Insurance Pricing in Darknet Drug Markets

Madeline Hess

March 9, 2019

Abstract

Dark Net Markets create an ideal environment to study insurance mechanisms, because they have asymmetric information and little to no contract enforcement. This study uses data collected on the Dream Market from 2015 and 2017 to explore the impact of two weak insurance mechanisms, (1) reputation signaling through vendor ratings and (2) contract enforcement through escrow options, on product prices. I find that a one star increase in rating is associated with a 33.8% increase in the price of one gram of pure cocaine, and that product listings that offer escrow are associated with a 13.0% decrease in price. I conclude that buyers are willing to pay a premium to purchase insurance through reputation signaling and to avoid purchasing insurance through contract enforcement.

Keywords: Dark Net Markets, Insurance Premium, Reputation Signaling, Escrow

1 Introduction

"I am sorry guys but I have scammed you." (9THWonder, qtd. in Christian)

Internet markets are riddled with scams. Exit scams occur during buyer-seller interactions when a buyer pays the seller, but the seller exits the market without providing buyer with the promised good or service (Pearson 2015). Scamming issues resulting from asymmetric information have been documented in a variety of markets, from eBay (Resnick and Zeckhauser 2002) to the darknet, but darknet drug markets provide an ideal space to study this phenomenon. In addition to providing access to large volumes of data, dark net markets (DNMs) are entirely anonymous, have little or no contract enforcement, face adverse selection and asymmetric information, facilitate low levels of trust between buyers and sellers, and lack market insurance by construction.

A variety of weak insurance mechanisms have been implemented by market administrators to reduce the occurrence of scams. These mechanisms include feedback systems (in which buyers review transactions and generate seller reputations) and escrow payment systems (in which the administrators of marketplaces hold funds until a buyer verifies a transaction has been completed). Through these mechanisms, DNMs offer buyers insurance via (1) reputation signaling, because ratings and reviews give buyers updated information with which to predict vendors' expected behavior; and (2) weakly improved contract enforcement using the escrow option.

Classical economic theory leads us to believe that buyers will be willing to pay some premium in exchange for insurance that enables them to maximize their expected value in a risky transaction (Pauly 1968). How much are people willing to pay for even weak insurance when they have no insurance whatsoever? I seek to identify this premium by testing for a price differential between products with and without the forms of insurance available on DNMs. This study focuses on the impact of reputation signaling through vendor ratings, as previous work has already illustrated an association between the escrow mechanism and increased product prices (Chun 2018). I first test this theory on a dataset of cocaine market listings, then expand my analysis to a full market sample to test the external validity of my findings.

2 Literature Review

The market for illicit services and substances on the darknet is massive. Data collected on the Silk Road alone indicated \$27.0 million in drug sales from 2013 to 2015 (*The Economist* 2016). In 2015, the market is thought to have had a gross turnover of \$150-\$180 million (ibid.). MDMA and ecstasy, marijuana, and cocaine make up the biggest share of the online drug market, and were valued at \$7.7 million, \$5.7 million and \$5.2 million respectively over 2013 to 2015 (ibid.). Further evidence of market size is visible in the use of its primary currency and payment method, Bitcoin. Approximately 26% of Bitcoin users surveyed predominantly used the currency for illegal activity, amounting to \$76 billion of business per year (Foley et al. 2018, 23-24).

Buyers tend to buy small rather than large quantities of drugs at a time. Demand for drugs on DNMs largely suggests that buyers purchase drugs for personal use or social drug dealing, rather than for redistribution (Demant et al. 2015, 42). The majority (89%) of transactions sampled were for purchase of products that were valued at \$300 or below (ibid. 59). One study found that just 10% of buyers accounted for 50% of drug purchases during the study period and the vast majority of buyers did not make regular repeated transactions (Norbutas 2018, 96).

Seller feedback seems to be a reasonably accurate proxy for observing actual product quality. Scamming behavior generates huge reputation costs to sellers, as angry buyers often leverage reviews systems to prevent other buyers from being scammed (Bolton et al. 2004).

Resnick and Zeckhauser (2002) examined the role of reputation systems at deterring scams on eBay and identifies several major findings about seller feedback. Buyers provided feedback for sellers for 52.1% of transactions, 99.1% of comments were positive, and feedback was predictive of seller performance (Resnick and Zeckhauser 2002, 11). I assume that response rate and quality of seller feedback will be similarly high, if not better, for illegal markets, in which buyers depend on this information in assessing risk and making purchase decisions. As Lorenzo-Dus et al. (2018) explain, "Trust is a key concern in the hidden net; those behind the creation and/or administration of crypto-(drug) markets are known to go to considerable lengths to show that members can trust that transactions therein are 'safe', that is, there is a low risk of being caught by law enforcement and of being scammed by other members" (2). The findings from the study conducted by Lorenzo-Dus et al. on data from the Silk Road corroborate this claim that buyers on dark net markets are actively engaged in provision and analysis of feedback and advice (ibid. 17).

Previous research indicates consumers are willing to pay for moderately improved contract enforcement in DNMs. Chun (2018) studied the price differential between products with and without escrow using Everling's (2017) data on cocaine prices and vendor information. He found that product listings offering escrow were associated with an 11.2% increase in price. Despite countermeasures like ratings and escrow, although they are popularly used, buyers in DNMs continue to face a nonzero chance of being ripped off (Chun 2018). Consequently, I assume that insurance mechanisms are weak, incomplete and imperfect.

My study builds on Chun's (2018) findings and aims to diagnose the relationship between price and seller rating in the same dataset to elucidate buyers' willingness to pay for insurance through reputation signaling. As a means of validating the external validity of my findings, I later expand the analysis to consider a sample of the full market, including all market categories.

3 Data

My analysis examines snapshots of the Dream Market, a widely known DNM, in 2015 and 2017. I use two datasets in my analysis, one of which is original.

First, Skip Everling, a data scientist and researcher at the artificial intelligence company Clarifai, constructed a dataset with roughly 1,500 product listings for cocaine and accompanying vendor reviews with a scrape of the dark net in July of 2017 (Everling 2017). I use this dataset in my preferred specification, so as to have comparable results with Chun (2018).

Next, Branwen et al. released a publicly available dataset considering 3 years of near daily web crawls of 89 DNMs. I constructed a dataset of 800 observations of listings for all product categories and vendor information using a simple random sample of approximately 30 observations per day. I scraped this information from the Dream Market archives in Branwen et al.'s DNM Archives crawl set covering January 1st, 2015 through July 3rd, 2015. Information scraped from product listings includes vendor name and ID number, vendor rating, number of successful transactions, Bitcoin price of product listed, local price of product listed, whether escrow was offered on the product or not, and the date of the product listing. I use this dataset to construct a robustness check to test the external validity of my findings.

4 Empirical Analysis

4.1 Estimating Equation

Building on Chun's (2018) results that the escrow insurance mechanism is associated with increased product prices, I intend to examine the relationship between ratings (as a reputation signal and insurance mechanism) and product prices. In accordance with this aim, my primary null hypothesis is that variation in ratings is associated with no change in listed product price. To test this hypothesis I use the following estimating equation:

$$y = \beta_0 + \beta_1 x + \beta_2 z + \epsilon$$

In this equation, I take y to be the natural log of product prices. Next, I take x as the rating of the vendor who authored the product listing. Finally, I take z as a vector of controls, which is either empty or equal to some combination of a binary variable indicating whether or not escrow is offered for the product, and a continuous variable indicating how many successful transactions the vendor has previously completed by the time of the listing.

β_0,β_1 and β_2 are constants. β_1 is my main coefficient of interest.

4.2 Variable Transformations

I take the natural log of the price as per Chun (2018) and Everling (2017) to smooth the price data. In my main specification using Everling's cocaine market data, product prices are listed in Bitcoin values. In my robustness check, product price listings are converted from Bitcoin values to U.S. Dollars. This is helpful for accounting for variation in the exchange rate over time. Such a conversion is not necessary for processing the cocaine market dataset, because all listings were pulled at same date and time, thus there was little exchange rate fluctuation to bias the results.

4.3 Variable Baselines

Summary statistics on each of these variables can be found in Table 1. First, note that vendors have universally high ratings, because vendors with low ratings tend to exit the market. This could bias results (see Concerns). Second, note that escrow is offered more often than it is not offered on product listings in both samples.

5 Results

5.1 Primary Findings

The results of my main specification can be found in Table 2, and my preferred specification can be found in Column 4. In this specification, I find that a one star increase in vendor rating is associated with a 33.8% increase in listed price, with a 95% confidence interval of 7.7% to 59.9%. Because most vendors have above a 4.0 rating, it can be helpful to contextualize this result by saying each 0.1 unit increase in average rating relates to a 3.38% increase in price. These results imply a socially optimal equilibrium with regard to vendor rating. Vendors are incentivized to perform well, because obtaining higher ratings enables them to charge higher prices.

5.2 Secondary Findings

I also find that not offering escrow is associated with a 13.0% increase in listed price, with a 95% confidence interval of -5.7% to -20.3%. This finding contrasts with the results from Chun (2018). I propose this finding makes sense because escrow is a very weak contract enforcement mechanism, which arguably opens buyers up to increased risk via market exit scams (see Concerns).

5.3 Robustness Check: External Validity

I expand my analysis to consider not just cocaine product listings like Everling (2017) and Chun (2018), but all product categories. The results of this analysis are documented in Table 3.

Interestingly, I find a large reversal of the effect found in my main specification which is not statistically significant. In this specification, I find that a one star increase in rating is associated with a 19.4% decrease in price. This conflicting result indicates that my theory and analysis do not have complete external validity, and more testing will be necessary to find conclusive results before making market-wide statements. I was unable to include a control for product category and speculate that this change could be a result. Product type may drive buyers to behave differently, and they may not consider ratings for certain purchase categories. For instance, many listings on the Dream Market are for pornography; in this case, pictures associated with the product may be more impactful than vendor ratings in determining demand and therefore product price.

Second, I find that offering escrow is associated with a 20.5% decrease in product price, which is significant at the $p < 0.1$ level. This is a similar coefficient to the one found in my main analysis and is within the confidence interval indicated in my main results. This adds credibility to the finding that buyers are willing to pay a premium to avoid purchasing escrow.

5.4 Concerns

As evidenced in Table 1, vendor ratings are biased upwards. This is because vendors with ratings below a certain threshold tend to leave the market (Resnick and Zeckhauser 2002). This cutoff of observations in my independent variable should not dramatically distort my main coefficient of interest, as the trend I observe is expected to be linear and hold for all product listings with vendors rated above that threshold. If it were to bias my main coefficient, I expect that it would cause this analysis to underestimate the effect of ratings on prices, because those vendors who did not exit the market would still be able to charge unusually high prices, thus I would find a smaller price differential between high rated vendors and low rated vendors than is realistic.

I find unintuitive results regarding the coefficient on my escrow control. I argue that this is the case because buyers know purchasing products with escrow increases their risk of market exit scam, even though it minimizes their risk of vendor market scam. Periodically, administrators will disappear with all the money buyers placed in escrow and shut down the market. By placing their money in escrow, buyers modestly increase the chance that this will happen, and they will lose not just their money but also access to the market (which we expect buyers value as we saw that transactions are mostly small and regular rather than large and infrequent (Demant et al. 2015)). I conclude that the market contract enforcement insurance mechanism is so weak people are willing to pay a premium to avoid using it.

6 Conclusions

This analysis suggests that buyers are willing to pay an insurance premium for weak insurance mechanisms when faced with environments that have virtually no insurance by construction. I find that a one unit change in seller rating is associated with a 33.8% increase in the price of one gram of pure cocaine, indicating that buyers place trust in other buyers and are willing to pay for reputation signaling as a form of insurance. I also find that offering escrow on a product listing is associated with a 13.0% decrease the price of one gram of pure cocaine. Finally, I also note that my findings on the relationship between vendor rating and the price of cocaine cannot be universally applied across all product categories until more conclusive findings emerge from further research.

I identify two key areas of expansion for this subject moving forward. First, the lack of significant findings and change in direction of the effect of vendor rating on product price between the cocaine market and full market analyses gives cause for further research. Limitations to data availability through web scraping prevented me from controlling for product category in the full market analysis. Controlling for different trends across product categories could change the direction of the effect, causing it to align with the main results of this study. Second, the high significance level of both the ratings and escrow variables is promising but is not significant to the level necessary to pass the Bonferroni correction. A repetition of this analysis on a wider dataset could enable stronger multiple hypothesis testing.

7 Appendix

Table 1: Summary Statistics

Table 1(A): Cocaine Market Sample

Variable	(1)	Mean	Std. Dev.	Min	Max
ln(price)	1,504	-3.466	0.626	-14.483	-1.659
Vendor Rating	1,504	4.884	0.121	4.39	5.00
Escrow	1,504	---	---	0	1
Number of Vendor Transactions	1,504	339.879	527.966	0	3250

Table 1(B): Full Market Sample

Variable	(1)	Mean	Std. Dev.	Min	Max
ln(price)	802	3.933	1.331	.913	7.936
Vendor Rating	767	4.915	.092	4.5	5
Escrow	802	---	---	1	3
Number of Vendor Transactions	802	97.113	99.091	0	537

Table 2: Results from main specification.

	(1) ln(price)	(2) ln(price)	(3) ln(price)	(4) ln(price)
Average Vendor Rating	0.370^{***} (0.133)	0.352^{***} (0.133)	0.354^{***} (0.133)	0.338^{**} (0.133)
Escrow offered? Yes		-0.132^{***} (0.0373)		-0.130^{***} (0.0373)
Number of Vendor Transactions			0.0000568^{*} (0.0000306)	0.0000540^{*} (0.0000304)
Constant	-5.273^{***} (0.649)	-5.088^{***} (0.649)	-5.217^{***} (0.650)	-5.038^{***} (0.649)
N	1504	1504	1504	1504

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

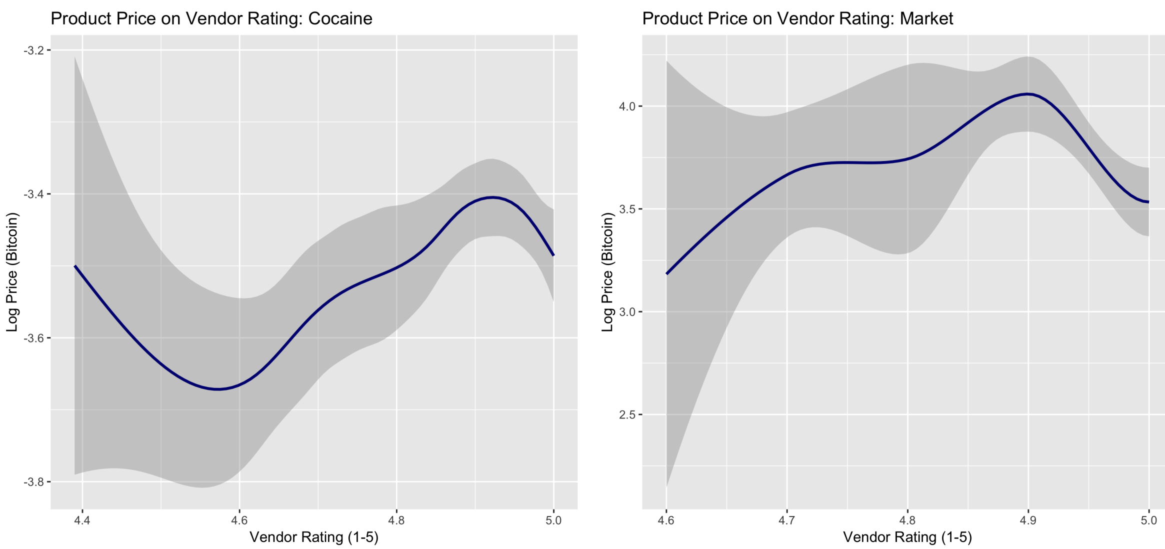
Table 3: Results from robusness check.

	(1) ln(price)	(2) ln(price)	(3) ln(price)	(4) ln(price)
Average Vendor Rating	-0.201 (0.520)	-0.363 (0.541)	0.0377 (0.538)	-0.194 (0.568)
Escrow offered? Unknown		-0.465 (0.427)		-0.394 (0.433)
Escrow offered? Yes		-0.239^{**} (0.104)		-0.205^{*} (0.109)
Number of Vendor Transactions			0.000867^{*} (0.000502)	0.000525 (0.000531)
Constant	4.891^{*} (2.558)	5.854^{**} (2.667)	3.628 (2.657)	4.943^{*} (2.822)
N	767	767	767	767

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

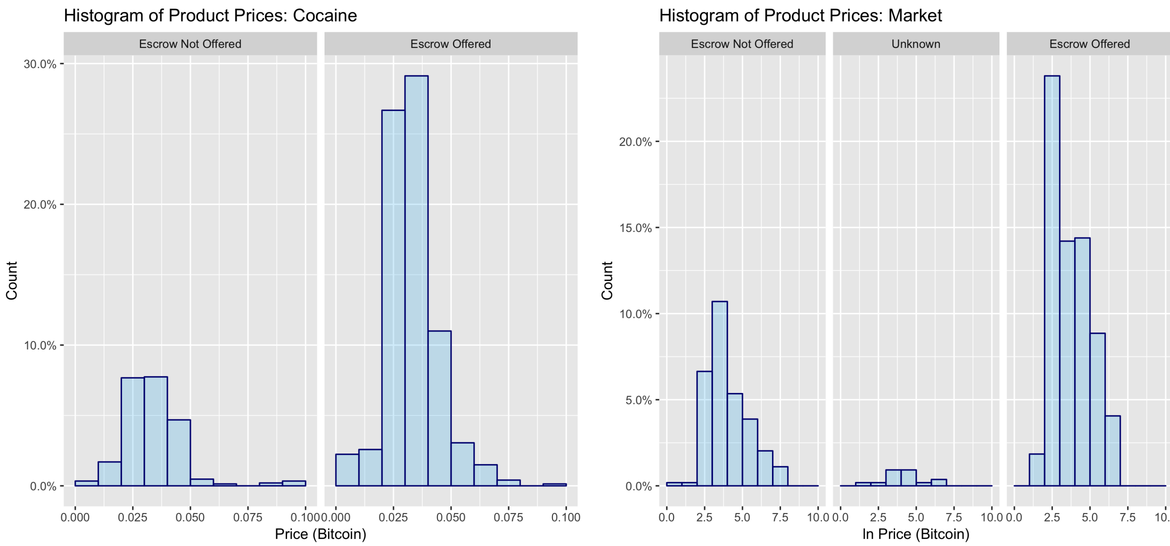
. **Figure 1:**

Regression visualization on cocaine market and full market samples.



. **Figure 2:**

Visualization of escrow distribution.



Note: *Escrow is offered more than it is not offered:*
The mean price of one gram of pure cocaine with escrow offered is 0.815 Bitcoin. The mean price of the same product without escrow is 2.17 Bitcoin.The mean price of products with escrow across the full market sample is 1.679 Bitcoin. The mean price of products without escrow across the full market sample is 1.839 Bitcoin.

.

References

[1] Bolton, Gary E., et al. "How Effective Are Electronic Reputation Mechanisms? An Experimental Investigation." *Management Science*, vol. 50, no. 11, Nov. 2004, pp. 1587–602. doi:10.1287/mnsc.1030.0199.

[2] Branwen, Gwern. *Darknet Market Archives (2013-2015) - Gwern.Net.* 1 Dec. 2013, https://www.gwern.net/DNM-archives.

[3] Christian, Jon. "The 'Exit Scam' Is the Darknet's Perfect Crime." *Vice Motherboard*, 4 Feb. 2015, https://motherboard.vice.com/en_us/article/xyw7xn/darknet-slang-watch-exit-scam.

[4] Demant, Jakob, et al. "Personal Use, Social Supply or Redistribution? Cryptomarket Demand on Silk Road 2 and Agora." *Trends in Organized Crime*, 4 Feb. 2015, https://motherboard.vice.com/en_us/article/xyw7xn/darknet-slang-watch-exit-scam.

[5] "Shedding Light on the Dark Web." *The Economist*, The Economist Newspaper, 16 July 2016, www.economist.com/international/2016/07/16/shedding-light-on-the-dark-web.

[6] Everling, Skip "Dark Market Regression: Calculating the Price Distribution of Cocaine from Market Listings." *Medium*, https://medium.com/thought-skipper/dark-market-regression-calculating-the-price-distribution-of-cocaine-from-market-listings-10aeff1e89e0. Accessed 30 Oct. 2018.

[7] Foley, Sean, et al. "The Economics of Ride Hailing: Driver Revenue, Expenses and Taxes." *Sex, Drugs, and Bitcoin: How Much Illegal Activity Is Financed Through Cryptocurrencies?*, SSRN Scholarly Paper, ID 3102645, Social Science Research Network, 21 Oct. 2018. https://papers.ssrn.com/abstract=3102645.

[8] Norbutas, Lukas. "Offline Constraints in Online Drug Marketplaces: An Exploratory Analysis of a Cryptomarket Trade Network." *International Journal of Drug Policy*, vol. 56, June 2018, pp. 92–100. *ScienceDirect*, doi:10.1016/j.drugpo.2018.03.016.

[9] Lorenzo-Dus, Nuria, and Matteo Di Cristofaro. "'I Know This Whole Market Is Based on the Trust You Put in Me and I Don't Take That Lightly': Trust, Community and Discourse in Crypto-Drug Markets." *Discourse & Communication* May 2018, p. 175048131877142. doi:10.1177/1750481318771429.

[10] Pearson, Jordan. "The Economics of Moral Hazard: Comment." *Vice Motherboard*, 12 Nov. 2015, https://motherboard.vice.com/en_us/article/78kpwa/ai-could-tell-when-your-dark-web-drug-dealer-is-about-to-scam-you.

[11] Pauly, Mark V. "AI Could Tell When Your Dark Web Drug Dealer Is About to Scam You." *The American Economic Review*, vol. 58, no. 3, 1968, pp. 531–537. *JSTOR*, www.jstor.org/stable/1813785.

[12] Resnick, Paul, and Richard Zeckhauser. "Trust among Strangers in Internet Transactions: Empirical Analysis of EBay' s Reputation System." *Advances in Applied Microeconomics*, vol. 11, Emerald (MCB UP), 2002, pp. 127–57. doi:10.1016/S0278-0984(02)11030-3.

[13] Chun, Steven. "The Limits of Reputation Signaling in Adversely Selected Markets: Applications to Dark Net Cocaine Markets." Student research paper, unpublished. June 2018, https://drive.google.com/file/d/1HshW1AXExxaqmFieS3WwmZ8Z6UlVDU_5/view?usp=embed_facebook. Accessed 30 Oct. 2018.