well this analysis picked up on both slang and profanity. After viewing these consumer reviews and their scores, it was determined that the VADER lexicon analysis worked well in determining positive and negative reviews, given the restraints listed by Khoo and Johnkan (2018). For example, from the counterfeit items data frame an extremely positive review received an average score for this item of 0.968 reads, "GOD OF WATCHES full trust perfect quality amazing VENDOR excellent communication NICE BRO". On the contrary, an item with an average sentiment score of -0.92 from the cannabis category says, "SCAM!!!! CHEATER!!!! He is stolen my money…dont send nothing…". However, it appeared from the face validity check that the VADER analysis did not do as well with profanity used in a positive connotation, since the profanity scores are already negatively scored through the set lexicon. Certain items with comments containing profanity were classified as negative when they were positive reviews, but in other circumstances, it read the reviews with profanity correctly as positive. So, while there are limitations with using the VADER approach, Bonta and colleagues (2019) pitted this approach against various other lexicon-based approaches, and VADER scored at 77% accuracy, compared to the other approaches at 74% and 62%. Future research should explore these consumer reviews using a machine learning approach of sentiment analysis due to the extreme use of profanity in a positive light and slang that may not be indexed in the lexicon produced by Hutto and Gilbert (2014).

Theoretical Implications

The findings of this study provide some support for signaling theory and the rational choice perspective, while also extending these frameworks within the context of online illicit marketplaces. Consistent with signaling theory (Spence, 1973; Connelly et al., 2011), vendor ratings function as costly and credible signals that reduce information asymmetry and allow buyers to infer unobservable qualities such as trustworthiness and reliability. Since reputations require consistent, successful transactions to build and are difficult to falsify, they serve as reliable indicators of vendor quality, demonstrating how vendors are able to convert reputation into economic value, supporting the notion that reputation functions not merely as a trust-facilitating mechanism, but as a monetizable asset for vendors.

At the same time, the substantial heterogeneity observed across product categories refines signaling theory by demonstrating that the economic value of reputational signals is conditional rather than uniform. While signaling theory emphasizes the credibility and costliness of signals (Spence, 1973), the present findings indicate that signal effectiveness also depends critically on the degree of uncertainty and risk a signal mitigates. Products characterized by higher perceived risks and greater uncertainty, such as stimulants, weapons, and fraud, exhibited significantly larger reputation-based price premiums. In contrast, lower-risk products such as cannabis demonstrated weaker rating-price relationships. This suggests that credible signals do not generate equal pricing power across all transactions but instead exert stronger economic effects where the consequences of failure are more severe.

These findings also provide support for the rational choice perspective, which argues that individuals seek to maximize benefits by weighing perceived costs, benefits, and risks when making decisions under uncertainty (Gül, 2009; Thomas & Vogel, 2019). Within dark web market environments, where anonymity, legal exposure, and information asymmetry elevate transaction risk, reputation signals become crucial inputs into buyers' cost-benefit calculations. Consistent with prior research showing that perceived certainty and risk impact shape decision-making (Albonetti, 1986; Klepper & Nagin, 1989; Pogarsky et al., 2018), the present findings demonstrate that sellers charge price premiums to reduce uncertainty, particularly for high-risk products.

The especially strong reputation premiums observed for non-drug products, including fraud and weapons, further reinforce the relevance of the rational choice perspective in understanding online illicit market behavior. These products often involve heightened legal penalties, health risks, and delivery concerns, which increase perceived risks for consumers. Vendor behavior is tied to consumer behavior through their ability to mark prices up for reducing these perceived risks. By contrast, cannabis transactions typically involve lower perceived legal and health risks, potentially reducing the economic leverage of reputation. Interestingly, opioids did not exhibit a significantly different rating-price relationship compared to cannabis, which may reflect the influence of substance dependence on decision-making and subsequently pricing, a finding supported by Olmstead and colleagues (2016). In these contexts, immediate access and affordability may outweigh concerns about vendor reputation, decreasing the extent to which trust can be monetized. These findings underscore how outside factors such as perceived risk and substance use can influence decision-making, and therefore, impact vendor pricing strategies. Vendors for opioids may attempt to set a more affordable price so consumers will purchase their product, rather than charge higher prices because consumers may be weighing availability and affordability more in their decision-making calculus compared to perceived risk.

Furthermore, there may be other factors beyond perceived risk that may influence decision-making and vendor pricing. As shown above, substance dependence may shift vendor pricing strategies, such as large supply, rarity of items, and specialized items. A supply shortage occurs when the quantity supplied of a product decreases, causing vendors to charge higher prices (Frank et al., 2021). By this logic, it would then be expected that during a supply surplus, product prices would drop, impacting the overall price of the item. Rare items may have the ability to be priced higher because the supply is low. Similar to a supply shortage, the smaller quantity supplied of these items may result in a markup in price that is somewhat independent of vendor reputation. Lastly, specialized items could include listings, typically for drug products, that are custom. Custom listings were included in the current study for drug products if the description included a valid weight and the vendor had feedback and previous sales. These custom listings presumably occur between buyers and sellers who have worked together before and have already established trust and had favorable past experiences. Therefore, the prices of these listings could experience both premiums and discounts. Vendors of custom listings could choose to set a higher price because they are going out of their way to ship an item they do not typically sell, or prices could be lower because they want to continue conducting business with the consumer. All of these unobserved characteristics of pricing could therefore influence price, absent of reputation on these dark web marketplaces, and future research should consider them when investigating price formation on dark web marketplaces.

The findings raise important questions regarding the generalizability of the reputation-price relationship across illicit markets. While reputation premiums appear to operate broadly across both drug and non-drug product categories, the magnitude and consistency of these effects vary considerably. The intercepts or base price of body modification drug product for the reputation-price relationships are 3.35 for rating-price and 3.28 for review-price, suggesting that the price begins higher than many of the drug product categories. This higher intercept and smaller variation in price ($3.50 to $903.52), when compared with other drug products, may lend to explain the insignificant findings for this product category. Additionally, body modification drugs are the second smallest drug category (N = 1,187 for ratings, N = 1,112 for reviews), which could also influence the magnitude of the relationship between reputation and price. Another example of intercepts potentially influencing the magnitude of the relationship would be guides and tutorials, where the intercepts are on the lower end for non-drug products at 1.33 for the rating-price relationship, and 1.34 for the review-price relationship. This product category though has one of the smaller price variations ($0.01 to $700) but ranks as the third largest non-drug category (N = 1,291 for ratings, N = 1,086 for reviews) which may allow for the magnitude of the relationship to be captured. Guides and tutorials in both models displayed a positive, significant association between reputation and price. So, while there are pricing differences displayed through the intercepts that do not factor in reputation, generally, many products, regardless of how large their intercepts are, display price premiums associated with vendor reputation.

This suggests that reputation operates as a general mechanism of market coordination and is sensitive to product-specific risk profiles. This conditional generalizability aligns with prior literature emphasizing that rational decision-making processes are moderated by context (Nagin & Paternoster, 1993; Paternoster & Simpson, 1996; Gül, 2009). For example, Nagin and Paternoster (1993) found that the propensity to offend is dependent on both individual factors and situational factors, demonstrating that decision-making is shaped by contextual conditions rather than being uniform across an environment. Similarly, Paternoster and Simpson (1996) applied the rational choice perspective to corporate crime and found that the decision to commit an offense was significantly associated with the organizational context of the firm, along with the perceived benefits and costs. The organizational context refers to how the organization of the firm encourages corporate crime**.** Together, these findings suggest that individuals evaluate risks and rewards within the specific environments in which decisions occur. Gül (2009) additionally notes that offenders do their best with the limited information available to them, further highlighting how decision-making is constrained by situational uncertainty. Thus, rather than conceptualizing reputation as a uniform pricing mechanism, the present study demonstrates that it functions as a signal whose economic value depends on how effectively it reduces uncertainty around risk for certain products. This decision-making process, dependent on context, highlights how framing from the rational choice perspective, the value of reputation signals will vary depending on how much uncertainty buyers face and therefore, how much risk a vendor believes their reputation can mitigate within the context of these dark web marketplaces.

Control Variables

Beyond the central reputation measures of ratings and reviews, several control variables yielded meaningful insights into marketplace dynamics. The first control variable of interest is the sales-feedback ratio. The sales-feedback ratio refers to the number of sales a listing has compared to the amount of feedback for that item. From table Appendix-1.2 displaying the descriptive statistics for the sales-feedback ratio for the rating-price relationship, guides and tutorials show a mean ratio of approximately 40 sales per feedback. This means that for every piece of feedback given for this product category, there are 40 sales. Additionally, for cannabis, the sales-feedback ratio mean is around 1.7, suggesting that on average, cannabis vendors are receiving close to two sales per a piece of feedback. The negative association between the sales-feedback ratio for various products for both reputation and price relationship suggests that as vendors sales increase but their number of feedback does not, the price of the product tends to decrease slightly. This finding is expected because positive seller reputations have been found to related to higher sale volumes for online illicit marketplaces (Przepriórka et al., 2017; Andrei & Veltri, 2025) and in online licit marketplaces (Diekmann et al., 2014). Since higher ratings are tied to consistently generating positive feedback through efficient package concealment, short delivery times, and quick vendor replies (Tzanetakis et al., 2016), the number of consumer feedback from ratings and reviews needs to closely mirror the number of sales for a vendor to appear trustworthy, and therefore, able to charge a price premium.

Weight displays a positive relationship for both the rating-price and review-price relationship. However, interpreting these results shows that a 1% increase in weight for drug products is always related to a less than 1% increase in price, suggesting that there are bulk discounts for heavier and larger orders. This finding is backed by prior literature that states that bulk discounts are typically offered for higher quantity and weight products (Aldridge & Décary-Hétu, 2014; Munksgaard & Tzanetakis, 2022). This suggests that buying in illicit marketplaces is a viable option for intermediaries and can function as a distributor, while still allowing street dealers to experience monetary gain. This result suggests that not only are vendors using their favorable reputations to set price but also looking at the quantity they are looking to sell. Possible explanations of these quantity discounts may be attributed to vendors not wanting to hold onto large quantities of illicit drugs and determining that risks of detection and legal consequences may outweigh the ability to charge higher prices. Also, vendors may price larger quantities lower to incentive intermediary buyers to purchase from them again, and once they are satisfied, leave a favorable review for other consumers to see.

Domestic shipping results are mostly as expected, with many vendors who ship products strictly domestically, generating price premiums net of reputation for many products categories other than weapons, which had a negative relationship between only shipping domestically and price. Psychedelics, carded items, counterfeit items, and fraud products all did not have a significant association with price if the vendor strictly shipped domestically for the rating and price relationship. Results suggest that products vary vastly in their shipping risks and perhaps that if a vendor has a favorable rating, consumers may view that as a factor that can decrease uncertainties and risks.

Since prior literature has established that vendors who ship domestically tend to have lower ratings (Décary-Hétu et al., 2016), so through this logic, vendors who ship strictly domestically would be assumed to have higher ratings. These higher ratings can generate from successful delivery (Tzanetakis et al., 2016), which can be tied to how well law enforcement in a given country is at intercepting packages. Moreover, if a vendor perceives their country's law enforcement is effective at intercepting packages, and they do not want to face the consequences of shipping illicit goods, they may opt to ship strictly domestically to avoid their goods traveling across borders. So, by shipping strictly domestically, vendors may generate more favorable reputations than vendors willing to ship internationally as well, allowing them to charge a price premium through displaying their success in prior deliveries.

Lastly, the physical package measure is strongly positive and significantly related to price for both products, net of reputation, for carded items and fraud. This means that vendors who ship their product in a physical package charge higher prices for these products compared to vendors who transfer their products digitally. The physical package control is included because there are different risks associated with shipping physical goods and transferring goods online. This result suggests that shipping a physical package impacts vendor pricing strategy. Potential reasons for this include that costs more to ship a physical package compared to transferring a digital product, and this increase in price due to shipping costs is included in the price.

Policy and Enforcement Implications

The findings from the current study carry important implications for law enforcement strategies and platform regulation for online illicit marketplaces. Through demonstrating that reputation functions as central mechanism of credibility generation and price formation, these results highlight vulnerability and resilience of these online illicit marketplaces. Understanding how reputation influences vendor and consumer behavior can help inform more targeted and impactful intervention by law enforcement.

Destabilizing the reputation systems that operate within these marketplaces, opposed to a full market shutdown, may influence consumer decision-making and vendor success. A potential infiltration of a marketplace targeting reputation would cause vendors to lose their favorable reputations, therefore, introducing more uncertainties surrounding transactions for consumers. By leveling the playing field, vendors could lose their ability to command price premiums, because their credible signals of favorable rating and positive reviews would not be able to reduce uncertainties and risks for consumers, not allowing vendors to monetize reputation anymore. These large market-wide shutdowns such as Operation Onymous targeted whole marketplaces, and the effects of this intervention were short-lived, with vendors simply moving to other sites (Décary-Hétu & Giommoni, 2017). This law enforcement intervention targets the supply of goods and services. However, since marketplaces following this attempt to disrupt supply led to an increase in marketplace security measures for these targeted marketplaces' successors (Décary-Hétu & Giommoni, 2017), perhaps a demand-side intervention should be attempted. By lowering the demand for goods and services through increasing risk and uncertainties around all products on these dark web marketplaces, sales may decrease, ultimately pushing vendors out of business.

The differential valuation of reputation across products, particularly with many non-drug products displaying stronger price premiums than drug products, various enforcement strategies may be needed to disrupt these marketplaces. Since non-drug products appear to be extremely dependent on their reputation systems to generate price premiums, especially through their ratings, a demand-side approach such as disrupting the reputations of vendors which then discourages consumers from making informed purchases may be a feasible option. However, drug products may need to take a different approach, such as allocating more resources to the postal and customs services who have the potential to intercept these packages and studying what countries who are more successful in package interception.

The postal service, where many of these products are traveling through, must be thoroughly informed about what to look for, and allocated more resources to increase package interceptions. Additionally, certain countries, like Australia are known to be poor locations to ship products to due to their high rate of package interception (Martin, 2014). Therefore, by studying what the government is doing in Australia to gain a reputation like this would be beneficial for countries to determine what the most effective strategy for interception is. Shipping strictly domestically was associated with price premiums for many products, suggesting that knowing a product does not have to go through customs reduces consumer and vendor risk. Therefore, if domestic shipping is seen as "less risky" and listing that are strictly domestic shipping are shown to be positively associated with price for many products, strategies for intercepting domestic packages with products from online illicit marketplaces need to increase in efficiency.

Limitations and Future Directions

This study makes several important contributions to understanding vendor reputation can impact price formation on online illicit marketplaces, such as its diverse product categories that allow for comparison in how reputation functions and can be monetized across products with various risk profiles. However, several limitations should be considered along with avenues for future research.

First, since the data provides just a snapshot of a three-day span of marketplace listings, temporal ordering cannot be disentangled if favorable reputations cause higher prices, or if vendors with higher prices are perceived to have higher quality products and then generate a favorable reputation. Przepiórka and colleagues (2017), however, in their data from the Silk Road 1.0 were able to capture vendor reputation changes over time, and how that impacted the pricing of their aggregate drugs measure. Their finding that highly rated sellers set their prices higher, then disentangles the temporal ordering of the ratings and prices, giving support to the current study's findings. A longitudinal analysis that tracks vendors over time would allow for temporal ordering in models and could better capture characteristics of vendors that could impact the reputation-price relationship.

Second, as shown in Appendix-3, there are a variety of subcategories of products located within the larger product categories used for this study. While the larger sample sizes of the categories studied here aid in obtaining accurate results, there may be issues with examining all products in their aggregate forms. For example, the mean price per gram of cannabis for the whole product category is around $90. This price per gram of the total category reflects the traditional buds and flower form of cannabis but also concentrates that tend to be more expensive. The differences in product categories would be interesting to parse out into product subcategories to explore if there could be differences in the rating-price relationship within categories as well.

Third, while this study theorizes about risk as a key mechanism that influences consumer decision-making and subsequently vendor pricing strategies, it is not directly measured. Product categories were assigned risks based on prior literature, however, risk is multidimensional, and future research would benefit from operationalizing it. Décary-Hétu and colleagues (2016) operationalized perceived effectiveness of law enforcement, yet no explanation of how or where the measure came from is offered. Integrating legal penalties, seizure rates, self-report measures of risk perceptions for vendors and consumers, and delivery success rates would all strengthen conclusions regarding how reputational signals function to mitigate risk within these uncertain environments.

Fourth, vendor-level clustering would reduce bias in the estimates. Vendors who sell large volumes of products may exert disproportionate influence on pricing norms and reputation dynamics, potentially biasing aggregate estimates. Future research and data collection should focus on including vendor names or an identification of vendors in data, so clustering during analyses can be performed to ensure accurate estimates.

Fifth, this study relies exclusively on scraped listing data from a single marketplace, AlphaBay. While previous studies have linked favorable reputations to price premiums, this may not be true for marketplaces with vastly different structures. Marketplaces can all function differently in terms of reputation systems, so future research should pursue comparative analyses across platforms to assess if there is heterogeneity in reputation and price formation not only between products, but between the same products on different marketplaces.

Finally, qualitative research could enrich understanding of truly how much reputation factors into pricing for vendors and decision-making for consumers. While behavioral patterns can be inferred from examining pricing dynamics, qualitative interviews or exploring dark web forums could provide another way to understand decision-making is impacted under such uncertain conditions. Masson and Bancroft (2018) conducted nine interviews with users of the dark web to collect information regarding how marketplaces operate and how individuals can build community within them. Interestingly, one participant noted that he had been scammed when purchasing from a vendor with a lower reputation (Masson & Bancroft, 2018), an answer that could be further examined at a larger scale with more participants and reputation and risk focused questions.

Conclusion

The current study demonstrates that reputation is a central economic mechanism through which trust, risk, and uncertainty are balanced in decision-making on dark web marketplaces. Drawing on signaling theory and rational choice perspectives, the analyses reveal that ratings are a dominant signal for shaping price across both drug and non-drug product categories, generating price premiums for products of varying risk profiles. These findings indicate that reputation operates as monetized trust and reliability, enabling vendors to convert favorable reputations into financial gain under conditions of uncertainty where buyers attempt to mitigate risks from information asymmetry. Importantly, products of varying risk profile differ significantly in their rating-price relationship, suggesting that reputation can be monetized, but perhaps the level of economic value relies on how much perceived risk the reputation can decrease. Finally, the current study also highlights that certain products yield stronger relationships with reviews and price opposed to ratings and price, highlighting that not only are there differences between how trust is monetized between products, but also how different reputation systems are used to mitigate risk and monetize reputation.

These findings advance signaling theory and the rational choice perspective by illustrating that the economic value of a credible signal of reputation is contingent on risk. This extends the application of the rational choice perspective to illicit online markets by showing that uncertainties surrounding risk influence decision-making in these uncertain environments. By showing that risk factors into how much economic value can be placed on a reputation signal extends signaling theory by highlighting that credible signals do not function uniformly but rather rely on how much uncertainty they reduce. From a policy and enforcement standpoint, the centrality of reputation systems highlights both vulnerabilities and intervention opportunities for law enforcement to explore. Disrupting trust infrastructures and ultimately the demand for products destabilizing these marketplaces. Non-drug products appear to be good targets for this type of intervention because many of these products have stronger rating-price relationships than drug products. Drug product interventions may benefit from investigating what other, high-interception rate countries are doing. Together, these insights underscore the value of theoretically informed enforcement strategies and contribute to a more nuanced understanding of governance, risk, and trust in illicit online markets.

Appendix

Supplemental Descriptive Statistics for the Rating-Price Relationship

Table Appendix-1.1: Descriptive Statistics for Vendor Levels

Data Frame	Mean	Median	Min	Max	SD	Total
Benzodiazepines	9.763	10	3	20	3.611	2390
Body Modification	9.856	11	4	17	2.907	1187
Cannabis	10.314	10	4	20	4.104	11414
Dissociatives	10.111	11	4	20	3.912	639
Ecstasy	9.829	10	4	20	4.008	3999
Opioids	9.734	10	3	20	3.619	3440
Prescription	9.394	9	4	17	3.524	2606
Psychedelics	9.51	10	3	20	3.332	2708
Stimulants	9.532	9	3	20	4.025	4908
Carded Items	10.147	11	3	14	2.964	517
Counterfeit Items	9.113	10	3	15	2.842	1154
Digital Products	9.965	10	4	15	3.127	1355
Fraud	8.722	9	3	20	2.657	4544
Guides and Tutorials	8.778	9	3	17	2.413	1291
Software and Security	8.375	8	3	15	2.211	648
Weapons	7.334	7	2	11	2.075	428

Table Appendix-1.2: Descriptive Statistics for Sales-Feedback Ratio

Data Frame	Mean	Median	Min	Max	SD	Total
Benzodiazepines	1.894	1.5	1	87.5	2.683	2390
Body Modification	2	1.731	1	11	1.188	1187
Cannabis	1.688	1.423	1	105	1.595	11414
Dissociatives	2.406	1.868	1	55	2.804	639
Ecstasy	1.986	1.667	1	126	2.398	3999
Opioids	1.866	1.5	1	36	1.568	3440
Prescription	1.924	1.59	1	22	1.35	2606
Psychedelics	1.971	1.667	1	17	1.17	2708
Stimulants	1.891	1.532	1	65	1.918	4908
Carded Items	2.627	1.5	1	88	5.552	517
Counterfeit Items	2.874	2	1	300	10.056	1154
Digital Products	6.593	2	1	3024.333	83.518	1355
Fraud	5.981	2	1	2540.818	45.387	4544
Guides and Tutorials	40.997	2.756	1	10356	445.501	1291

Software and Security	10.444	2.955	1	832	45.952	648
Weapons	1.955	1.321	1	56	3.166	428

Table Appendix-1.3: Descriptive Statistics for Domestic Shipping

Data Frame	Mean	Median	Min	Max	SD	Total
Benzodiazepines	0.564	1	0	1	0.496	2390
Body Modification	0.457	0	0	1	0.498	1187
Cannabis	0.539	1	0	1	0.499	11414
Dissociatives	0.357	0	0	1	0.479	639
Ecstasy	0.44	0	0	1	0.496	3999
Opioids	0.517	1	0	1	0.5	3440
Prescription	0.612	1	0	1	0.487	2606
Psychedelics	0.439	0	0	1	0.496	2708
Stimulants	0.401	0	0	1	0.49	4908
Carded Items	0.017	0	0	1	0.131	517
Counterfeit Items	0.076	0	0	1	0.266	1154
Fraud	0.015	0	0	1	0.12	4544
Weapons	0.145	0	0	1	0.352	428

Table Appendix-1.4: Descriptive Statistics for Weight in Milligrams

Data Frame	Mean	Median	Min	Max	SD	Total
Benzodiazepines	8651.62	200	0.05	5000000	116583.75	2390
Body Modification	6861.811	1000	0.001	1000000	53342.046	1187
Ecstasy	40350.076	5500	0.1	2000000	135633.05	3999
Opioids	42194.623	500	0.01	5443104	295041.31	3440
Prescription	3771.029	200	0.2	350000	16018.427	2606

Table Appendix-1.5: Descriptive Statistics for Weight in Grams

Data Frame	Mean	Median	Min	Max	SD	Total
Cannabis	52.432	10	0	20411.7	246.121	11414
Dissociatives	26.842	3.5	0.01	1000	90.833	639
Psychedelics	127.226	0.125	0	31250	1243.835	2708
Stimulants	39.662	3.5	0.005	5000	197.699	4908

Table Appendix-1.6: Descriptive Statistics for Physical Package						
Data Frame	**Mean**	**Median**	**Min**	**Max**	**SD**	**Total**
Carded Items	0.491	0	0	1	0.5	517
Fraud	0.103	0	0	1	0.304	4544

Supplemental Descriptive Statistics for the Review-Price Relationship

Table Appendix-2.1: Descriptive Statistics for Vendor Levels						
Data Frame	**Mean**	**Median**	**Min**	**Max**	**SD**	**N**
Benzodiazepines	9.812	10	3	20	3.608	2314
Body Modification	9.923	11	4	17	2.887	1112
Cannabis	10.345	10	4	20	4.107	11081
Dissociatives	10.165	11	4	20	3.923	619
Ecstasy	9.884	10	4	20	4.005	3891
Opioids	9.77	10	3	20	3.629	3342
Prescription	9.439	9	4	17	3.52	2487
Psychedelics	9.551	10	3	20	3.325	2627
Stimulants	9.589	10	3	20	4.034	4753
Carded Items	10.201	11	3	14	2.958	457
Counterfeit Items	9.132	10	3	15	2.84	1057
Digital Products	10.042	10	4	15	3.118	1155
Fraud	8.795	9	3	20	2.686	3952
Guides and Tutorials	8.82	9	3	17	2.407	1086
Software and Security	8.474	8	3	15	2.168	559
Weapons	7.334	7	2	11	2.083	398

Table Appendix-2.2: Descriptive Statistics for Sales-Feedback Ratio						
Data Frame	**Mean**	**Median**	**Min**	**Max**	**SD**	**N**
Benzodiazepines	1.886	1.5	1	87.5	2.692	2314
Body Modification	2.01	1.745	1	11	1.188	1112
Cannabis	1.683	1.429	1	105	1.595	11081
Dissociatives	2.381	1.857	1	55	2.796	619
Ecstasy	1.987	1.667	1	126	2.419	3891
Opioids	1.865	1.5	1	36	1.574	3342
Prescription	1.915	1.595	1	22	1.319	2487
Psychedelics	1.964	1.667	1	17	1.129	2627
Stimulants	1.886	1.533	1	65	1.921	4753
Carded Items	2.678	1.5	1	88	5.873	457
Counterfeit Items	2.622	2	1	109.5	5.079	1057

Digital Products	6.693	2	1	3024.333	89.826	1155
Fraud	6.196	2	1	2540.818	48.462	3952
Guides and Tutorials	38.07	2.75	1	10356	400.871	1086
Software and Security	10.056	2.933	1	832	43.748	559
Weapons	1.968	1.333	1	56	3.265	398

Table Appendix-2.3: Descriptive Statistics for Domestic Shipping

Data Frame	Mean	Median	Min	Max	SD	N
Benzodiazepines	0.564	1	0	1	0.496	2314
Body Modification	0.466	0	0	1	0.499	1112
Cannabis	0.539	1	0	1	0.498	11081
Dissociatives	0.355	0	0	1	0.479	619
Ecstasy	0.444	0	0	1	0.497	3891
Opioids	0.521	1	0	1	0.5	3342
Prescription	0.609	1	0	1	0.488	2487
Psychedelics	0.44	0	0	1	0.497	2627
Stimulants	0.4	0	0	1	0.49	4753
Carded Items	0.018	0	0	1	0.131	457
Counterfeit Items	0.078	0	0	1	0.268	1057
Fraud	0.016	0	0	1	0.126	3952
Weapons	0.143	0	0	1	0.351	398

Table Appendix-2.4: Descriptive Statistics for Weight in Milligrams

Data Frame	Mean	Median	Min	Max	SD	N
Benzodiazepines	8177.081	200	0.05	5000000	117126.38	2314
Body Modification	6307.333	1000	0.001	756250	46339.048	1112
Ecstasy	40292.212	5500	0.1	2000000	135509.78	3891
Opioids	41579.944	500	0.01	5443104	296684.61	3342
Prescription	3844.011	200	0.2	350000	16335.256	2487

Table Appendix-2.5: Descriptive Statistics for Weight in Grams

Data Frame	Mean	Median	Min	Max	SD	N
Cannabis	52.055	9	0	20411.7	248.209	11081
Dissociatives	26.657	3.5	0.01	1000	90.199	619
Psychedelics	126.985	0.11	0	31250	1257.182	2627
Stimulants	37.558	3.5	0.005	5000	180.022	4753

Table Appendix-2.6: Descriptive Statistics for Physical Package						
Data Frame	**Mean**	**Median**	**Min**	**Max**	**SD**	**N**
Carded Items	0.495	0	0	1	0.501	457
Fraud	0.107	0	0	1	0.31	3952

Product Categories Expanded

Appendix-3: Product Categories							
Drugs				**Non-Drugs**			
Data Frame	Product Type	Data Frame	Product Type	Data Frame	Product Type	Data Frame	Product Type
Benzodiazepines	Pills	Opioids	Pills	Carded Items	Digital	Software and Security	Hosting
	Powder		Fentanyl & RCs		Electronics		Socks
Body Modification	Steroids		Heroin		Appliances		VPN
	Weight Loss	Prescription	Prescription	Counterfeit Items	Money		Botnets & Malware
Cannabis	Buds & Flowers	Psychedelics	Shrooms		Electronics		Exploits
	Concentrates		NBOME		Fake IDs		Security Software
	Synthetic		LSD		Jewelry		Exploit Kits
	Edibles		DMT		Clothing		Legit Software
	Topicals & Others		2C-B	Digital Products	E-Books		Fraud Software
	Other		DMA / DOX		Game Keys	Weapons	Hand Weapons
	Hash		LSA	Fraud	Accounts & Bank Drops		Ammunition
	Shake		Mescaline		CVV & Cards		Explosives
	Prerolls	Stimulants	Cocaine		Personal Information & Scans		Pistols
	Seeds		Speed		Dumps		Long-Range Guns
Dissociatives	Ketamine		Crack	Guides and Tutorials	Fraud		
	MXE		Meth		Drugs		
	GHB		Pressed Pills		Security & Anonymity		
Ecstasy	Pills				Hacking		
	MDMA				Social Engineering		
	MDA						

Other Methylone & BK

Pairwise Comparisons for All Products

Appendix-4.1: Equality of Coefficients Test for Drug Products

Comparison	z	p-value
Benzodiazepines vs. Body Modification	2.37	0.018*
Benzodiazepines vs. Cannabis	-0.8	0.427
Benzodiazepines vs. Dissociatives	0.6	0.549
Benzodiazepines vs. Ecstasy	-0.22	0.829
Benzodiazepines vs. Opioids	-1.77	0.076
Benzodiazepines vs. Prescription	0.52	0.605
Benzodiazepines vs. Psychedelics	-3.31	0.001***
Benzodiazepines vs. Stimulants	-4.59	0.000***
Body Modification vs. Cannabis	-3.63	0.000***
Body Modification vs. Dissociatives	-1.54	0.124
Body Modification vs. Ecstasy	-2.97	0.003**
Body Modification vs. Opioids	-3.98	0.000***
Body Modification vs. Prescription	-1.58	0.115
Body Modification vs. Psychedelics	-5.27	0.000***
Body Modification vs. Stimulants	-6.73	0.000***
Cannabis vs. Dissociatives	1.36	0.174
Cannabis vs. Ecstasy	0.89	0.374
Cannabis vs. Opioids	-1.57	0.116
Cannabis vs. Prescription	1.24	0.217
Cannabis vs. Psychedelics	-3.51	0.000***
Cannabis vs. Stimulants	-6.33	0.000***
Dissociatives vs. Ecstasy	-0.87	0.385
Dissociatives vs. Opioids	-2.13	0.033*
Dissociatives vs. Prescription	-0.06	0.949
Dissociatives vs. Psychedelics	-3.48	0.001***
Dissociatives vs. Stimulants	-4.45	0.000***
Ecstasy vs. Opioids	-1.97	0.049*
Ecstasy vs. Prescription	0.77	0.444
Ecstasy vs. Psychedelics	-3.75	0.000***
Ecstasy vs. Stimulants	-6.09	0.000***
Opioids vs. Prescription	2.02	0.043*
Opioids vs. Psychedelics	-1.66	0.097
Opioids vs. Stimulants	-2.5	0.013*
Prescription vs. Psychedelics	-3.35	0.001***

Prescription vs. Stimulants	-4.26	0.000***
Psychedelics vs. Stimulants	-0.34	0.731

Appendix-4.2: Equality of Coefficients Test for Drug and Non-Drug Products

Comparison	z	p-value
Benzodiazepines vs. Carded Items	-3.12	0.002**
Benzodiazepines vs. Counterfeit Items	-4.15	0.000***
Benzodiazepines vs. Digital Products	-2.09	0.036*
Benzodiazepines vs. Fraud	-7.77	0.000***
Benzodiazepines vs. Guides and Tutorials	-0.6	0.546
Benzodiazepines vs. Software and Security	-3.09	0.002**
Benzodiazepines vs. Weapons	-2.5	0.012*
Body Modification vs. Carded Items	-3.95	0.000***
Body Modification vs. Counterfeit Items	-5.6	0.000***
Body Modification vs. Digital Products	-3.94	0.000***
Body Modification vs. Fraud	-9.35	0.000***
Body Modification vs. Guides and Tutorials	-2.41	0.016*
Body Modification vs. Software and Security	-4.46	0.000***
Body Modification vs. Weapons	-3.23	0.001**
Cannabis vs. Carded Items	-2.99	0.003**
Cannabis vs. Counterfeit Items	-4.18	0.000***
Cannabis vs. Digital Products	-1.91	0.056
Cannabis vs. Fraud	-9.18	0.000***
Cannabis vs. Guides and Tutorials	-0.18	0.856
Cannabis vs. Software and Security	-2.97	0.003**
Cannabis vs. Weapons	-2.37	0.018*
Dissociatives vs. Carded Items	-3.29	0.001**
Dissociatives vs. Counterfeit Items	-4.31	0.000***
Dissociatives vs. Digital Products	-2.4	0.016*
Dissociatives vs. Fraud	-7.39	0.000***
Dissociatives vs. Guides and Tutorials	-1.03	0.304
Dissociatives vs. Software and Security	-3.31	0.001***
Dissociatives vs. Weapons	-2.66	0.008**
Ecstasy vs. Carded Items	-3.12	0.002**
Ecstasy vs. Counterfeit Items	-4.37	0.000***
Ecstasy vs. Digital Products	-2.21	0.027*
Ecstasy vs. Fraud	-9.06	0.000***
Ecstasy vs. Guides and Tutorials	-0.52	0.600
Ecstasy vs. Software and Security	-3.18	0.001**
Ecstasy vs. Weapons	-2.48	0.013*

Opioids vs. Carded Items	-2.52	0.012*
Opioids vs. Counterfeit Items	-3.01	0.003**
Opioids vs. Digital Products	-0.66	0.506
Opioids vs. Fraud	-6.13	0.000***
Opioids vs. Guides and Tutorials	0.72	0.472
Opioids vs. Software and Security	-2.06	0.040*
Opioids vs. Weapons	-1.99	0.047*
Prescription vs. Carded Items	-3.25	0.001**
Prescription vs. Counterfeit Items	-4.22	0.000***
Prescription vs. Digital Products	-2.31	0.021*
Prescription vs. Fraud	-7.19	0.000***
Prescription vs. Guides and Tutorials	-0.96	0.337
Prescription vs. Software and Security	-3.24	0.001**
Prescription vs. Weapons	-2.63	0.008**
Psychedelics vs. Carded Items	-1.91	0.056
Psychedelics vs. Counterfeit Items	-1.8	0.072
Psychedelics vs. Digital Products	0.73	0.464
Psychedelics vs. Fraud	-4.22	0.000***
Psychedelics vs. Guides and Tutorials	1.96	0.050*
Psychedelics vs. Software and Security	-1	0.319
Psychedelics vs. Weapons	-1.46	0.143
Stimulants vs. Carded Items	-1.85	0.064
Stimulants vs. Counterfeit Items	-1.76	0.078
Stimulants vs. Digital Products	1.14	0.256
Stimulants vs. Fraud	-4.85	0.000***
Stimulants vs. Guides and Tutorials	2.49	0.013*
Stimulants vs. Software and Security	-0.88	0.378
Stimulants vs. Weapons	-1.4	0.162

References

Ackerman, D., Hu, J., & Gross, B. (2024). Whose Opinions do We Listen to? The Influence of Online Product Ratings and Price on Consumers. *Journal of Applied Marketing Theory*, *11*(1), 19–33. https://doi.org/10.20429/jamt.2024.110103

Albonetti, C. A. (1986). CRIMINALITY, PROSECUTORIAL SCREENING, AND UNCERTAINTY: TOWARD A THEORY OF DISCRETIONARY DECISION MAKING IN FELONY CASE PROCESSINGS. *Criminology*, *24*(4), 623–644. https://doi.org/10.1111/j.1745-9125.1986.tb01505.x

Aldridge, J., & Décary-Hétu, D. (2014). Not an "Ebay for Drugs": The Cryptomarket "Silk Road" as a Paradigm Shifting Criminal Innovation. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2436643

Andrei, F., & Veltri, G. A. (2024). Social influence in the darknet market: The impact of product descriptions on cocaine sales. *International Journal of Drug Policy*, *124*, 104328. https://doi.org/10.1016/j.drugpo.2024.104328

Andrei, F., & Veltri, G. A. (2025a). Signalling strategies and opportunistic behaviour: Insights from dark-net markets. *PLOS ONE*, *20*(3), e0319794. https://doi.org/10.1371/journal.pone.0319794

Andrei, F., & Veltri, G. A. (2025b). Status Spill-Over in Cryptomarket for Illegal Goods. *Social Science Computer Review*, *43*(3), 626–648. https://doi.org/10.1177/08944393241286339

Barratt, M. J., & Aldridge, J. (2016). Everything you always wanted to know about drug cryptomarkets* (*but were afraid to ask). *International Journal of Drug Policy*, *35*, 1–6. https://doi.org/10.1016/j.drugpo.2016.07.005

Beccaria, C. (1764). *On Crimes and Punishment*. Bobbs-Merril.

Becker, G. S. (Ed.). (1968). Crime and Punishment: An Economic Approach. *Journal of Political Economy*, *76*(2), 169–217.

Behrman, A. D. (2008). Luck of the Draw: Common Adulterants Found in Illicit Drugs. *Journal of Emergency Nursing*, *34*(1), 80–82. https://doi.org/10.1016/j.jen.2007.10.001

Bentham, J. (1781). *Principles of Morals and Legislation*. Athlone.

Bonnet, U., Specka, M., Soyka, M., Alberti, T., Bender, S., Grigoleit, T., Hermle, L., Hilger, J., Hillemacher, T., Kuhlmann, T., Kuhn, J., Luckhaus, C., Lüdecke, C., Reimer, J., Schneider, U., Schroeder, W., Stuppe, M., Wiesbeck, G. A., Wodarz, N., … Scherbaum, N. (2020). Ranking the Harm of Psychoactive Drugs Including Prescription Analgesics to Users and Others–A Perspective of German Addiction Medicine Experts. *Frontiers in Psychiatry*, *11*, 592199. https://doi.org/10.3389/fpsyt.2020.592199

Bonta, V., Kumaresh, N., & Janardhan, N. (2019). A Comprehensive Study on Lexicon Based Approaches for Sentiment Analysis. *Asian Journal of Computer Science and Technology*, *8*(S2), 1–6. https://doi.org/10.51983/ajcst-2019.8.S2.2037

Bruce, N., Haruvy, E., & Rao, R. (2004). Seller rating, price, and default in online auctions. *Journal of Interactive Marketing*, *18*(4), 37–50. https://doi.org/10.1002/dir.20021

Childs, A., Coomber, R., & Bull, M. (2020). Do Online Illicit Drug Market Exchanges Afford Rationality? *Contemporary Drug Problems*, *47*(4), 302–319. https://doi.org/10.1177/0091450920934186

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling Theory: A Review and Assessment. *Journal of Management*, *37*(1), 39–67. https://doi.org/10.1177/0149206310388419

Connelly, B. L., Certo, S. T., Reutzel, C. R., DesJardine, M. R., & Zhou, Y. S. (2025). Signaling Theory: State of the Theory and Its Future. *Journal of Management*, *51*(1), 24–61. https://doi.org/10.1177/01492063241268459

Décary-Hétu, D., & Giommoni, L. (2017). Do police crackdowns disrupt drug cryptomarkets? A longitudinal analysis of the effects of Operation Onymous. *Crime, Law and Social Change*, *67*(1), 55–75. https://doi.org/10.1007/s10611-016-9644-4

Décary-Hétu, D., Paquet-Clouston, M., & Aldridge, J. (2016). Going international? Risk taking by cryptomarket drug vendors. *International Journal of Drug Policy*, *35*, 69–76. https://doi.org/10.1016/j.drugpo.2016.06.003

Diekmann, A., Jann, B., Przepiorka, W., & Wehrli, S. (2014). Reputation Formation and the Evolution of Cooperation in Anonymous Online Markets. *American Sociological Review*, *79*(1), 65–85. https://doi.org/10.1177/0003122413512316

ElBahrawy, A., Alessandretti, L., Rusnac, L., Goldsmith, D., Teytelboym, A., & Baronchelli, A. (2020). Collective dynamics of dark web marketplaces. *Scientific Reports*, *10*(1), 18827. https://doi.org/10.1038/s41598-020-74416-y

Espinosa, R. (2019). Scamming and the reputation of drug dealers on Darknet Markets. *International Journal of Industrial Organization*, *67*, 102523. https://doi.org/10.1016/j.ijindorg.2019.102523

Frank, R. G., Mcguire, T. G., & Nason, I. (2021). The Evolution of Supply and Demand in Markets for Generic Drugs. *The Milbank Quarterly*, *99*(3), 828–852. https://doi.org/10.1111/1468-0009.12517

Georgoulias, D., Pedersen, J. M., Falch, M., & Vasilomanolakis, E. (2021). A qualitative mapping of Darkweb marketplaces. *2021 APWG Symposium on Electronic Crime Research (eCrime)*, 1–15. https://doi.org/10.1109/eCrime54498.2021.9738766

Goonetilleke, P., Knorre, A., & Kuriksha, A. (2023). Hydra: Lessons from the world's largest darknet market. *Criminology & Public Policy*, *22*(4), 735–777. https://doi.org/10.1111/1745-9133.12647

Gül, S. K. (2009). An Evaluation of the Rational Choice Theory in Criminology. *Sociology and Applied Science*, *4*(8), 36-44

Haynie, D. L., & Duxbury, S. W. (2024). Online Illegal Cryptomarkets. *Annual Review of Sociology*, *50*(1), 671–690. https://doi.org/10.1146/annurev-soc-090523-052916

Hutto, C., & Gilbert, E. (2014). VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. *Proceedings of the International AAAI Conference on Web and Social Media*, *8*(1), 216–225. https://doi.org/10.1609/icwsm.v8i1.14550

Jacoby, J. (1984). Perspectives on Information Overload. *Journal of Consumer Research, 10*(4), 432-435. https://doi.org/10.1086/208981

Jacques, S., Allen, A., & Wright, R. (2014). Drug Dealers' Rational Choices on Which Customers to Rip-O. *International Journal of Drug Policy*, *25*(2), 251–256. https://doi.org/10.1016/j.drugpo.2013.11.010

Khoo, C. S., & Johnkhan, S. B. (2018). Lexicon-based sentiment analysis: Comparative evaluation of six sentiment lexicons. *Journal of Information Science*, *44*(4), 491–511. https://doi.org/10.1177/0165551517703514

Knight, F. H. (1921). *Risk, uncertainty and profit*. Houghton Mifflin.

Ladegaard, I. (2020). Open Secrecy: How Police Crackdowns and Creative Problem-Solving Brought Illegal Markets out of the Shadows. *Social Forces*, *99*(2), 532–559. https://doi.org/10.1093/sf/soz140

Lee, C., & Nolte, K. B. (2001). Two separate unintentional fatalities with the same revolver. *Annals of Emergency Medicine*, *37*(3), 333–336. https://doi.org/10.1067/mem.2001.112251

LeRoy, S. F., & Singell, L. D. (1987). Knight on Risk and Uncertainty. *Journal of Political Economy*, *95*(2), 394–406. https://doi.org/10.1086/261461

Li, T., Wang, X., & Wu, Y. (2020). Pricing Strategies in Presence of Online Consumer Ratings—From the Product Customization Perspective. *Journal of Theoretical and Applied Electronic Commerce Research*, *15*(3), 84–100. https://doi.org/10.4067/S0718-18762020000300107

Ma, Q., Huang, J., Basar, T., Liu, J., & Chen, X. (2021). Reputation and Pricing Dynamics in Online Markets. *IEEE/ACM Transactions on Networking*, *29*(4), 1745–1759. https://doi.org/10.1109/TNET.2021.3071506

Martin, J. (2014). Lost on the *Silk Road*: Online drug distribution and the 'cryptomarket.' *Criminology & Criminal Justice*, *14*(3), 351–367. https://doi.org/10.1177/1748895813505234

Martin, J., Munksgaard, R., Coomber, R., Demant, J., & Barratt, M. J. (2020). Selling Drugs on Darkweb Cryptomarkets: Differentiated Pathways, Risks and Rewards. *The British Journal of Criminology*, *60*(3), 559–578. https://doi.org/10.1093/bjc/azz075

Masson, K., & Bancroft, A. (2018). 'Nice people doing shady things': Drugs and the morality of exchange in the darknet cryptomarkets. *International Journal of Drug Policy*, *58*, 78–84. https://doi.org/10.1016/j.drugpo.2018.05.008

Mavlanova, T., Benbunan-Fich, R., & Koufaris, M. (2012). Signaling theory and information asymmetry in online commerce. *Information & Management*, *49*(5), 240–247. https://doi.org/10.1016/j.im.2012.05.004

Miech, R. A., Johnston, L. D., Patrick, M. E., & O'Malley, P. M. (2025). *Overview and detailed results for secondary school students*.
Moeller, K., Munksgaard, R., & Demant, J. (2021). Illicit drug prices and quantity discounts: A comparison between a cryptomarket, social media, and police data. *International Journal of Drug Policy*, *91*, 102969. https://doi.org/10.1016/j.drugpo.2020.102969
Moeller, K., & Sandberg, S. (2019). Putting a price on drugs: An economic sociological study of price formation in illegal drug markets. *Criminology*, *57*(2), 289–313. https://doi.org/10.1111/1745-9125.12202
Munksgaard, R. (2024). Marketness and Governance: A Typology of Illicit Online Markets. *Deviant Behavior*, *45*(12), 1711–1728. https://doi.org/10.1080/01639625.2024.2323526
Munksgaard, R., & Tzanetakis, M. (2022). Uncertainty and risk: A framework for understanding pricing in online drug markets. *International Journal of Drug Policy*, *101*, 103535. https://doi.org/10.1016/j.drugpo.2021.103535
Nagin, D. S. (2013). Deterrence: A Review of the Evidence by a Criminologist for Economists. *Annual Review of Economics*, *5*(1), 83–105. https://doi.org/10.1146/annurev-economics-072412-131310
Nagin, D. S., & Paternoster, R. (1993). Enduring Individual Differences and Rational Choice Theories of Crime. *Law and Society Review, 27*(3), 467. https://doi.org/10.2307/3054102
Ngo, F. T., Marcum, C., & Belshaw, S. (2023). The Dark Web: What Is It, How to Access It, and Why We Need to Study It. *Journal of Contemporary Criminal Justice*, *39*(2), 160–166. https://doi.org/10.1177/10439862231159774
Nolan, M. L., Shamasunder, S., Colon-Berezin, C., Kunins, H. V., & Paone, D. (2019). Increased Presence of Fentanyl in Cocaine-Involved Fatal Overdoses: Implications for Prevention. *Journal of Urban Health*, *96*(1), 49–54. https://doi.org/10.1007/s11524-018-00343-z
Nutt, D., King, L. A., Saulsbury, W., & Blakemore, C. (2007). Development of a rational scale to assess the harm of drugs of potential misuse. *The Lancet*, *369*(9566), 1047–1053. https://doi.org/10.1016/S0140-6736(07)60464-4
Olmstead, T. A., Alessi, S. M., Kline, B., Pacula, R. L., & Petry, N. M. (2015). The price elasticity of demand for heroin: Matched longitudinal and experimental evidence. *Journal of Health Economics*, *41*, 59–71. https://doi.org/10.1016/j.jhealeco.2015.01.008
Paternoster, R., Brame, R., Mazerolle, P., & Piquero, A. (1998). USING THE CORRECT STATISTICAL TEST FOR THE EQUALITY OF REGRESSION COEFFICIENTS. *Criminology*, *36*(4), 859–866. https://doi.org/10.1111/j.1745-9125.1998.tb01268.x
Paternoster, R., & Simpson, S. (1996). Sanction Threats and Appeals to Morality: Testing a Rational Choice Model of Corporate Crime. *Law & Society Review*, *30*(3), 549–583. https://doi.org/10.2307/3054128
Pogarsky, G., Roche, S. P., & Pickett, J. T. (2018). Offender Decision-Making in Criminology: Contributions from Behavioral Economics. *Annual Review of Criminology*, *1*(1), 379–400. https://doi.org/10.1146/annurev-criminol-032317-092036
Przepiórka, W., Norbutas, L., & Corten, R. (2017). Order without Law: Reputation Promotes Cooperation in a Cryptomarket for Illegal Drugs. *European Sociological Review*, *33*(6), 752–764. https://doi.org/10.1093/esr/jcx072
Resnick, P., Kuwabara, K., Zeckhauser, R., & Friedman, E. (2000). Reputation systems. *Communications of the ACM, 43(12),* 45-48.
Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics*, *69*(1), 239-258. https://doi.org/10.2307/1884852
Spence, M. (1973). Job Market Signaling. *The Quarterly Journal of Economics*, *87*(3), 355. https://doi.org/10.2307/1882010
Substance Abuse and Mental Health Services Adminstration. (2021) *Key Substance Use and Mental Health Indicators in the United States: Results from the 2021 National Survey on Drug Use and Health*.
Sunada, T. (2024). Why Do Product Prices Affect Review Ratings? Evidence from a Japanese Online Travel Agency. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4814344

Taylor, M., Mackay, K., Murphy, J., McIntosh, A., McIntosh, C., Anderson, S., & Welch, K. (2012). Quantifying the RR of harm to self and others from substance misuse: Results from a survey of clinical experts across Scotland. *BMJ Open*, *2*(4), e000774. https://doi.org/10.1136/bmjopen-2011-000774

Thomas, K. J., & Vogel, M. (2019). Testing a rational choice model of "desistance:" Decomposing changing expectations and changing utilities. *Criminology*, *57*(4), 687–714. https://doi.org/10.1111/1745-9125.12223

Thompson, S., & Haynes, M. (2017). The Value of Online Seller Reputation: Evidence from a Price Comparison Site. *Managerial and Decision Economics*, *38*(3), 302–313. https://doi.org/10.1002/mde.2777

Tzanetakis, M. (2018). Comparing cryptomarkets for drugs. A characterisation of sellers and buyers over time. *International Journal of Drug Policy*, *56*, 176–186. https://doi.org/10.1016/j.drugpo.2018.01.022

Tzanetakis, M., Kamphausen, G., Werse, B., & Von Laufenberg, R. (2016). The transparency paradox. Building trust, resolving disputes and optimising logistics on conventional and online drugs markets. *International Journal of Drug Policy*, *35*, 58–68. https://doi.org/10.1016/j.drugpo.2015.12.010

van Waardenberg, L. (2021). *Reputation in AlphaBay: The effect of forum discussions on the business success of cryptomarket sellers*.

Zambiasi, D. (2022). Drugs on the Web, Crime in the Streets. The Impact of Shutdowns of Dark Net Marketplaces on Street Crime. *Journal of Economic Behavior & Organization*, *202*, 274–306. https://doi.org/10.1016/j.jebo.2022.08.008