A REPUTATION FOR THE GOOD STUFF: USER FEEDBACK SIGNALING AND THE DEEP WEB MARKET SILK ROAD

by

James Matthew Sears

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ABSTRACT

Despite complete user anonymity, asymmetrical information, and incomplete enforcement mechanisms, the deep web market Silk Road facilitated approximately $200 million in illegal drug sales in 34 months. This study tests how the site's reputation system facilitated successful transactions and how user feedback functioned as the primary signal of seller quality in the absence of formal contract enforcement. Using novel data from the site on marijuana, amphetamine, and meth transactions, listings, and vendors, I find strong evidence that consumers engaged with the site's reputation system and relied on both item and seller-level information. Hedonic regressions provide evidence of a "bad news" learning environment, estimating a 3 to 11% price discount for negative item reviews. Seller ratings are found to act as an effective proxy for permanent seller characteristics, and named trains act as a primary source of quality (and price) differentiation for marijuana. I find no evidence of price penalties or signal heterogeneity for new sellers. This study is the first to shed light on the value of reputation on the deep web's largest marketplace, yielding new insight into the mechanisms modern markets use to overcome social distance and prevent market failure.

INTRODUCTION

In 34 months, the deep web market Silk Road facilitated an estimated $200 million in illegal drug sales (Flitter, 2015). Despite minimal consumer protections or means of redress in the case of transaction failure, the site quickly grew notorious as an "Amazon for drugs" that saw sales of $15 million in its first year and $200 million by its closure in 2013 (Christin, 2013; Flitter, 2015). Either consumers will go to any lengths imaginable to acquire drugs, or there exists a mechanism that can overcome social distance and incomplete contracts to facilitate anonymous trade. This paper investigates the role of reputation as this mechanism.

Considerable economic literature is devoted to the theory of firm reputation under uncertainty, finding that investment in reputation can be profitable in the face of imperfect information (Fudenberg and Levine, 1989; Kreps and Wilson, 1982). As online markets have grown ubiquitous and brought expanded concerns of social distance and contract enforcement, empirical studies have sought to understand the role of reputation in facilitating trade in the absence of face-to-face interaction. However, few studies have analyzed markets operating under truly uncertain conditions. Using 18 months of transaction data for marijuana, amphetamine (speed), and methamphetamine (meth) sales on Silk Road, I test the role of the site's reputation system as the primary signal of vendor quality in the face of considerable uncertainty and the absence of formal contracting mechanisms.

When formal contract enforcement mechanisms are not present in a market or are unreliable, market failure is a likely outcome (Akerlof, 1970). In order to avoid market failure, additional signals must exist allowing firms and consumers to overcome information asymmetries. Conventional theoretical wisdom suggests that reputation can fulfill this role and elicit long-run benefits for market agents (Fudenberg and Levine, 1989; Kreps and Wilson, 1982; Milgrom and Roberts, 1982). Present empirical studies find

reputation effects even in low-uncertainty environments for homogeneous goods (Houser and Wooders, 2006; Kalyanam and McIntyre, 2001).To motivate my analysis, I provide a review of reputation theory and current empirical studies – with particular concern for works concerning black markets. In the theoretical framework I draw on game-theoretic literature on reputation investment to develop a goods-purchase game in which the strength of a quality signal directly impacts optimal behavior for both consumer and vendor behavior. Model results provide insight into the possible causes of market failure and requirements for reputation's value on Silk Road.

I next develop an empirical model to evaluate the effect the site's reputation system had on realized item prices using a fixed effect hedonic price regression approach. To test reputation's role in facilitating transactions on Silk Road, I employ a novel dataset of market transactions for marijuana, speed, and meth that includes information on item listings, vendors, and feedback back to the market's beginning, and price information for February through July 2012 (Christin, 2013). I next augment the data with information on Bitcoin exchange rates and estimate the value of reputation.

In my empirical strategy I estimate the effect of aggregate seller reputation and changes in item reputation on drug prices. Controlling for elements unaccounted for in previous studies, I find evidence of a "bad news" learning environment in which consumers quickly react to negative item reputation (Hardy and Norgaard, 2015). Across drug types, item listings suffer price penalties between 3 and 11% when they acquire negative reviews. I find evidence of aggregate seller reputation premiums of $1-5\%$ for a percentage point change in vendor ratings, but that this measure largely proxies for permanent vendor characteristics.

Further, I find consistent empirical evidence for a substantial price premium for high-quality marijuana strains on Silk Road. Models consistently estimate $8-9\%$ premiums for high-quality named strains relative to their lower-quality counterparts, and that these

premium items were primarily sold by premium vendors. This finding provides empirical evidence for the role of strains as a primary source of product quality differentiation within the marijuana market.

This is the first study to directly comment on the role of reputation as a successful signal of vendor quality on the original, iconic deep web market Silk Road. I am able to control for important determinants of price and product quality, and I find evidence that these attributes are a primary margin for product differentiation. Further, the similarity in institutions between Silk Road and conventional online markets allows newfound understanding of how social distance and incomplete contracts affect consumer valuations of reputation.

4

THE SILK ROAD MARKET

The Silk Road was an anonymous online marketplace and the first deep web marketplace.[1] Although available goods spanned hundreds of categories – with some as innocuous as books or art – the site quickly gained a reputation for illegal drugs. The site began operation in February 2011 and continued until its seizure by the FBI in October 2013. A successor to the original site soon arose and a titular successor of some form has remained in operation ever since (though controlled and operated by different parties). As a Tor hidden service, the site could only be reached through the anonymity network's own platform and was unreachable on traditional web browsers. Its use of peer-to-peer digital cryptocurrency Bitcoin further obfuscated the identities of transacting parties.[2]

Although technical and software requirements limited access for some consumers, Silk Road provided a means for technically-savvy users to engage in black market transactions with a newfound level of safety and anonymity. Use of the Tor network and Bitcoin allowed consumers to effectively hide their identities from law enforcement. Consumers and resellers could attain quality product while avoiding local, face-to-face transactions. The ability to avoid in-person purchasing reduced risk borne by consumers. Aldridge and Décary-Hétu (2014) postulate that use of a virtual transaction environment reduced violence and intimidation in local drug markets.

Additionally, consumers enjoyed a newfound variety of product. Whereas consumers in local drug markets face limited options, buyers on the Silk Road faced a paralyzing amount of choice. For example, cannabis consumers in the United States who narrowed

[1]The deep web refers to content on the World Wide Web that is not indexed by typical search engines that operate on the "surface web." Access to deep web sites requires additional software or authorization. Many use the terms deep web and Dark Net as synonyms even though Dark Net refers to a specific subset of deep web sites that rely on peer-to-peer networks such as Tor or I2P. While Silk Road was a Dark Net site, I will refer to it and all other nonindexed services as deep web content.

[2]See Appendix A for additional details on the Tor network, Appendix B for an overview of Bitcoin, and Christin (2013) for a detailed review of site access and market characteristics.

their search down to the Sour Diesel strain, a well-known marijuana variety known for its unique characteristics, still faced a major choice: during 2012, Silk Road offered 168 unique listings for Sour Diesel marijuana from 160 sellers. Many users treated the Silk Road as a source for boutique product and spent more money to purchase higher quality drugs than were available in local market conditions. As of August 2013, Silk Road users paid an average of $12.10 per gram of marijuana versus the $9.50 prevailing street price – a 27% premium (Mahapatra, 2013).[3] A recent drug use survey conducted in the United States, Britain, and Australia found that, out of 1056 respondents who reported purchasing drugs from Silk Road, many cited a wider range of product (75-89%), better quality (72-77%), improved convenience (67-69%), and the use of a vendor rating system (60-65%) as their primary reasons for purchasing from the site (Barratt et al., 2013).

Purchasing on the Silk Road

After creating a user account and logging in, Silk Road participants were greeted by the site's main page. This page provided links to product categories and new item listings, the current Bitcoin to U.S. dollar exchange rate, and the ten most recent feedback responses. Figure 2.1 shows an early version of the main page from July 2011. Clicking a category link connects to a directory of all item listings within a given category (Chen, 2011). As Figure 2.2 shows, each row provides the listing title, the item's price in Bitcoin, the country of origin, shipping destinations, the seller's unique screen name, and (of particular interest for this paper) the seller's reputation. The site reports seller reputation as the percent of transactions resulting in positive feedback – the same measure reported by many conventional markets like eBay and Amazon.

[3] A September 2013 warrant request by the Federal Bureau of Investigation to search JTAN.com, a small Pennsylvania IT firm allegedly controlling backups of Silk Road servers, mentions 56 cases when the agency made undercover purchases of Silk Road drugs and conducted laboratory tests on the compounds. In all but two cases, the purchased drugs were found to be of high purity (United States District Court, 2014).

Although consumers could purchase an item directly from the category directory by using the "add to cart" button, clicking on the listing title led to a dedicated item page containing additional item information. Figure 2.3 shows the item page. The item page gave a textual description, shipping market, price, and feedback information for the item. Similar to Amazon, the item page corresponded to a permanent, unique good that could be purchased over and over again.[4] Directly under the item's price appeared the seller's name, with their overall percent positive rating displayed immediately adjacent. Further down the page, all prior customer reviews – both textual and numeric 1 to 5 – were reported in order of recency. Once an item was added to the cart, users selected their preferred shipping method before confirming the order. After an order was placed, the buyer's Bitcoins were transferred to the site's escrow account, converted to U.S. dollars, and held until the seller completed the order. Buyers could follow the status of an order from their account page, leave feedback once an item was received, release funds from escrow, or resolve an issue through the site's claim system.

Curious consumers could gather further information about a given seller by visiting the vendor page. Figures 2.4 and 2.5 provide an example of a vendor page. Although not a required destination during the purchasing process, the vendor page could easily be reached from links on the category directory or the item page and provided additional information on a seller's entire product portfolio and performance history. The top half of a vendor page (Figure 2.4) reported account age, date last seen, positive feedback percent across all transactions, ranking across all sellers, links to message, follow, or report a seller in addition to a textual description and a PGP public key (used for the encryption of messages between buyers and sellers). The bottom half of the page (Figure 2.5) provided links to

[4] As item pages corresponded to a unique good, vendors on Silk Road often ran multiple listings within a given product category, offering goods with different characteristics at different prices (e.g. a seller posting 5 listings for different strains of marijuana).

each of a seller's active items as well as past reviews in order of recency.[5] Reviews were broken up into multiple pages for sellers with a large transaction history. Freshness was measured in hours for reviews placed within the last 24 hours and in daily increments for reviews older than 1 day.

Value of the Reputation System

Without any additional effort, market users were confronted with multiple measures of item and vendor reputation prior to making a purchase. At a minimum, consumers observed past item-specific feedback in addition to a contemporaneous measure of aggregated seller reputation, the percent favorable rating. Users who took advantage of vendor pages obtained additional information as to a seller's other items and individual reputations for each item.

The vendor description in Figure 2.4 contains an informative quote as to vendors' perception of reputation value:

> If you leave less than 5/5 feedback without messaging me with your issue first, expect to be blocked from further orders and blacklisted in the Vendor forums. Sorry if this does not seem fair but due to SR policy regarding buyer feedback this is what vendors have to do to protect their reputation.

The vendor represents reputation as a high-stakes environment: if they receive even one instance of a strongly negative review, it can have an irreparable effect on the vendor's reputation and severely impact their ability to conduct future sales. Such a view lends credence to the value of reputation – or more precisely the value in preserving the positive nature of one's reputation. Indeed, negative reviews are a general rarity on Silk Road, with

[5]Note that the user account balance and item prices are listed in U.S. dollar prices, and not Bitcoins. This change came about as part of a redesign announced by the site's operator (known on the site by the pseudonym Dread Pirate Roberts) on July 22, 2012 that came into effect shortly after. Before the update, account balances and prices were displayed in Bitcoin with a BTC to USD exchange rate displayed in the bottom left corner of every page.

1 star reviews accounting for just 1% of all transactions and 2-3 star reviews an additional 1% (Christin, 2013).[6] Similar language is found in the site's Seller Guide: "Reputation is everything here and the best way to cultivate it is to treat your customers with respect and courtesy." The site presents reputation as inherently valuable to vendors, likely as a means of promoting honest behavior.

Figures 2.4 and 2.5 give a strong example of the effect even a small number of negative reviews can have on a seller. In 2 months of activity, the pictured vendor conducted 135 transactions with 96.5% positive feedback. Although only 5 transactions resulted in negative reviews, the ubiquity of positive reputations on Silk Road placed the vendor in the 43^{rd} percentile of all sellers – a potentially troublesome signal for consumers. Although the vendor has only been active for two months, they have conducted over 100 transactions. However, recent feedback is mixed. Some buyers commented on high-quality marijuana and methamphetamine (meth) while two reviews in the last day are negative and make reference to both low-quality product and poor customer service. The conclusion consumers make about this vendor (e.g., whether their product will be high-quality or whether they are likely to make the delivery in the first place) depends on the information set being considered, the information the consumer values, individual preferences, and their particular level of risk aversion.

A main research goal of this paper is to shed light on the decision-making process Silk Road consumers used to overcome information asymmetries and mitigate transaction risk. Of particular interest are the signals by which consumers reached purchasing decisions.

[6]While the positive share of reviews varies between Silk Road product categories (ranging from 99.5% positive for hallucinogenic mushrooms to 95% for amphetamines), the average across categories compares favorably with reputation profiles on eBay. Resnick and Zeckhauser (2002) report 99.1% positive feedback for over 50,000 transactions across item categories in 1999. Similarly, Cabral and Hortaçsu (2004) report 99.1% positive feedback for sellers of IBM Thinkpad laptop computers, a range of collectible coins, and 1998 Holiday Teddy Beanie Babies, while Dewally and Ederington (2006) report 99% positive for sellers of classic comic books.

Silk Road vendor resources suggest the site's administrators viewed reputation as the primary informational signal. Vendor pages and the presence of and activity on site forums suggest negative reputation may be the chief reputation mechanism through which consumers made purchasing decisions.

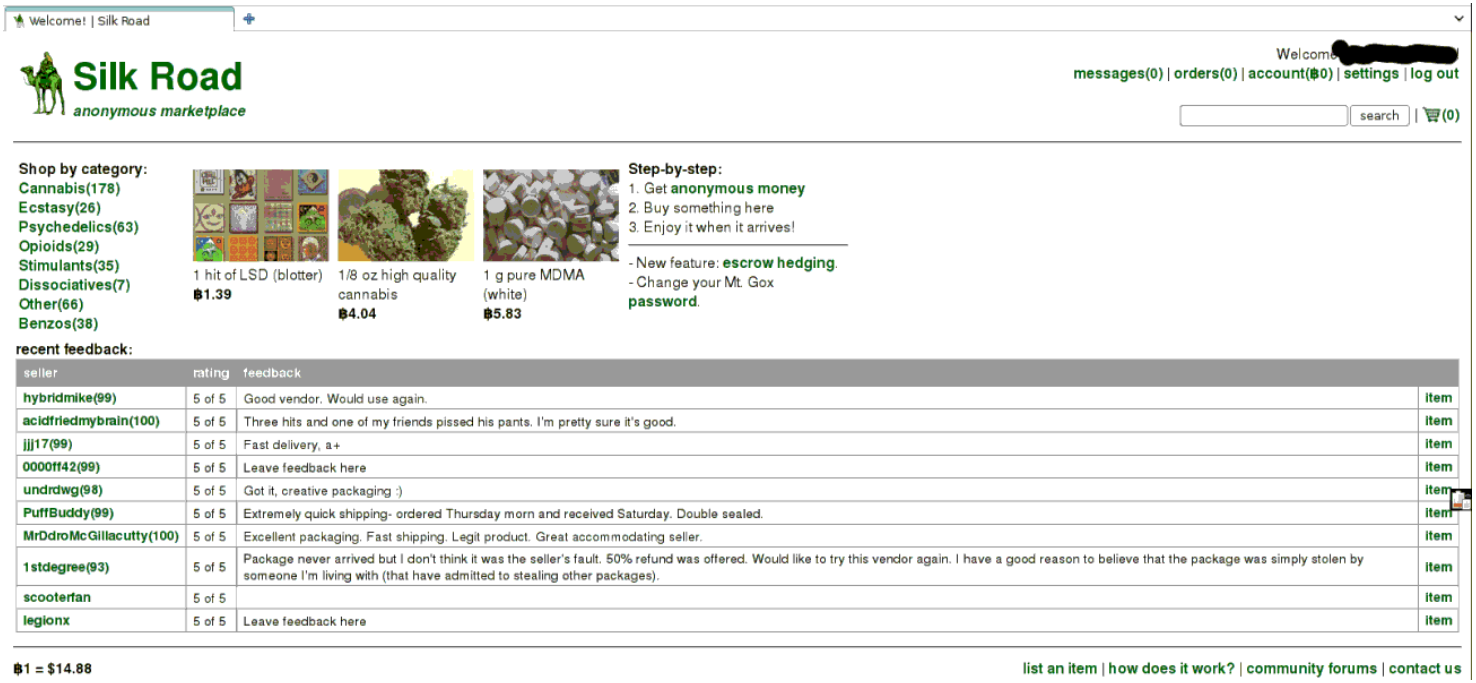


Figure 2.1: Silk Road Main Page, July 2011

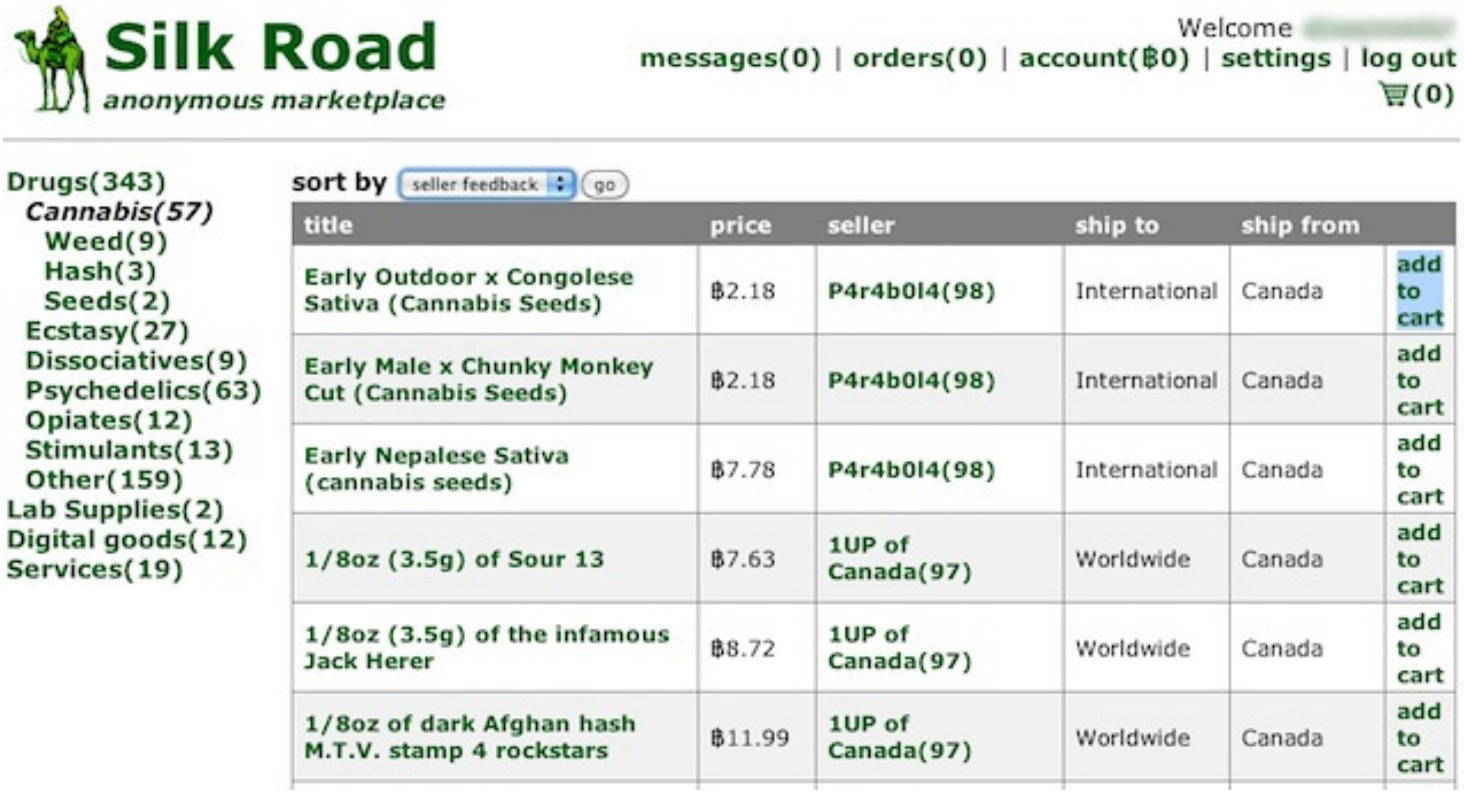


Figure 2.2: Marijuana Product Category

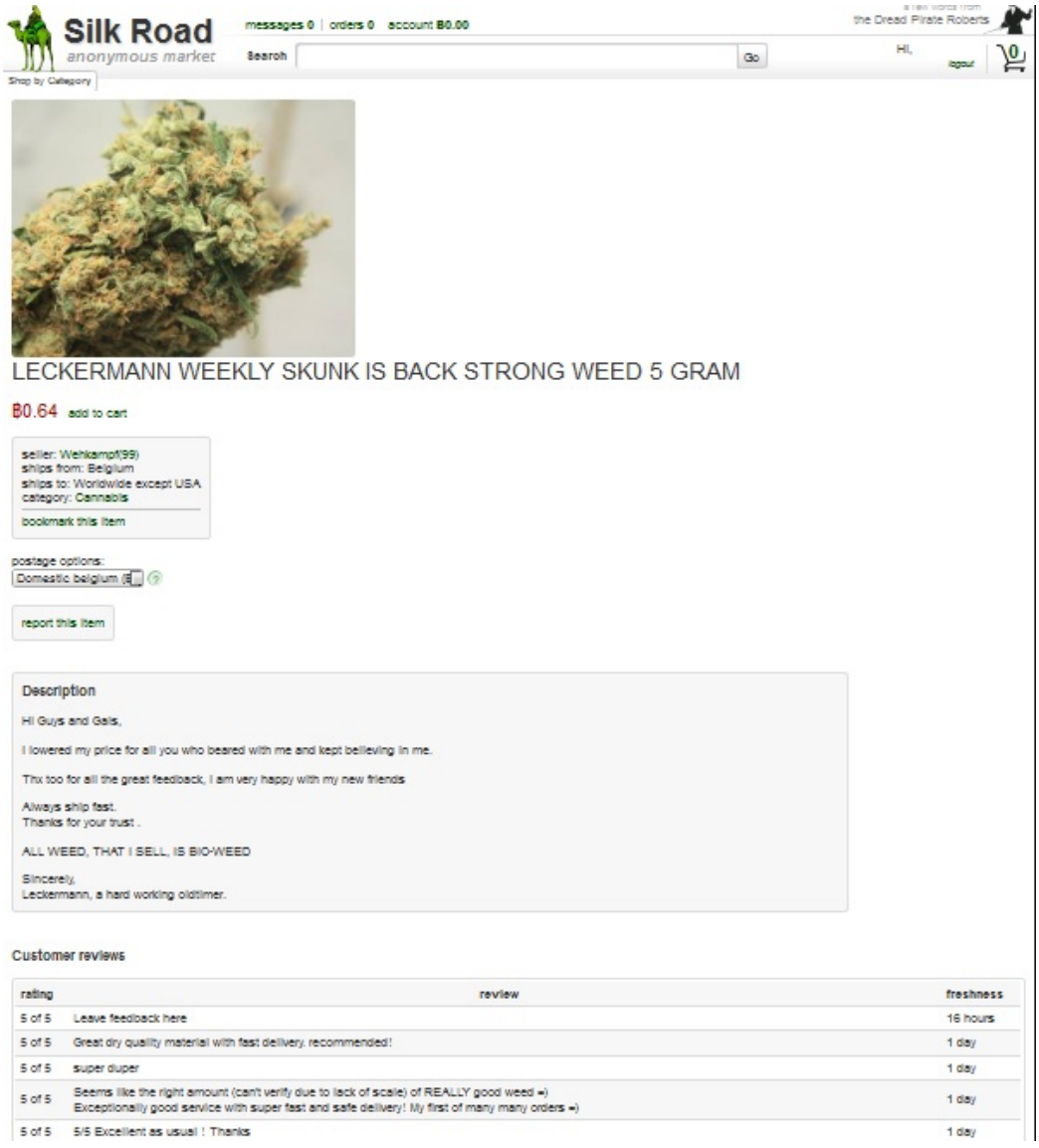


Figure 2.3: Marijuana Item Listing Page

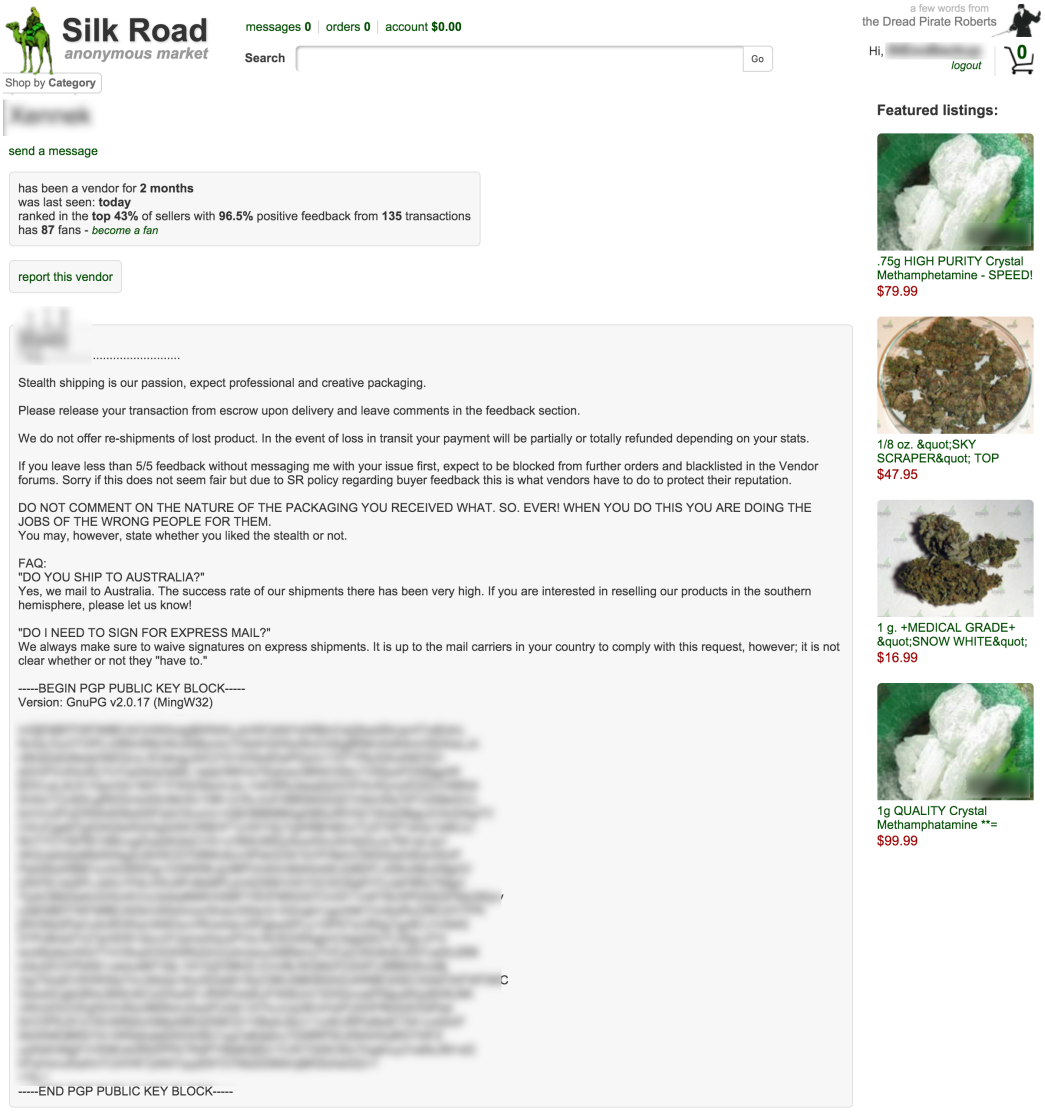


Figure 2.4: Silk Road Vendor Profile, Top Half

category	title	price	ship to	ship from	
Meth	7g QUALITY Crystal Methamphatamine - * "ICE" *	$659.99	Worldwide	United States of America	add to cart
Drugs	1.75 g .QUALITY Crystal Methamphatamine = "ICE" =	$146.95	Worldwide	United States of America	add to cart
Meth	1g QUALITY Crystal Methamphatamine **= "ICE" =**	$99.99	Worldwide	United States of America	add to cart
Meth	14g QUALITY Crystal Methamphatamine - * "ICE" *	$929.99	Worldwide	United States of America	add to cart
Books	HELL'S ANGELS by Hunter S. Thompson (AUDIOBOOK)	$9.99	Worldwide	United States of America	add to cart
Meth	3.5g QUALITY Crystal Methamphatamine - * "ICE" *	$299.00	Worldwide	United States of America	add to cart
Stimulants	Methylphenidate ER 36mg (AKA Ritalin) =*Qty. 5*=	$74.99	Worldwide	United States of America	add to cart
Drugs	1/8 oz. "SKY SCRAPER" TOP SHELF INDICA CANNABIS	$47.95	Worldwide	United States of America	add to cart
Weed	1 g. +MEDICAL GRADE+ "SNOW WHITE" - Indica Hybrid	$16.99	Worldwide	United States of America	add to cart
Meth	.75g HIGH PURITY Crystal Methamphetamine - SPEED!	$79.99	Worldwide	United States of America	add to cart
Books	CIA Book of Dirty Tricks *BANNED EBOOK* GET EVEN!	$3.99	Worldwide	United States of America	add to cart

rating	review	freshness	item
5 of 5	Good delivery time. good product. Cheers.	10 hours	item
5 of 5	Took just over 2 weeks to Oz. Nice Job all round!	17 hours	item
5 of 5	I have been on SR for well over 18 months and have tried many vendors' methamphetamine, but this is BY FAR THE BEST that I have had the pleasure of trying! I will be back for more undoubtedly! 10/5 :)	17 hours	item
5 of 5	Great bud, will be back	20 hours	item
1 of 5	Looking back I just can't give this transaction any kind words. I messaged the vendor early Thursday morning and asked if they shipped orders on Saturday, since I needed it sooner rather than later. They stated that they did. Saturday came and went, order is still processing, so I was a little pissed. Yeah I know that same or next day shipping isn't possible for everyone, I dont see why it should be a problem for new vendors with a handful of customers though. If you can't do something, just say you can't Anyway, I ordered 2 products from [redacted], some weed and meth. The weed was supposed to be medical grade, tasted more like mid-grade. Oh, and the majority of the crystal tasted like salt, had no burn at all when snorted, and did not vaporize correctly. There may have been a few crumbs in the bag that were actually meth. :(I thought "Ok, maybe he's be one of the cool vendors that understands shit happens from time to time, and you can end up with a bad batch. This this batch from [redacted] made me want to sleep more than anything else, and gave me a headache. Sad. I have been a member here 8 months, I realize isn't that that long, but long enough to know this isn't how you treat your customers if you want to remain a vendor for very long. And no I am not trying to "scam" anyone, I have bought meth on silk road from over 6 or 7 different vendors and been more than satisfied every time. With [redacted] I simply did not get the product I paid for (which is bullshit). It would have been nice for him to offer at least some form of at least small compensation , a partial reship? But he in not so many words told me to go fuck myself. Great Guy.	1 day	item
1 of 5		1 day	item
5 of 5	Arrived safe in 2 and a half weeks. Crystals are all broken up, for stealth I guess. But is still the purest iv had off here!	1 day	item
5 of 5	Excellent communication, super fast express shipping OS, stealth postage, top product! HIGHLY RECOMMENDED!!	1 day	item
5 of 5	As promised.	1 day	item
5 of 5	Decent product.. ok stealth but think about including a decoy..	1 day	item

1 2 3 > Last ›

Figure 2.5: Silk Road Vendor Profile, Bottom Half

REVIEW OF THEORETICAL LITERATURE

Complications arise when evaluating markets under asymmetrical information. One need only look to Akerlof's (1970) seminal "lemons" paper for a concrete example in the used car market. When a used car's type (good quality or a lemon) cannot be known with certainty by consumers and no mechanism exists to completely eliminate the asymmetry in information, good cars will sell for the same price as bad cars. Lemons eventually crowd the good cars out of the market as buyers have no means of distinguishing between the two types. If the price of used cars is more than consumers are willing to pay for a lemon, then the market fails and no transactions take place (Akerlof, 1970). If, however, the credibility of a seller could be accurately determined by consumers (and thus the probable car type) prior to purchase, the likelihood of purchasing a lemon would be greatly reduced and market failure would be avoided.

The one-shot nature of used car sales eliminates the potential for previous behavior to inform a signal of vehicle quality; in a continuous environment with long-lived sellers, reputation can compensate for asymmetric information and function as this signal. Early game theoretic literature on reputation effects by Kreps and Wilson (1982) and Milgrom and Roberts (1982) provide justification for the presence of and investment into reputation by a long-lived incumbent firm sequentially challenged by would-be rivals when potential entrants observe imperfect information as to the incumbent's payoffs. In finitely repeated chain store games, the presence of even a small amount of imperfect information can dramatically impact the flow of play and give rise to actions investing in reputation (Kreps and Wilson, 1982). Such investment arises in the repeated environment due to the incumbent player's ability to maximize long-run payoffs at the expense of short-run profits (Milgrom and Roberts, 1982). Fudenberg and Levine (1989) generalize these findings to all games with a positive probability that the encumbent plays their preferred pure strategy

profile whenever the short-run challenger chooses their best response. More recent work by Ely and Välimäki (2003) provides a credence good variation in which both scrupulous and unscrupulous long-lived players engage in behavior to maintain their long-run reputation.[1]

[1]Ely and Välimäki (2003) model the long-run reputation of a car mechanic who interacts with short-lived players in need of service. In the basic model, the motorist's vehicle requires one of two repairs (minor tune-up or engine replacement) with equal probability. The mechanic observes the required repair and recommends a repair conditional on first observing the vehicle's state. If the mechanic chooses the repair that does not match the vehicle's state, then the motorist observes negative payoffs and would prefer to avoid a mechanic who makes such suggestions. When the mechanic's incentives align with those of the motorist or is sufficiently likely to be good, then the mechanic will recommend the correct repair in each period and is optimally hired by the motorist. However, reputational incentives can distort behavior when motorists' only signal of a mechanic's honesty is past repairs. A truly unlucky mechanic can observe car after car in need of an engine replacement. If they recommended the appropriate repair in each case, future motorists would likely conclude that the mechanic is dishonest and tries to upsell costly repairs. As a result, the mechanic will likely under-diagnose repairs to preserve their honest reputation even when such action goes against the interest of clients.

REVIEW OF EMPIRICAL STUDIES

The proliferation of online markets revolutionized how consumers and vendors interact, reducing search and transaction costs while prompting new concerns of social distance and trust. As web markets matured along with data collection methods, researchers became able to investigate the mechanisms that allowed internet transactions to prosper. Considerable interest has been paid to the means by which online markets overcome issues of social distance and transaction uncertainty, with particular concern given to the role of feedback and reputation systems. While the vast majority of empirical reputation papers have focused on the auction site eBay, more recent works have sought to comment on reputation's effects beyond legal markets.

The Value of eBay Reputation

Reputation studies on eBay provide further confirmation of theoretical predictions; see Bajari and Hortaçsu (2004) or Resnick et al. (2006) for a detailed overview of existing literature. Although results and specific model details vary, the results are consistent with the notion of reputation affecting willingness-to-pay in the expected manner. Several works evaluating the probability of sale find positive feedback increases the probability of sale, negative feedback decreases the probability of sale, or both simultaneously (Eaton, 2002; Jin and Kato, 2004; Livingston, 2005; Melnick and Alm, 2002). Most studies specifying price as a dependent variable find that feedback (positive or negative) impacts price in the expected direction (Ba and Pavlou, 2002; Houser and Wooders, 2006; Kalyanam and McIntyre, 2001; McDonald and Slawson, 2002; Melnick and Alm, 2002). Other studies of reputation on price find no significant effect of positive feedback (Eaton, 2002; Lucking-Reiley et al., 2007), negative feedback (Bajari and Hortaçsu, 2003; Livingston, 2005), or both (Cabral and Hortaçsu, 2004; Jin and Kato, 2004; Yin, 2004). Randomized

experimental analysis confirms the presence of experience effects: when seller identity is randomized, willingness-to-pay for vintage postcards from an established seller was 8.5% higher than for the same item from a new seller (Resnick et al., 2006).

If reputation plays a role on eBay, then it can be expected to play a similar, if not larger, role in Silk Road transactions. Several eBay studies find reputation plays a larger role when uncertainty is greater: Ba and Pavlou (2002) find that feedback variation has a larger impact for more expensive items, and Dewally and Ederington (2006) find a greater effect for ungraded items when professional grading is possible.[1]

The tendency of Silk Road transactions towards expensive sales (as high as $6,027 for the largest oberserved marijuana order) for illegal drugs suggests feedback should play a relatively larger role on the market in comparison to eBay. Further, the increased stakes of unverified quality ensure greater Silk Road consumer reliance on reputation.[2] If consumers on the Silk Road are not overwhelmingly more risk-loving than typical eBay users, as shown in Chapter 2, they should consider reputation more important when purchasing illegal drugs instead of vintage postcards.

Reputation on Illegal Markets

Although data limitations have historically prevented extensive empirical analysis of illegal markets, the virtual location of modern black markets has facilitated a new era of exploration. Logan and Shah (2013) employ data from a major male sex worker website to investigate signaling behavior in the absence of formal contract enforcement mechanisms.

[1] To test for differential effects of reputation between cheap and expensive items, Ba and Pavlou (2002) compare the effect of reputation for a mix of music CD's ($8.5-$10) against the effect for expensive items like Canon camcorders ($1,100), Sony cameras ($800), and Microsoft Windows server software ($1,400). Dewally and Ederington (2006) include a measure of whether a classic comic book is professionally graded in their eBay estimates.

[2] Certification ensures a collectable coin is not scratched or visually imperfect; drug certification ensures you will not die from use.

Utilizing a hedonic regression approach to test whether a quality signal – face pictures – confers a price premium and proxies for basic escort quality, they find escorts who post face pictures receive prices in excess of 20% higher than those for escorts with no face pictures. Vectors of escort characteristics and locations control for attribute preferences and regional heterogeneity. The analyzed site employs a feedback system similar to that on Silk Road: users can provide both a numeric rating and a more involved, textual response. One limitation of the signaling mechanism they observe is the potential for anyone – including escorts – to post reviews.[3] The effect of face pictures remains statistically significant when both the logged number of textual reviews and logged survey reviews are added to control for service quality, suggesting accurate portrayal of the escort's appearance and willingness to risk public identification function as a sufficient signal of quality for male escorts (Logan and Shah, 2013).

A recent paper attempts to disentangle the role of reputation on a deep web market using a later successor to the Silk Road. Hardy and Norgaard (2015) use data from Silk Road 2, a titular successor to Silk Road, to evaluate the effect of positive reputation on marijuana listings and to estimate vendor discount rates.[4] While they find evidence of a relationship between item ratings and marijuana transactions, their estimates of vendor discount factors are statistically insignificant and highly sensitive to assumed values for signal clarity and buyer reputation parameters. Additionally, they do not control for unobserved shipping costs beyond a free shipping indicator or allow for differences in costs

[3]In contrast, feedback on Silk Road could only be left by buyers after orders were made. A link to leave feedback for an item only appeared in the "orders" account tab after a purchase, ensuring only consumers of the specific product could leave comments.

[4]Silk Road 2 arose weeks after FBI agents seized Silk Road, its operator, and approximately $3.6 million in user funds (O'Neill, 2013). During its brief 11 month life, Silk Road 2 saw multiple administrator arrests, two different site operators, an extended escrow lockout, server changes, and a raid where hackers stole 4,474 Bitcoins ($2.7 million at the time) from user accounts (Berkman, 2013). Comparatively, Silk Road suffered few site disruptions or intrusions with notably fewer prior to 2013, during my observation period and gained a reputation as a revolutionary modern market (Chen, 2011; Speri, 2014).

between routes. Lastly, they assume that no marijuana strain holds a price premium over another requiring that strain is not a margin for marijuana quality differentiation.[5]

The Silk Road market replicated many of the institutions of conventional markets, differing mainly in the types of products sold. As a result, the dynamics of reputation on Silk Road parallel those of formal markets. In this manner a theoretical framework for black market reputation can readily extend from existing reputation theory, incorporating nuances particular to the exchange of elicit goods.

[5]My results in Chapter 8 and the data presented in Appendix C provide empirical evidence that named marijuana strains are a primary source of quality differentiation on Silk Road and that high-quality strains receive a substantial premium over less potent alternatives.

THEORETICAL FRAMEWORK

Consider a simple extensive form, sequential goods purchase game with a long-lived seller (S) and short-run consumers (C) as depicted in Figure 5.1. As in the classic formulation, sellers are one of two types – honest or dishonest. Honest sellers attempt delivery on every sale and accurately represent their products prior to transactions. Conversely, dishonest sellers decide for each transaction whether to send representative goods or to take advantage of the buyer. Once mailed, an item avoids interception (by authorities, the postal service, etc.) and reaches the buyer with probability θ. The true type of the seller is not known with certainty by consumers. Let σ be the probability that the seller is honest – our reputation mechanism. Given an initial σ, consumers in sequence choose whether or not to purchase a good from the long-lived seller and observe all past plays. If C chooses not to buy from S, then both parties realize zero payoffs. With probability σ, S is honest and attempts delivery. With probability θ delivery succeeds and both parties realize payoffs of one. If delivery fails (probability 1 - θ) then both parties realize payoffs of -1. With probability $(1-\sigma)$, S is dishonest and has the choice of whether to deliver the good or not. If S delivers the good, then payoffs and probabilities are the same as described for the honest seller. If instead he takes advantage of the consumer, S realizes a payoff of 3 while C receives -1.

This specification is akin to the fourth example presented by Fudenberg and Levine (1989) with the addition of seller types and interception.[1] There an example of low μ (the probability of producing high quality, equivalent to delivery in this formulation) is used to show the seller cannot always guarantee an almost-Stackelberg payoff. Here it is enough to recognize that the behavior of a dishonest seller depends on the initial value of σ and its sensitivity to updating. Given the payoffs, a dishonest seller has the incentive to engage

[1] See pages 770-771 of Fudenberg and Levine (1989) for a full discussion of their game.

in enough "honest" transactions to maintain his appearance as trustworthy. If one failed delivery for consumer n immediately reduces σ to near zero, then all future consumers will view the seller as dishonest and choose not to buy – the market fails. If, however, $\sigma = \sigma_0$ and cannot be updated or if the signal is resistant to change (if for example consumers are incredibly trusting and do not consider a failed delivery as indicative of future outcomes) then a dishonest seller can engage in a mixed strategy that yields higher payoffs than those of a truly honest seller.

If no possibility of interception existed, the game would proceed as follows. Honest sellers would deliver one hundred percent of the time, and consumers would always realize a return of 1 when purchasing from such a seller. As a result, dishonest sellers would be perfectly identified as soon as they chose not to deliver for the first time. Here, σ updates to zero immediately following the first undelivered item and subsequent consumers would choose not to purchase from the dishonest seller. In an infinitely-repeated environment with reasonable discounting between periods, dishonest sellers maximize returns by behaving as honest sellers. Dishonest seller behavior in a finitely-repeated setting differs only in the final period, when the seller does not deliver, defrauds the final consumer, and then exits the market.

With a nonzero probability of interception θ, bad luck can confound an honest seller's signal. The consumer's goal is to accurately determine a seller's true type. Ely and Välimäki (2003) illustrates a similar scenario in which a truly honest mechanic facing a string of bad luck (all cars coming in for service require engine) acquires reputation as dishonest, and is incentivized to recommend incorrect, less extensive repairs in order to maintain their reputation for honesty. Here, bad luck manifests itself in the form of repeated interception. Although unlikely, the possibility exists that the postal service repeatedly loses every package an honest seller mails, resulting in negative outcomes for a sequence

of consumers. Aware of the scenario's unlikelihood, future consumers update the reputation signal σ to approach zero and incorrectly conclude the seller is dishonest.

Seller and consumer behavior is therefore largely determined by the size of θ. For a large θ near one, play approaches behavior in the absence of interception. Conversely, market failure is a likely outcome of low θ. The lower θ is, the easier it becomes for a dishonest seller to "pass off" fraud as interception; the optimal mixed strategy will include a greater proportion of fraudulent transactions. Without a way for potential consumers to determine whether past failed outcomes were the result of fraud or interception, σ represents the likelihood of receiving the product. Consumers then choose to do business with the seller based on σ and their personal risk preferences.

The above transaction game presents evidence of reputation as a valuable signal in the absence of formal contracting and enforcement mechanisms. In order to empirically test reputation's role under heightened uncertainty, I obtain transaction data from the deep web market Silk Road.

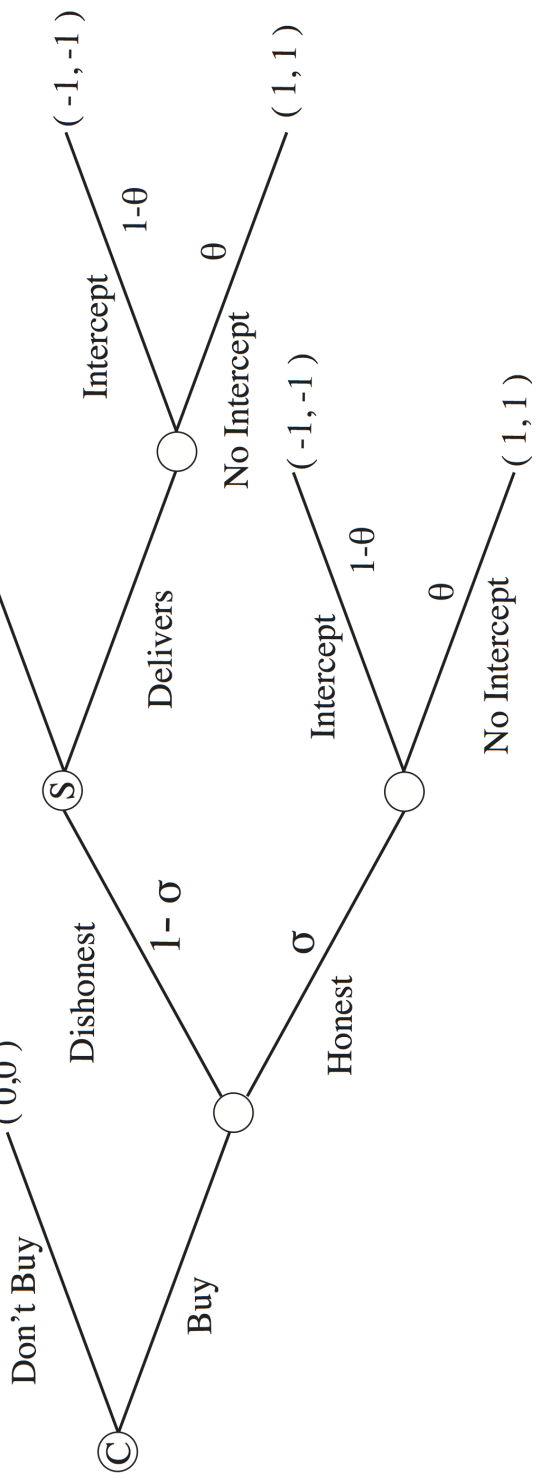


Figure 5.1: Sequential Goods Purchase Game

DATA

The employed sample utilizes Silk Road data scraped by Christin (2013) and includes information on item listings, transactions, and sellers.[1] The sample contains information on transactions conducted from July 7, 2011 to July 24, 2012 and price data for transactions from January 21, 2012 through July 24, 2012. I obtain this data in three separate SQL tables: one for item listings, one for feedback, and one for prices.

The item listing table contains unique item identifiers, textual titles and descriptions, location and market characteristics, time first seen, and time last seen for 24,385 item listings. The feedback table contains user-submitted responses, both numeric and textual, from 184,804 observed transactions along with the corresponding item identifier. The price table contains nearly 800,000 observations for 6 months of high-resolution price series linked to the observed item listings. Listed price is observed on average 1.1 - 1.2 times per day, with maximum observation rates of 5, 6, and 7 for methamphetamine, amphetamine, and marijuana listings respectively.

To create the utilized dataset, I first merge item listings with their specific feedback responses. This table accounts for a given item's transaction history over time and includes all scraped information except for price. I then add prices, first matching on the exact scrape time in Unix time (seconds elapsed since 00:00:00 on Thursday, 1 January 1970). Only 13,200 observations match on the exact second. I next compute a daily arithmetic mean price for each item listing (the sum of observed prices on a given day, divided by the number of price observations). When listing prices are observed on the transaction date but no exact second match is found, I assign the daily average price.[2] Use of the daily

[1] For a detailed discussion of the scraping process and an extensive overview of the whole market, see Christin (2013).

[2] For example, if a marijuana listing has prices equal to \$58 at 7:55am and \$62 at 11:04pm and a transaction occurs at noon, no match occurs on the exact Unix time. I therefore assign the transaction price as $\frac{58+62}{2} = \$60$. Results in Chapter 8 do not change substantively when I use the prior observed price (in this case \$58)

average prices increases complete observations to approximately 50,000. Finally, I merge in a panel of Bitcoin data that includes information on hourly exchange rates and daily trading volume.

Before analysis can occur, a purely objective quantity measure is required. Many categories are dropped due to lack of uniformity in quantity.[3] Listing quantity is scraped from textual item titles and descriptions, and then personally confirmed by visual inspection. Published imperial quantities are then converted to grams. Ultimately, three item categories are retained for analysis: marijuana, amphetamine (speed), and methamphetamine (meth). All three categories exhibit considerable variation in feedback ratings, have easily quantifiable listing volumes, and heterogeneous item attributes that can be held constant in later empirical models.[4]

Table 6.1 reports summary statistics for transaction characteristics by drug type. As expected, marijuana is the least expensive, averaging 2.82 Bitcoins per gram (equivalent to $15.27). Marijuana listings are the largest quantity-wise, averaging around 11 grams per listing (roughly 40% of an ounce) and costing 20.06 BTC ($110). Speed tends to be 40% more expensive, running 4.01 BTC and $21.34 per gram. Total listing value runs closer to 12 BTC ($66) as average listing quantity is closer to 6 grams. Although only exhibiting an average quantity of 0.86 grams per listing, methamphetamine leads total value with 23.63 BTC ($127.69) per listing due to a significantly higher unit price of 32.51 BTC ($178) per gram.

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or an average of the two most recent prices, before and after, weighted by the seconds since observation (here computed as $58 * (1 - \frac{14700}{54540}) + 62 * (1 - \frac{39840}{54540}) = \$59.08$).

[3]Some categories like LSD are dropped as only a fraction of listings report an objective quantity measure, while others (such as edibles) lack quantitative measures altogether. Listings for marijuana advertise in either imperial or metric weights which are easily converted to grams, whereas edibles (marijuana-infused baked goods) or LSD tabs are measured in nonstandard quantities like cookies or tabs, and are therefore considerably harder to quantify.

[4]Listings for meth and speed are advertised in grams, while marijuana listings advertise in both imperial and metric.

When compared to eBay, the Silk Road reputation system exhibits greater variation in feedback ratings. Empirical eBay studies confirm that, across time and item types, seller feedback on eBay is characterized by near uniformly positive reputations. Resnick and Zeckhauser (2002) find that, although only 51.7% of transactions result in seller feedback, 99.03% of feedback responses are positive. Similarly, Cabral and Hortaçsu (2004) report a mean favorable rating of 99.26% across auctions for IBM Thinkpad notebooks, collectible coins, and 1998 holiday Beanie Babies. Dewally and Ederington (2006) confirm the highly positive feedback situation, finding an average favorable rating of, unsurprisingly, 99% for sellers and 98% for buyers. In contrast, Silk Road exhbits higher instances of negative feedback across the analyzed items. Average ratings range from 4.75 out of 5 stars (95%) for speed, 4.81 (96.2%) for meth, and 4.92 (98.4%) for marijuana listings. Sellers exhibit similar ratings, with averages of 96.73, 97.77, and 98.61 percent favorable for sellers of speed, meth, and marijuana, respectively.

Table 6.2 summarizes listing characteristics. Significant variability exists in both prior transactions and accrued negative reviews. Although the average number of transactions per listing ranges across drug types from 44.41 to 71.98, standard deviations for marijuana and amphetamine are larger than their means (62.09 and 83.22, respectively). Marijuana listings had the highest average rating and the fewest prior negative ratings at 4.92 and 0.66, respectively. Speed and meth both exhibit greater ratings volatility, with nearly 3 negative reviews per item listing and average ratings of 4.75 and 4.81, respectively. While less than ten percent of speed and meth listings ship domestically, approximately half of marijuana listings ship only within the country of origin. Only 10% of marijuana and amphetamine observations occur when listings have exactly one negative rating, with 17% for methamphetamine. Half the observed amphetamine sales occur on listings that have already accumulated two or more negative reviews. In contrast, only 34% of methamphetamine sales and a mere 16% of marijuana transactions occur on listings with

two or more negative reviews. Item listings tend to be relatively young, realize transactions roughly 2.5 times per day, and offer very short descriptions (approximately 8 to 16 average-length words).

Table 6.3 reports descriptive statistics for seller-level characteristics. Sellers on the Silk Road tend to vary in age and transactions, though they average over 3 months of activity and over 200 maximum transactions across all categories. Cumulative transactions are highly variable, ranging from low single digits to over a thousand. Although sellers are generally young, they are not considered "new" by Silk Road. New sellers were defined as vendors younger than one month and with fewer than 35 lifetime transactions. By this definition only 6% of speed vendors and 12% of marijuana and meth vendors qualify as new. Of marijuana vendors, only 59% have received any negative reviews; this share increases to 76% for meth vendors and 87% for speed vendors. Marijuana vendors average 6 negative reviews across all items, with meth and speed vendors averaging closer to 11.

Table 6.4 reports descriptive statistics for marijuana item characteristics. Few sellers mention the species of a given marijuana strain; although all marijuana strains belong to either *cannabis sativa* or *cannabis indica*, only 8% of transactions advertise the product as *indica* while 18% advertise as *sativa*. Organic products account for 7% of marijuana sales, while only 4% are grown indoors and 1% are advertised as a listing for leftover trimmings or clippings. Using a marijuana strain quality index as developed by Anderson et al. (2013) from price information in *High Times*, 41% of sales correspond to listings identified as "high-quality."[5] Listings advertising as medical-grade, high-quality, and high-value correspond to 7%, 13%, and 5% of transactions respectively.

[5]For additional discussion of the strain indicator, see the empirical strategy discussion in Chapter 7.

Table 6.5 reports item characteristics for amphetamine (speed) transactions. Although only 9% of speed listings advertise lab testing, 16% mention the listing's percent purity.[6] The majority of sales occur for powdered amphetamine, while 30% correspond to a paste form (7% advertise as base and 23% as paste). Only 6% of sales are for street-quality amphetamines. Among the named production countries, the United Kingdom and Poland correspond to 3% and 2% of transactions, respectively, while 34% of sales are for Dutch-produced speed. Amphetamine salts – as found in prescription drugs like Adderall – represent 10% of sales, with amphetamine sulphate corresponding to 7% and amphetamine phosphate 3%. Listings advertising as medical-grade, high-purity, high-quality, and high-value represent 3%, 9%, 16%, and 3% of speed sales respectively.

Table 6.6 presents descriptive statistics for methamphetamine (meth) characteristics. As a highly-concentrated substituted amphetamine compound, meth is typically sold in crystal form. Unlike speed, no meth listings advertise lab-tested purity percentages or countries of origin. Rather, sellers differentiate in mention of purity, quality, or value. Sales for street-quality meth accounts for only 1% of sales, while 10% of sales advertise for high-purity, 28% for high-quality, and 5% for high-value.

Advantages of Silk Road Data

The market structure of Silk Road presents several advantages for conducting empirical analysis of reputation. First, characteristics of the site's escrow system provide for both near-perfect occurrence of feedback and identification of transactions. The Silk Road employed an escrow system designed to mitigate volatility risk and encourage market participation: after purchase, each Bitcoin sale was converted to U.S. dollars and held by

[6] Although percent purity ranges from 35-90% for amphetamine, the percent purity variable reported in Table 2b evaluates to zero in the absence of reported purity. As a result, the average value for this purity variable is only 16%. Among listings that do report, the average purity is 71.6%.

the site. Only when buyers received the goods and left feedback (or a requisite amount of time elapsed without feedback) were funds converted back into Bitcoin and released to the vendor. Sellers were guaranteed the full U.S. dollar value of each purchase as the site administrators realized any gain or loss due to cryptocurrency volatility.

The escrow system largely fulfilled its intended goal as a hedging mechanism, however it fells short as an enforcement mechanism. Although buyers could turn to site arbitration in the case of unrepresentative or undelivered items, textual user feedback paints it as risky and unreliable – in contrast to systems on most formal online markets. Table 6.7 provides examples of user reviews for marijuana, speed, and meth transactions discussing their escrow experiences. Many negative reviews recount a story of incomplete or denied refunds. Indeed the refund distribution is heavily clustered around three values: 0-10%, 50% , and 100%. Such unpredictability meant consumers could not rely on arbitration for a guaranteed refund in the case of a failed transaction, entailing reliance on alternative signals to ensure seller performance.

Second, item listings on the Silk Road remain over time and allow for repeat sales of the same good. Item listings within a given category are differentiated based on their advertised characteristics, and therefore each category can be thought of as a distinct heterogeneous product market. Specific items listed by unique sellers can be tracked over time as they accumulate transactions and feedback. Item quantity and price can be determined for a given transaction, as can the feedback received from that transaction, all prior item feedback, and accrued seller reputation. The panel nature of the data allows for variation in prices and feedback across items and sellers in addition to variation within a given item or seller over time. These sources of variation within and across both items and sellers form the basis of later empirical analysis. Further, the uniform appearance of item listings and vendor pages eliminates a source of omitted variable bias that affects auction sites such as eBay and can dramatically impact price (Resnick et al. 2006; Yin 2002). eBay

allows sellers to add up to a dozen featured photos (and more embedded on the page) and design custom HTML web pages for their listings. In contrast, all Silk Road listings used the same format and appearance. The only opportunity for visual differentiation arose in a single photo featured on each post and the exact content of the textual description.

Third, the Silk Road reputation system allows for more information-rich reviews than that of eBay. Whereas eBay allows for a positive, neutral or negative numeric rating and a one-line text comment, the Silk Road employed a numeric 1-5 rating and an open textual response. Observed feedback ranges from short text phrases to involved, multiple paragraph descriptions covering every aspect of a transaction, from seller communication to item packaging and product quality. The variation in text allows for more nuanced analysis of feedback by the type of transaction failure and offers another source of rating variation to exploit.

Finally, the requirement to purchase a seller account greatly diminishes the likelihood of identity switching. On markets like eBay, users are free to sacrifice an existing identity (and thus its reputation) and create new user accounts at any point. Agents can therefore dispose of negative reputations by shedding their current identity and creating a new account. The ease of identity change reduces trust between buyers and sellers – particularly towards new sellers as consumers cannot discern between genuinely new sellers and opportunistic switching (Wibral, 2014).

When the Silk Road began, vendor registration was free and open to all users. Any party interested in conducting business could register a vendor account and operate on the market. However, this policy changed in June 2011 (prior to the observation period) after threats appeared that a vendor would be mailing poisonous, toxic substances instead of the advertised drugs. From then on, new vendors were required to purchase accounts. Vendor accounts initially sold for as little as $10, but steadily grew in price: by February 19,

2013, new vendor accounts cost $505.90 (Hansen, 2013).[7] Purchase of a vendor account therefore entailed a substantial sunk cost. Accordingly, identity switching would have been altogether eliminated except in cases where the discounting effect of bad reputation was deemed larger than the pecuniary cost of a new account.[8]

These strengths of Silk Road institutions provide a strong foundation for empirical analysis. In order to take advantage of these institutional strengths, an empirical model must be designed that can exploit these advantages in order to provide insight on the role of reputation on a deep web market.

[7]The inclusion of time fixed effects helps to control for the upward trend in account prices and the potential for sellers offsetting the account cost by raising prices.

[8]The existence of a secondary market for seller accounts supports this notion. Rather than purchase a fresh account from the site administrators, potential vendors could purchase an existing account from an interested vendor and operate under the established pseudonym. The presence of a secondary account market, with prices largely determined by the volume and quality of accrued reputation, suggests that vendors also considered feedback a credible signal to consumers. While such account sales were generally mentioned on forums or discussed in item descriptions, secret account purchases may still have occurred. Clandestine account sales would allow a new seller to immediately obtain a credible seller reputation; however they would still need to create new item listings for their specific goods. Thus if consumers suspected purchasing of senior accounts to be a common occurrence, they would likely be distrustful of accrued seller reputation and instead use item-specific ratings to inform their decisions.

Table 6.1: Descriptive Statistics by Drug Type - Transaction Characteristics

	Marijuana	Speed	Meth	
Variable	Mean (S.D)	Mean (S.D.)	Mean (S.D.)	Description
Price	20.06 (37.55)	11.96 (19.94)	23.63 (21.31)	Price, Bitcoin
Price USD	109.97 (208.15)	65.61 (110.79)	127.69 (114.51)	Price, USD
USD to BTC Exchange	5.58 (0.99)	5.54 (0.95)	5.52 (1.03)	Exchange rate, USD to BTC
Quantity	11.20 (31.29)	5.88 (18.70)	0.86 (0.89)	Quantity, grams
Price per Gram USD	15.27 (6.12)	21.34 (27.71)	177.95 (24.1)	Price per unit, USD per gram
Strain	0.41 (0.49)	--	--	=1 for high-quality marijuana strains, =0 otherwise
Feedback Rating	4.92 (0.47)	4.75 (0.83)	4.81 (0.79)	Numeric Feedback rating
Feedback Length	81.54 (106.98)	70.87 (84.33)	112.75 (158.87)	Character length of textual feedback
Date	May 1, 2012 (51.27)	Apr 30, 2012 (49.87)	Apr 26, 2012 (50.81)	Calendar date of transaction (Standard Deviation in days)
N	12,305	2,091	1,636	Observations

Notes: The above table reports characteristics of transactions on the deep web marketplace Silk Road. Item listings and vendor pages were scraped by Christin (2012) from November 2011 through July 24, 2012, with near-daily crawls performed February through July 2012. Data includes seller and reputation information on transactions before the scraping window (as far back as February 2011) while prices are captured during the daily crawl period (February through July 2012). The marijuana strain indicator employs the classification devised by Anderson et al. (2013).

Table 6.2: Descriptive Statistics by Drug Type - Listing Characteristics

	Marijuana	Speed	Meth	
Variable	Mean (S.D)	Mean (S.D.)	Mean (S.D.)	Description
Prior Transactions	44.41 (62.09)	71.98 (83.22)	60.93 (55.92)	Cumulative number of prior item transactions
Prior Negative Reviews	0.66 (1.90)	2.97 (3.77)	2.58 (4.96)	Cumulative number of prior negative item reviews (rating < 4)
Any Negative Reviews	0.10 (0.29)	0.10 (0.31)	0.17 (0.38)	=1 if listing has exactly 1 negative review, =0 otherwise
Average Rating	4.92 (0.19)	4.75 (0.24)	4.81 (0.21)	Average rating across all of an item's transactions, 1-5
Item Age	39.78 (38.99)	48.49 (43.95)	43.24 (35.65)	Listing age, days
Days Since Transaction	0.45 (1.40)	0.40 (0.99)	0.40 (0.80)	Days since last transaction
Days Since Negative	38.16 (43.55)	18.64 (24.43)	28.75 (33.74)	Days since last negative review
Domestic Only	0.55 (0.50)	0.07 (0.26)	0.08 (0.28)	=1 if item only ships within country of origin, =0 otherwise
Description Length	98.49 (155.99)	48.86 (33.36)	87.19 (64.66)	Character length of textual item description
N	12,305	2,091	1,636	Observations

Notes: The above table reports characteristics of item listings on the deep web marketplace Silk Road. Item listing and vendor pages were scraped by Christin (2012) from November 2011 through July 24, 2012, with near-daily crawls performed February through July 2012. Data includes seller and reputation information on transactions before the scraping window (as far back as February 2011) while prices are captured during the daily crawl period (February through July 2012).

Table 6.3: Descriptive Statistics by Drug Type - Seller Characteristics

	Marijuana	Speed	Meth	
Variable	Mean (S.D)	Mean (S.D.)	Mean (S.D.)	Description
Seller Age	99.64 (78.79)	139.78 (105.24)	92.78 (55.90)	Age of seller, days
Transactions	268.38 (220.13)	226.67 (163.39)	208.57 (102.99)	Maximum transactions by sellers in category
Category Share	0.98 (0.09)	0.92 (0.18)	0.93 (0.18)	Share of a seller's transactions within a given item category
Multiple Categories?	0.04 (0.21)	0.36 (0.48)	0.14 (0.35)	=1 if seller participates in multiple item categories
New Seller	0.12 (0.32)	0.06 (0.24)	0.12 (0.32)	=1 if seller has fewer than 35 lifetime transactions and is younger than 1 month, =0 otherwise
Items by Seller	18.51 (18.46)	6.53 (3.38)	7.07 (6.82)	Count of a seller's item listings across all categories
In-Category Items	12.41 (13.21)	5.31 (2.33)	5.63 (1.94)	Maximum listings by seller within the specified category
% Favorable Rating	98.46 (2.09)	94.88 (3.51)	96.29 (3.09)	Percent favorable vendor rating across all of a seller's items
Any Negative Seller Reviews	0.59 (0.49)	0.87 (0.34)	0.76 (0.43)	=1 if seller has any negative reviews, =0 otherwise
Negative Ratings	6.05 (10.10)	11.25 (11.64)	10.54 (14.95)	Count of negative reviews accrued across all items
Sellers	240	34	28	Number of unique sellers by category
N	12,305	2,091	1,636	Observations

Notes: The above table reports characteristics of sellers on the deep web marketplace Silk Road. Item listing and vendor pages were scraped by Christin (2012) from November 2011 through July 24, 2012, with near-daily crawls performed February through July 2012. Data includes seller and reputation information on transactions before the scraping window (as far back as February 2011) while prices are captured during the daily crawl period (February through July 2012).

Table 6.4: Descriptive Statistics - Marijuana Characteristics

	Marijuana	
Variable	Mean (S.D)	Description
Indica	0.08 (0.27)	=1 if listing advertises as *cannabis indica*, =0 otherwise
Sativa	0.18 (0.38)	=1 if listing advertises as *cannabis sativa*, =0 otherwise
Bio/Organic	0.07 (0.25)	=1 if listing advertises as bio/organic, =0 otherwise
Indoor	0.04 (0.19)	=1 if listing is for marijuana grown indoors, =0 otherwise
Strain	0.41 (0.49)	=1 for high-quality marijuana strains, =0 otherwise
Clippings	0.01 (0.12)	=1 if listing is for marijuana trim/clippings, =0 otherwise
Medical	0.07 (0.26)	=1 if advertised as medical-grade, =0 otherwise
Quality	0.13 (0.34)	=1 if listing text makes reference to high quality, =0 otherwise
Value	0.05 (0.21)	=1 if listing text makes reference to high value or sale/promo, =0 otherwise
N	12,305	Observations

Notes: The above table reports differentiating item characteristics for marijuana transactions obtained from crawls of the Silk Road marketplace carried out by Christin (2012) from November 2011 through July 24, 2012. The above variables are first constructed using textual scrapes of item names and descriptions, before being manually verified.

Table 6.5: Descriptive Statistics - Amphetamine (Speed) Characteristics

Variable	Mean	(Standard Dev.)	Description
Lab Tested	0.09	(0.28)	=1 if listing advertises as lab-tested for purity, =0 otherwise
Reports Purity	0.16	(0.37)	=1 if listing reports percent purity, =0 otherwise
Percent Purity	11.47	(26.72)	Percent purity if reported, =0 otherwise
Base	0.07	(0.26)	=1 if listing advertises as base form, =0 otherwise
Paste	0.23	(0.42)	=1 if listing advertises as paste form, =0 otherwise
Street	0.06	(0.18)	=1 if listing is for street quality amphetamine, =0 otherwise
UK	0.03	(0.18)	=1 if listing is for speed produced in the United Kingdom, =0 otherwise
Polish	0.02	(0.14)	=1 if listing is for speed produced in Poland, =0 otherwise
Dutch	0.34	(0.47)	=1 if listing is for speed produced in the Netherlands, =0 otherwise
Sulphate	0.07	(0.26)	=1 if listing is for amphetamine sulphate, =0 otherwise
Phosphate	0.03	(0.18)	=1 if listing is for amphetamine phosphate, =0 otherwise
Medical	0.03	(0.18)	=1 if advertised as medical-grade, =0 otherwise
Pure	0.09	(0.29)	=1 if listing advertises as high purity, =0 otherwise
Quality	0.16	(0.36)	=1 if listing text makes reference to high quality, =0 otherwise
Value	0.03	(0.16)	=1 if listing text makes reference to high value or a sale/promo,
N	2,091		Observations

Notes: The above table reports differentiating item characteristics for amphetamine (speed) transactions obtained from crawls of the Silk Road marketplace carried out by Christin (2012) from November 2011 through July 24, 2012. The above variables are first constructed using textual scrapes of item names and descriptions, before being manually verified.

Table 6.6: Descriptive Statistics - Methamphetamine (Meth) Characteristics

Variable	Mean	(Standard Dev.)	Description
Street	0.01	(0.09)	=1 if listing is for street quality amphetamine, =0 otherwise
Pure	0.10	(0.31)	=1 if listing advertises as high purity, =0 otherwise
Quality	0.28	(0.45)	=1 if listing text makes reference to high quality, =0 otherwise
Value	0.05	(0.22)	=1 if listing text makes reference to high value or a sale/promotion price
N	1,636		Observations

Notes: The above table reports differentiating item characteristics for methamphetamine (meth) transactions obtained from crawls of the Silk Road marketplace carried out by Christin (2012) from November 2011 through July 24, 2012. The above variables are first constructed using textual scrapes of item names and descriptions, before being manually verified.

Table 6.7: User Experiences with Escrow and Arbitration

Drug Type	Numeric Rating	Textual Review
Marijuana	1	the order didn't arrive and after a long resolution process the moderator gave me a 1/2 refund
Marijuana	1	hasn't arrived yet. no refund. sux!
Meth	1	package was never sent so vmm has basically taken my money dispite me constantly messaging asking for a refund. avoid like the plague.
Meth	1	never got anything in the mail. seller didn't respond to msgs, and we ended up having to resolve it. only got half my money back.
Meth	1	never arrived…sr admin decided on a 50% settlement. how is this fair? i lost $75 to this asshole, good luck.
Meth	1	never get anything, always promising heaven, get 10% refund
Speed	1	package never arrived,no offer of a resend or refund
Speed	1	50% refund and just joking when i asked about delivery
Marijuana	2	50% eventually handed back by sr after custom seize
Marijuana	3	2 weeks and order never arrived…so got a refund.
Meth	3	product never arrived. full refund.
Speed	3	order never arrived got 50% refund
Marijuana	5	didn’t show so got full refund. thanks.
Speed	5	dont believe it will make it. i knew no refund and who knows what happened. not necessarily dd fault but i will not ask for resend. peace

Notes: Table 3 presents excerpts from user reviews that reference an experience with the Silk Road escrow system or arbitration process. Examples are reported for marijuana, speed, and meth transactions across numeric ratings.

EMPIRICAL STRATEGY

The anonymous environment of the Silk Road market provides an ideal informational setting in which to test seller reputation as a mechanism for consumer decision-making. The primary empirical questions of interest are (i) whether negative reputation has a discounting effect on item price, and (ii) whether item or seller-specific reputation drives the effect. Initial models address the first question by specifying reputation according to a naive consumer before introducing a range of controls to isolate the effect of reputation. Later models employ alternate reputation measures to further identify whether consumers use additional seller information to inform purchasing decisions.

Extending from the empirical eBay reputation literature, I employ a hedonic regression of drug price on item characteristics and reputation measures to estimate willingness-to-pay in the presence of negative feedback. As first formalized by Rosen (1974), hedonic regression provides a framework for decomposing the price of a heterogeneous good according to its characteristics. Through this process, consumer willingness-to-pay for specific item attributes is estimated, providing an estimate of attribute value and allowing the price function to be identified even in the case of unobserved product attributes (Bajari and Hortaçsu, 2004). Here, the use of actual, observed prices in place of stated prices elicited from contingent valuation methods bypasses a major source of criticism of the hedonic literature, ignoring issues inherent in survey data (Diamond and Hausman, 1993).

If potential consumers use accrued feedback to infer seller type and therefore the probability of delivery or accurate product representation, then a willingness-to-pay for reputation characteristics can be estimated through a hedonic approach. I specify two reputation vectors: one for item-level reputation and another for seller-level measures.

In order to estimate consumer willingness-to-pay for reputation, the specified model must mitigate concerns of omitted variable bias. The key identifying assumption is that the

model does not omit relevant variables correlated both with listing price and the reputation measures of interest. To minimize omitted variable concerns, I include three control vectors that target potential sources of bias. The model can then be estimated as:

$$ln(P_{ijt}) = \alpha + \delta \mathbf{F_{ijt}} + \beta \mathbf{Z_{ijt}} + \gamma \mathbf{L_{ijt}} + \theta \mathbf{S_{jt}} + \pi \mathbf{T_t} + \epsilon_{ijt}$$

The price for item i sold by seller j at time t is regressed on item-specific reputation measures $\mathbf{F_{it}}$, item characteristics $\mathbf{Z_{ijt}}$, market identifiers $\mathbf{L_{ijt}}$, seller-specific measures $\mathbf{S_{jt}}$, and time controls $\mathbf{T_t}$, with ϵ_{ijt} an independent random variable of mean zero. Following Houser and Wooders (2006) and Lucking-Reiley et al. (2007), the dependent variable is specified as the logarithm of the listed price in U.S. dollars. Listing quantity is specified similarly, using the logarithmic transformation.[1] All remaining covariates are retained in level form.

The item characteristic vector $\mathbf{Z_{it}}$ includes differentiated product attributes particular to each drug group. For Marijuana, this includes:

- Dummy variable equal to one if advertised as *cannabis indica*.
- Dummy variable equal to one if advertised as *cannabis sativa*.
- Dummy indicator equal to one if the transaction occurred within a week of April 20.
- Dummy variable equal to one if the listing is for marijuana trim, clippings, or shake (leftovers once the premium product is removed).
- Dummy variable equal to one if the listing is for organically or hydroponically grown marijuana

[1] Following Melnick and Alm (2005) and Resnick and Zeckhauser (2002), I restrict log-adjusted variables with minimums of zero to positive values by adding one. This is done to avoid taking the logarithm of zero and restrict the range to nonnegative values. As quantity and price are positive and nonzero for all observations, nothing is added to these variables. In later alternate specifications, one is added to the logarithms of positive and negative feedback, where zeros are observed.

- Dummy evaluating to one for high-potency and high-quality strains (for example, strains such as "Northern Lights" and "Sour Diesel").

The *indica* and *sativa* dummy variables control for whether a listing mentions the specific species of marijuana (i.e. *cannabis sativa* or *cannabis indica*), providing consumers information about the product's potential effects. I include a "420" time control to account for increased activity surrounding the date of April 20, the unofficial marijuana holiday.[2] The next dummy controls for whether a listing is for portions of the marijuana plant left over (commonly referred to as clippings, trimmings, or "shake") after the premium "bud" is removed. I also include a dummy that controls for organic and hydroponic product. Finally, I employ a marijuana strain quality index as developed by Anderson et al. (2013) from price information published in *High Times* magazine to construct an indicator evaluating to one for high-potency and high-quality strains. Established, named strains gain a reputation for their particular attributes and conferred state when consumed. Marijuana strain is a primary means for quality differentiation, and should therefore be included in hedonic models.[3]

Amphetamine item characteristics include:

- Numeric measure of percent purity.
- Dummy variable equal to one for amphetamine sulphate.
- Dummy variable equal to one for amphetamine phosphate.
- Dummy variable for a paste form.

[2]Estimated coefficients are statistically insignificant and indistinguishable from zero regardless of whether a period of one week or two weeks prior to April 20 is used.

[3]In their analysis of SR2 marijuana listings, Hardy and Norgaard (2015) make the assumption that advertised strains are highly competitive and therefore no one strain commands a premium over another. However, the existence of multiple online strain dictionaries and strain review sites and magazines such as High Times, The Cannabist, and Leafly suggest that a nontrivial portion of the marijuana community does use strain as a margin for quality differentiation. Given that consumers of marijuana on Silk Road are citing high quality as a motivating factor for site participation and are paying substantially higher prices than prevailing street prices, a potential for bias exists when strain is not accounted for within the empirical model.

- Dummy variables for Dutch, U.K., and Polish amphetamine.
- Dummy variable equal to one if the listing is advertised as having been lab-tested.
- Dummy variable equal to one for "street" quality amphetamine.

Similarly, methamphetamine characteristics include:

- Numeric measure of percent purity.
- Dummy variable equal to one for base form (paste)
- Dummy variable equal to one if the listing is advertised as having been lab tested.
- Dummy variable equal to one for "street" quality amphetamine.

Both speed and meth item characteristic vectors include controls for whether the listing has been lab-tested for purity, the percent purity (equal to the percent purity if provided, or zero if the listing has not been tested), and a dummy accounting for low-grade "street" quality products. Meth includes a further dummy controlling for base form while amphetamine accounts for paste form. The vector of speed characteristics further includes individual dummies for when the United Kingdom, the Netherlands, or Poland are the advertised countries of origin, and for when the listing is for a sulphate or phosphate-based product.

In addition to the above category-specific controls, all models include individual dummy variables for whether the listing text includes mention of each of high-value, high-quality, high-purity, medical-grade, and guaranteed shipping success.

The location control vector $\mathbf{L_{it}}$ accounts for all shipping routes active for a particular drug. Information on shipping costs present an initial hurdle: due to the lack of buyer information obtained through the scraping process, the exact destination of and shipping service for each observed transaction is not known. Roughly 50% of marijuana transactions were for items that offered international shipping – this share jumps to over 90% for

meth and speed. Additionally, multiple types of shipping services (domestic ground, overnight, etc.) were frequently offered. To mitigate this concern, I implement route-specific fixed effects for each country of origin and destination market combination active in each drug category.[4] Although 1,410 unique routes (drawn from 47 countries of origin by 30 destination markets) are theoretically possible, restriction to active routes reduces the number to 55 unique combinations. Methamphetamine models include indicators for 11 of these unique routes, amphetamine models include 16, and regressions for marijuana listings cover 41. While indicators for nation of origin and destination country would account for some of this variation, the use of network controls allows for route-specific differences in international shipping fees or import characteristics by accounting for an average shipping cost along a given network path.[5] Many routes are travelled by a limited number of items sold by a few sellers (or in the case of minimally traveled routes, such as domestic sales within Finland, by a single seller), and in these situations route controls will provide an accurate representation of shipping costs. As long as vendors do not respond to negative reviews by lowering shipping prices and retaining set listing prices, route-specific controls should mitigate bias concerns.[6]

The vector $\mathbf{T_t}$ includes the listing's age in days and weekly fixed effects (Monday through Sunday) for the price series observation period beginning January 21, 2012 and ending July 24, 2012. Weekly time controls allow greater flexibility in prevailing

[4]Domestic transactions within the United States represent the most frequently traveled shipping route, accounting for 23% of observed sales. Other common routes (greater than 1% of total transactions) include each of The Netherlands, The United States, Canada, The United Kingdom, South Africa, and Germany to worldwide destinations, Germany, Canada, and The Netherlands to The European Union, and domestic transactions within Australia and Germany.

[5]For instance, if shipments into Australia from Germany are more costly or more frequently intercepted by customs relative to shipments from other nations, and this information is known by consumers, then one can rationally expect a discounting effect to offset these outcomes.

[6]If vendors do behave in this manner, then the receipt of negative feedback would have no impact on an item's listed price and regression models should estimate coefficients of zero on negative reputation measures.

time trends and further account for short-run shocks to Bitcoin prices, seasonality and promotions, or market confidence.[7]

Models account for and differentiate between two levels of reputation: feedback particular to a specific item and reputation aggregated to the seller level. The item-specific reputation vector $\mathbf{F_{it}}$ initially includes an indicator for whether or not the item listing has received any negative reviews during its tenure on Silk Road. Later models prove robust to alternate specifications of negative feedback and inclusion of positive feedback measures and are discussed in Chapter 7.

The seller reputation vector $\mathbf{S_{jt}}$ initially includes one variable controlling for seller-specific reputation as immediately provided to Silk Road consumers: the aggregate percent favorable rating. The aggregate seller rating is calculated by summing numeric feedback ratings across all of a seller's transactions on all of their item listings up to time t. This sum is divided by the maximum possible rating sum (5 times the number of transactions) and converted to percentile form. Later specifications include separate measures for the cumulative number of positive or negative ratings across a seller's item portfolio.

While ϵ_{ijt} is likely independent from item listing to item listing due to differences in products and seller attributes, there exists potential for error correlation within a given item listing – along the i dimension. To mitigate this issue, all models cluster standard errors on the unique item listing.

[7]Models with monthly time trends or day of the week indicators have also been computed and the estimates for coefficients of interest are unaffected. When day of the week indicators are included, coefficients for Monday through Saturday estimate statistically significant coefficients equal to price discounts between 2% and 3% relative to Sunday sales.

RESULTS

Using the hedonic price model formulated above, I estimate consumer willingness-to-pay for reputation on the Silk Road market. I report results in the following manner. First, a specification progression is discussed for each of the three groups of drugs in Tables 8.1-3. Table 8.4 presents models with and without seller fixed effects that I use to draw initial conclusions as to whether and how reputation impacts drug prices on Silk Road. Next, in Tables 8.5-10 I employ models of alternate feedback specification to identify whether item reputation, seller reputation, or a combination of the two are driving reputation effects. Finally, I discuss prevailing identification concerns and present results of restricted sample analyses in Table 8.11 to further support the validity of the employed price-matching approach.

Table 8.1 reports results across progressive specifications for marijuana transactions. Column 1 presents results for a naive specification where the logged price is regressed on only the logarithm of quantity and the *Any Negative Review* indicator. Column 2 takes a similar approach and adds the percent favorable seller rating. Column 3 includes both reputation measures and the premium strain indicator. Columns 4-6 incrementally add control vectors: column 4 adds textual controls from $\mathbf{Z_{ijt}}$, column 5 adds time controls $\mathbf{T_t}$, and column 6 adds location and market controls $\mathbf{L_{ijt}}$. Column 7 adds seller-specific fixed effects from $\mathbf{S_{jt}}$.

Seller reputation appears to moderately inform consumer purchasing behavior for marijuana. Beginning in column 2, the coefficient on a seller's percent favorable rating – a measure of their overall positive reputation – signs as expected in 5 of 6 models and is statistically significant at the 95% level in 2 of the final 3. Columns 2-5 estimate a 1-2% premium for a one percentage point change in the seller's portfolio rating (i.e. changing from 98% to 99% positive). While any estimated effect disappears in column 6 in the

presence of location and market controls, the addition of seller fixed effects in column 7 restores a 1% premium significant at the 95% level.

Coefficients for the negative reputation indicator exhibit the predicted negative sign and some level of statistical significance in all cases. In the absence of seller fixed effects, column 6 reports a $\left(1 - e^{-.0611}\right)100 = 5.9\%$ price discount when an item listing gains its first negative review. The effect's magnitude grows to a 8.1% discount and becomes significant at the 99% level when seller fixed effects are added in column 7, suggesting that consumers value item-specific reputation even when permanent seller characteristics may inform product quality or outcomes.

Results for both amphetamine and methamphetamine sales in Tables 8.2 and 8.3 confirm the effects found for marijuana. The coefficient on the negative review indicator are, at a minimum, significant at the 95% level across all amphetamine models and predict between a 9 and 22% price discount once controls are added in columns 4-7. Negative reputation coefficients for meth are significant at the 99% level across all specifications and estimate a discount of 3 to 18% once controls are added. Seller reputation is signed as predicted in all specifications for both drugs. In both cases, the full specification without seller fixed effects in column 6 estimates a moderate premium (2% for a 1 percentage point change in the reputation of a meth vendor, and 5% for a speed vendor) while no effect is found once fixed effects are added in column 7.

The above results suggests that the site's reputation system does play a role in consumer decision-making. Even after controlling for permanent seller characteristics, models predict a pessimistic scenario in which even a first negative rating results in long-run item discounting. Consumers are quick to punish vendors for dishonesty and failed transactions by turning to other sellers' items until the vendor lowers prices enough to compensate for their failures. This observed sensitivity suggests that a consumer's impression of seller honesty, σ, is easily updated and does adapt as new information

is learned. Although feedback specification and thus coefficient interpretation differs across eBay studies, coefficient magnitudes reported above align with the higher end of estimates from eBay. In the most directly comparable approach, Lucking-Reiley et al. (2007) estimates an 11% price decrease when sellers move from 2 to 3 negative ratings.

Table 8.4 presents regression results across drug types. Columns 1-6 report full specification results with and without seller fixed effects for marijuana, speed (amphetamine), and meth (methamphetamine). Model specifications correspond to columns 6 and 7 of Tables 8.1-3. Negative feedback coefficients are signed as predicted across all drug types regardless of the presence of seller fixed effects. Although magnitudes and statistical significance differ slightly for models with seller fixed effects, negative feedback coefficients are not found to be statistically different across the two specifications. Interpreting coefficients from the fixed effects specifications yields a consistent story of "bad-news" market learning. When a marijuana listing acquires its first negative rating, price declines by 6-8.5%. The presence of any negative reviews carries a 9-11% discount for speed listings. Meth listings appear less sensitive to reputation, with negative reviews leading to a 3-5% decline in price.[1]

Results across drug types confirm the role of seller reputation as a proxy for permanent seller characteristics. Marijuana models estimate no effect without seller fixed effects, and a 1% premium for a 1 percentage point change in vendor reputation in their presence. While models for speed and meth estimate 2-5% price premiums in the absence of seller fixed effects, no effect is estimated when seller indicators are added. This shift suggests that percent favorable ratings signal permanent vendor characteristics to

[1]Dropping the top and bottom 1% of price outliers confirms reported results. For marijuana models, coefficients on reputation measures are unchanged in magnitude and increase in significance to the 99% level when seller fixed effects are added. Coefficient estimates for reputation measures in speed and meth models are statistically unchanged.

consumers, rather than reflect strategic changes in vendor behavior during their tenure on Silk Road.

Consumer Use of Additional Reputation Measures

The above models assume that Silk Road consumers utilize only the reputation measures immediately presented to them during the purchasing process. Consumers who navigated directly to an item page before conducting purchases were only exposed to the seller's percent favorable rating and historical item reviews (both numeric and textual, in chronological order). However, risk-averse consumers seeking a complete signal of seller honesty likely sought out additional measures of reputation to augment and update their perception of σ, the probability of seller honesty.

Tables 8.5, 8.6, and 8.7 explore three alternate specifications of item reputation for marijuana, speed, and meth transactions, respectively. Columns 1 and 2 add the natural logarithm of cumulative positive item reviews to the main models presented in Table 5. Columns 3 and 4 remove the *Any Negative Reviews* and *Ln (Positive Reviews)* indicators, replacing them with the natural log of negative reviews, plus one. Columns 5 and 6 specify item-level reputation as the overall item percent favorable rating (computed identically to the overall seller percent favorable rating, but for the individual item).

Models for speed and meth that include the log of positive reviews (Columns 1 and 2 in Tables 8.6 and 8.7) report reputation coefficients comparable to those in Table 8.4. Magnitudes and statistical significance for *Seller % Favorable* and *Any Negative Reviews* are the same as reported previously. Marijuana models in Table 8.5 reduce or lose statistical significance for *Any Negative Reviews* and predict a 0.6% price discount for every 1% increase in the number of positive item reviews. As the included measure of positive item reputation is highly collinear with the number of transactions, it is likely picking up the

effect of increased competition as the market developed. As Silk Road grew, considerable product entry occurred, increasing competition and reducing market share on individual items. One explanation for the observed coefficient estimate is that, over time, vendors were forced to cut prices on existing item listings in order to retain market share.

Columns 3 and 4 retain statistical significance on coefficients for seller reputation and estimated effects for *Ln (Negative Reviews)* reflect previous findings. For every 1% increase in the number of negative reviews, a 0.05% to 0.07% decrease in prices is predicted for marijuana, 0.1% for speed, and 0.03% for meth. Scaling these effects to represent a one negative review increase from the mean category values (a 100% increase moving from 1 to 2 negative reviews for marijuana and a 33% increase from 3 to 4 negative reviews for speed and meth) yields a 5 to 7% price discount for marijuana listings moving from 1 to 2 negative reviews, a 3.3% discount for speed listings moving from 3 to 4 reviews, and a 1% discount for meth listings moving from 3 to 4 negative reviews.

Columns 5 and 6 find little evidence to suggest that Silk Road consumers rely on an aggregate share measure of negative item-level reputation. No statistical significance is found on coefficients for *Item % Favorable* across all drug types in the absence of seller fixed effects.

Tables 8.8, 8.9, and 8.10 explore alternate measures of seller reputation. Columns 1 and 2 replace the item-level negative reputation indicator with a dummy for whether the seller has received any negative reviews. Further, they include the natural logarithm of prior positive seller reviews. Columns 3 and 4 specify seller reputation using logarithms of both positive and negative reviews. Columns 5 and 6 use no reputation measure. Instead, the logarithm of total transactions is included as a counterfactual, capturing the effect changes in sales volume over time had on prices received.

Results in Columns 1 and 2 for the seller-level indicator parallel those found for the item-level measure. When sellers acquire their first negative reviews, prices suffer

a 9% discount for marijuana and speed listings, and a 3.5% discount for meth listings. Coefficients for *Ln (Positive Seller Reviews)* estimate economically small magnitudes (0.06% price increases for marijuana for a 1% change in positive review volume, and a 0.02% increase for meth) and lose any statistical significance in the presence of seller fixed effects.

Columns 3 and 4 report comparable findings for *Ln (Positive Seller Reviews)* and find weak evidence for consumer use of an aggregate seller-level negative reputation measure. While speed and meth models estimate statistically significant coefficients in the absence of seller fixed effects, only speed remains weakly statistically significant once seller fixed effects enter. Further, magnitudes are economically small, estimating elasticities between -0.04 and -0.19. No effect is found for marijuana models.

Results for Columns 5 and 6 provide confirmation that vendor experience is a sufficient signal of seller honesty in the Silk Road market. When reputation measures are excluded, models for marijuana and methamphetamine estimate small, statistically significant elasticities (0.05 and 0.02, respectively) in the absence of seller fixed effects. Effects disappear when seller fixed effects are added. Amphetamine models estimate coefficients with weak statistical significance initially, before disappearing in the next column. No strong relationship is found between general seller experience and consumer trust, again suggesting that consumers primarily rely on information specific to the items of interest.

Alternate specifications of item and seller reputation in Tables 8.5 and 8.8 confirm the price premium received by high-quality marijuana strains. In the absence of seller fixed effects, all specifications of item and seller reputation estimate consistent price premiums for high-quality marijuana strains. Listings for high-potency strains receive prices 8 to 9% higher than equivalent listings for lower potency strains. Again, this effect loses statistical significance at conventional levels once seller fixed effects are included, further indicating

that only high-quality sellers are willing or able to put in the effort to produce or source high-potency marijuana strains.

Robustness

Despite efforts to design an unbiased hedonic regression model and to account for omitted variables, the nature of Silk Road data presents several complexities that lead to potential limitations of model application and lingering concerns to identification.

Potential Identification Concerns

During the Silk Road's operation, a user forum existed and exhibited active participation by vendors and consumers alike. Vendors created threads to discuss new products or sales and allow users to leave additional feedback. Consumers frequently used the forum as an additional means for self-policing: when a forum user experienced dishonesty or feared they had been cheated, they often began new threads warning other consumers. Oftentimes such threads would devolve into two sides: those in support of the vendor and those favoring the wronged consumer. Figure 8.1 provides an example of just such a forum thread.

In spite of the excessive profanity, clearly the user forum represented another means by which a subset of Silk Road consumers could gain additional information and inform perceptions of vendor honesty. If users relied on the forum as a primary signal of seller honesty instead of site feedback, then previous models would be attempting to identify a nonexistent effect and small, insignificant coefficients would be likely. However, reported results reject this hypothesis, finding evidence of the site's reputation as a signal of seller honesty.

One primary reason for the limited value of forum posts for general consumers is the redundancy of information. Forum posts regarding dishonest sellers do not represent

unique sources of signal origination. Based on consultation of archived Silk Road forum pages and observed feedback data, forum posts are nearly always expansions on negative reviews already left within the site's reputation system. Generally consumers used the forum as a way to engage with a particularly active subset of marketplace users and elaborate on experiences (i.e. by using images, posting lab test results) in a manner beyond what the site's reputation system allowed. Further, as a resource used by only a portion of the site's consumers, the Silk Road forum did not cater to the average Silk Road consumer.[2] Even so, future analysis can further mitigate forum signaling concerns by integrating forum posts into analyzed models. Backups of the Silk Road forum can be obtained online, and sufficient time and computational power would allow scraping in a similar manner to the current data and incorporated into new reputation measures.

Another potential concern relates to the presence of "stealth listings" on Silk Road. When creating an item listing, vendors could choose to create a stealth listing that would not be added to site directories. Instead, stealth listings were only accessible by direct link from the vendor. Accordingly, stealth listings cannot be viewed by users at large and as a result the utilized dataset contains no information on stealth listings.

While stealth listings would be a larger concern for estimating sales volume on the market, there is less concern for biasing estimates of reputation effects. As stealth listings were not publicly listed, consumers had to first contact and engage with a vendor before making a purchase from a stealth listing. The Silk Road Vendor Guide even states that the primary use of stealth listings is to create "custom listings meant only for a specific buyer." As a result, stealth transactions targeted custom sales to repeat consumers, where trust already existed between buyer and seller. The reputation system plays little role in informing stealth purchases – although it likely played a role in initial consumption

[2]No direct link to the forum existed on the site's main page, and access to the forums required another registration process.

decisions prior to repeat purchases in the stealth environment. If stealth listing information were included, reviews would likely be skewed positively as a result of selection bias, resulting in estimated effects attenuating towards zero.

Accuracy of Matched Prices

A remaining issue is the timeliness of observed reviews – and therefore the accuracy of matched prices. The exact time of a transaction is not observed; rather, the time of feedback is the means of observing a sale. During the dataset's creation, feedback is first matched to the observed item listing price using the exact Unix time of observation, therefore matching on the exact second. This price likely represents the true purchase price for transactions that were "finalized early" (reviewed and released from escrow immediately upon purchase), but may not be exact for standard transactions during highly volatile Bitcoin exchange periods. Matching then occurs using a daily mean price.[3] If feedback is left immediately after the order is placed and update once the good arrives, then this price will be representative of the true transaction price. However, if consumers instead leave feedback when the item arrives days or weeks after the transaction occurred, then matching on the daily mean price could introduce measurement error and ultimately bias estimates.

Table 8.11 presents evidence to suggest that measurement error due to matching delay does not drive the results in earlier models. Columns 1 and 2 report models from Table 8.5 for marijuana, speed, and meth with samples restricted to transactions where feedback text makes direct reference to finalizing early. This sample captures prices immediately when the transaction occurred. Despite considerably reduced sample sizes, the models in Table 8 tell an identical story to results using the complete sample. Although statistical significance falls for the negative review indicator, 5 of 6 remain at least weakly statistically

[3] See Chapter 6 for further discussion.

significant with magnitudes indistinguishable from prior estimates. Coefficients for seller ratings also remain directly comparable. Further, marijuana models find the high-quality strain premium to be statistically significant at the 99% level regardless of whether seller fixed effects are present, indicating that previous results may in fact understate the strain quality premium. Here the premium is unaffected by the addition of seller fixed effects, suggesting that the quality premium is invariant to the innate characteristics of the vendor who operates the listing. The strain premium may not be a proxy for seller quality; rather, it may be a direct result of desirable product characteristics. The strain premium may appear as a proxy in earlier models due to limited access to high-quality strains for lower quality vendors.

While the finalized early sample eliminates measurement error from matching delay, it introduces a new concern. When users finalized early, they typically did so for two reasons: either they were new members and were required by a particular vendor to finalize early due to a lack of reputation, or were engaging in repeat transactions with trusted vendors. As transactions were finalized before users recieved goods, they left positive numeric ratings and textual responses indicating that early finalization had occurred.[4] Reviews were then updated after goods were received to reflect the true transaction outcome. As site scraping stopped before Silk Road's FBI seizure, a portion of finalized early reviews included in Columns 3 and 4 represent initial positive reviews yet to be updated. As a result, estimated effects of negative reputation are likely, if anything, slightly underestimated.

[4]While the opposite scenario (consumers leaving low initial reviews before updating after receiving the item) occurs, it does so incredibly rarely. From a strategy perspective, if the consumer's goal is to maximize the likelihood that a seller attempts delivery and behaves "well" during the transaction, posting positive reviews with the threat of updating to negative if things go awry stands as a much more successful option than punishing the vendor before retraction.

Table 8.1: Reputation and the Price of Marijuana

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln (Quantity)	0.6873***	0.6883***	0.6931***	0.7027***	0.7019***	0.7162***	0.6628***
	(0.0279)	(0.0278)	(0.0272)	(0.0273)	(0.0271)	(0.0357)	(0.0432)
Any Negative Reviews	-0.1719***	-0.1575***	-0.1667***	-0.0906*	-0.0868*	-0.0611*	-0.0850***
	(0.0542)	(0.0555)	(0.0528)	(0.0527)	(0.0525)	(0.0346)	(0.0318)
Seller % Favorable	--	0.0072	0.0063	0.0098*	0.0110**	-0.0029	0.0100**
		(0.0051)	(0.0047)	(0.0049)	(0.0049)	(0.0044)	(0.0043)
Premium Strains	--	--	0.1345***	0.0843*	0.0996**	0.0923**	0.0621
			(0.0454)	(0.0437)	(0.0472)	(0.0439)	(0.0392)
Text/Characteristic Controls	--	--	--	Yes	Yes	Yes	Yes
Time Controls	--	--	--	--	Yes	Yes	Yes
Location/Market Controls	--	--	--	--	--	Yes	Yes
Seller Fixed Effects	--	--	--	--	--	--	Yes
N	12,305	12,305	12,305	12,305	12,305	12,305	12,305
R^2	.76	.77	.77	.79	.79	.82	.88

Notes: Results are reported for 12,305 observations of marijuana sales on the Silk Road marketplace through July 24, 2012. Column 1 regresses the log of U.S. dollar price on the log of quantity, the BTC exchange rate (not reported), and a binary indicator for whether the item listing has any negative reviews. Column 2 adds the seller percent favorable rating, while Column 3 reports both reputation measures with the premium strain indicator. Columns 4-7 add text and item characteristic controls (reported in Table 2a), weekly fixed effects, unique route controls, and seller fixed effects, respectively. Standard errors are clustered at the unique item listing level.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level

Table 8.2: Reputation and the Price of Amphetamine (Speed)

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln (Quantity)	0.7078***	0.6977***	0.6887***	0.7361***	0.7163***	0.8095***	0.8187***
	(0.0669)	(0.0658)	(0.0625)	(0.0488)	(0.0498)	(0.0266)	(0.0167)
Any Negative Reviews	-0.3448***	--	-0.2929**	-0.2191**	-0.1736**	-0.0906**	-0.1082***
	(0.1508)		(0.1380)	(0.1004)	(0.0697)	(0.0413)	(0.0330)
Seller % Favorable	--	0.0815***	0.0724***	0.0440**	0.0666***	0.0483***	0.0003
		(0.0210)	(0.0192)	(0.0214)	(0.0192)	(0.0098)	(0.0091)
Street Quality	--	--	--	-0.7084***	-1.050***	-0.6128***	-0.2119
				(0.2372)	(0.2287)	(0.1153)	(0.4498)
Text/Characteristic Controls	--	--	--	Yes	Yes	Yes	Yes
Time Controls	--	--	--	--	Yes	Yes	Yes
Location/Market Controls	--	--	--	--	--	Yes	Yes
Seller Fixed Effects	--	--	--	--	--	--	Yes
N	2,091	2,091	2,091	2,091	2,091	2,091	2,091
R^2	.58	.57	.69	.86	.90	.95	.97

Notes: Results are reported for 2,091 observations of amphetamine (speed) sales on the Silk Road marketplace through July 24, 2012. Column 1 regresses the log of US dollar price on the log of quantity, the BTC exchange rate (not reported), and a binary indicator for whether the item listing has any negative reviews. Column 2 replaces negative item reputation with the seller percent favorable rating, while Column 3 reports both reputation measures simultaneously. Columns 4-7 add text and item characteristic controls (reported in Table 2b), weekly fixed effects, unique route controls, and seller fixed effects, respectively. Standard errors are clustered at the unique item listing level.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level

Table 8.3: Reputation and the Price of Methamphetamine (Meth)

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln (Quantity)	0.7351***	0.7813***	0.7491***	0.7080***	0.7071***	0.8890***	0.8928***
	(0.0831)	(0.0857)	(0.0849)	(0.0775)	(0.0694)	(0.0142)	(0.0099)
Any Negative Reviews	-0.3135***	--	-0.2378***	-0.1905***	-0.1783***	-0.0475***	-0.0299***
	(0.0905)		(0.0878)	(0.0686)	(0.0606)	(0.0167)	(0.0111)
Seller % Favorable	--	0.0528***	0.0265**	0.0092	0.0142	0.0216***	0.0041
		(0.0164)	(0.0126)	(0.0085)	(0.0103)	(0.0035)	(0.0042)
High Value	--	--	--	-0.2426***	-0.2394***	-0.2848***	-0.3301***
				(0.0639)	(0.0642)	(0.0503)	(0.0885)
Text/Characteristic Controls	--	--	--	Yes	Yes	Yes	Yes
Time Controls	--	--	--	--	Yes	Yes	Yes
Location/Market Controls	--	--	--	--	--	Yes	Yes
Seller Fixed Effects	--	--	--	--	--	--	Yes
N	1,636	1,636	1,636	1,636	1,636	1,636	1,636
R^2	.32	.78	.80	.87	.88	.98	.99

Notes: Results are reported for 1,636 observations of methamphetamine (speed) sales on the Silk Road marketplace through July 24, 2012. Column 1 regresses the log of US dollar price on the log of quantity, the BTC exchange rate (not reported), and a binary indicator for whether the item listing has any negative reviews. Column 2 replaces negative item reputation with the seller percent favorable rating, while Column 3 reports both reputation measures simultaneously. Columns 4-7 add text and item characteristic controls (reported in Table 2b), weekly fixed effects, unique route controls, and seller fixed effects, respectively. Standard errors are clustered at the unique item listing level.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level

Table 8.4: The Role of Reputation Across Drug Types

	Marijuana		Speed		Meth	
Independent Variable	(1)	(2)	(1)	(2)	(1)	(2)
Ln (Quantity)	0.7162***	0.6628***	0.8095***	0.8187***	0.8890***	0.8928***
	(0.0357)	(0.0432)	(0.0266)	(0.0167)	(0.0142)	(0.0099)
Any Negative Reviews	-0.0611*	-0.0850***	-0.0906**	-0.1082***	-0.0475***	-0.0299***
	(0.0346)	(0.0318)	(0.0413)	(0.0330)	(0.0167)	(0.0111)
Seller % Favorable	-0.0029	0.0100**	0.0483***	0.0003	0.0216***	0.0041
	(0.0044)	(0.0043)	(0.0098)	(0.0091)	(0.0035)	(0.0042)
Premium Strains	0.0923**	0.06210	--	--	--	--
	(0.0439)	(0.0392)				
Location, Time, and Textual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Seller Fixed Effects	No	Yes	No	Yes	No	Yes
N	12,305	12,305	2,091	2,091	1,636	1,636
R^2	.82	.88	.91	.97	.98	.99

Notes: Reported models correspond to Columns 6 and 7 of Tables 3a, 3b, and 3c: full models for marijuana, speed, and meth with and without seller fixed effects. Models regress the log of U.S. dollar price on log quantity, reputation measures, and differentiating item characteristics and include time and route controls (Column 1) along with seller fixed effects in Column 2.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level.

Table 8.5: Marijuana Price and Alternate Measures of Item Reputation

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
Any Negative Reviews	-0.0566 (0.0386)	-0.0580* (0.0317)	--	--	--	--
Seller % Favorable	-0.0028 (0.0044)	0.0081* (0.0043)	-0.0013 (0.0047)	0.0122*** (0.0042)	0.0014 (0.0054)	0.0158*** (0.0050)
Ln(Positive Reviews)	-0.0075 (0.0156)	-0.0568*** (0.0317)	--	--	--	--
Ln(Negative Reviews)	--	--	-0.0493* (0.0294)	-0.0689** (0.0291)	--	--
Item % Favorable	--	--	--	--	0.0292 (0.1653)	0.0575 (0.1632)
Premium Strains	0.0920** (0.0438)	0.0565 (0.0387)	0.0858** (0.0430)	0.0641* (0.0391)	0.0834* (0.0434)	0.0573 (0.0397)
Seller Fixed Effects	No	Yes	No	Yes	No	Yes
N	12,305	12,305	12,305	12,305	12,305	12,305
R^2	.82	.88	.82	.88	.82	.88

Notes: Reported models estimate the effect of reputation on marijuana price and correspond to Columns 6 and 7 of Table 4a, but specify item-level reputation using alternate measures. Columns 1 and 2 include the log of positive item reviews and report results with and without seller fixed effects, respectively. Columns 3 and 4 specify negative feedback as the log of negative item reviews. Columns 5 and 6 include the item's percent favorable rating.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level.

Table 8.6: Amphetamine Price and Alternate Measures of Item Reputation

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
Any Negative Reviews	-0.0891**	-0.0876***	--	--	--	--
	(0.0404)	(0.0284)				
Seller % Favorable	0.0483***	-0.0003	0.0431***	-0.0098	0.0476***	0.0004
	(0.0101)	(0.0097)	(0.0101)	(0.0088)	(0.0103)	(0.0104)
Ln (Positive Reviews)	-0.0051	-0.0242	--	--	--	--
	(0.0278)	(0.0305)				
Ln (Negative Reviews)	--	--	-0.0962***	-0.1073***	--	--
			(0.0336)	(0.0327)		
Item % Favorable	--	--	--	--	0.3449	0.4490*
					(0.2443)	(0.2491)
Seller Fixed Effects	No	Yes	No	Yes	No	Yes
N	2,091	2,091	2,091	2,091	2,091	2,091
R^2	.95	.97	.95	.97	.95	.97

Notes: Reported models estimate the effect of reputation on amphetamine price and correspond to Columns 6 and 7 of Table 4b, but specify item-level reputation using alternate measures. Columns 1 and 2 include the log of positive item reviews and report results with and without seller fixed effects, respectively. Columns 3 and 4 specify negative feedback as the log of negative item reviews. Columns 5 and 6 include the item's percent favorable rating.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level.

Table 8.7: Meth Price and Alternate Measures of Item Reputation

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
Any Negative Reviews	-0.0490***	-0.0234*	--	--	--	--
	(0.0173)	(0.0122)				
Seller % Favorable	0.0217***	0.0032	0.0193***	0.0018	0.0231***	0.0004
	(0.0037)	(0.0046)	(0.0053)	(0.0051)	(0.0049)	(0.0044)
Ln (Positive Reviews)	0.0026	-0.0162*	--	--	--	--
	(0.0103)	(0.0089)				
Ln (Negative Reviews)	--	--	-0.0308*	-0.0282*	--	--
			(0.0171)	(0.0168)		
Item % Favorable	--	--	--	--	0.2682	0.5173*
					(0.2092)	(0.2983)
Seller Fixed Effects	No	Yes	No	Yes	No	Yes
N	1,636	1,636	1,636	1,636	1,636	1,636
R^2	.98	.99	.98	.99	.98	.99

Notes: Reported models estimate the effect of reputation on methamphetamine price and correspond to Columns 6 and 7 of Table 4c, but specify item-level reputation using alternate measures. Columns 1 and 2 include the log of positive item reviews and report results with and without seller fixed effects, respectively. Columns 3 and 4 specify negative feedback as the log of negative item reviews. Columns 5 and 6 include the item's percent favorable rating.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level.

Table 8.8: Marijuana Price and Alternate Measures of Vendor Reputation

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
Any Negative Seller Reviews	-0.0718*	-0.0991***	--	--	--	--
	(0.0388)	(0.0325)				
Ln (Positive Seller Reviews)	0.0579***	0.0139	0.0437***	0.0178	--	
	(0.0120)	(0.0124)	(0.0135)	(0.0134)		
Ln (Negative Seller Reviews)	--	--	0.0043	-0.0150	--	--
			(0.0198)	(0.0183)		
Ln (Transactions)	--	--	--	--	0.0531***	0.0058
					(0.0109)	(0.0148)
Premium Strains	0.0882**	0.0628	0.0812*	0.0585	0.0865*	0.0588
	(0.0433)	(0.0393)	(0.0434)	(0.0400)	(0.0430)	(0.0402)
Seller Fixed Effects	No	Yes	No	Yes	No	Yes
N	12,303	12,303	12,303	12,303	12,197	12,197
R^2	.82	.88	.82	.88	.83	.87

Notes: Reported models estimate the effect of reputation on marijuana price and correspond to Columns 6 and 7 of Table 4a, but specify reputation using only measures of seller-level reputation. Columns 1 and 2 use the log of positive seller reviews and a dummy variable for whether a seller has any negative reviews (akin to the item-level dummy employed in other models) and report results with and without seller fixed effects, respectively. Columns 3 and 4 specify reputation as the log of positive and log of negative seller reviews. Columns 5 and 6 include only the log of total seller transactions to investigate the sufficiency of seller experience as a signal of quality.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level.

Table 8.9: Amphetamine Price and Alternate Measures of Vendor Reputation

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
Any Negative Seller Reviews	-0.0865*	-0.1090***	--	--	--	--
	(0.0485)	(0.0346)				
Ln (Positive Seller Reviews)	-0.0316	0.0125	0.0702**	0.0204	--	--
	(0.0257)	(0.0174)	(0.0299)	(0.0181)		
Ln (Negative Seller Reviews)	--	--	-0.1881***	-0.0584*	--	--
			(0.0390)	(0.0337)		
Ln (Transactions)	--	--	--	--	-0.0649*	-0.0549
					(0.0345)	(0.0383)
Seller Fixed Effects	No	Yes	No	Yes	No	Yes
N	2,090	2,090	2,090	2,090	2,082	2,082
R^2	.94	.97	.95	.97	.94	.97

Notes: Reported models estimate the effect of reputation on amphetamine price and correspond to Columns 6 and 7 of Table 4b, but specify reputation using only measures of seller-level reputation. Columns 1 and 2 use a dummy variable for whether a seller has any negative reviews (akin to the item-level dummy employed in other models) and report results with and without seller fixed effects, respectively. Columns 3 and 4 specify reputation as the log of positive and log of negative seller reviews. Columns 5 and 6 include only the log of total seller transactions to investigate the sufficiency of seller experience as a signal of quality.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level.

Table 8.10: Meth Price and Alternate Measures of Vendor Reputation

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)
Any Negative Seller Reviews	-0.0879***	-0.0349***	--	--	--	--
	(0.0230)	(0.0117)				
Ln(Positive Seller Reviews)	0.0191**	0.0073	0.0323***	-0.0004	--	--
	(0.0075)	(0.0088)	(0.0120)	(0.0096)		
Ln (Negative Seller Reviews)	--	--	-0.0385**	0.0114	--	--
			(0.0191)	(0.0122)		
Ln (Transactions)	--	--	--	--	0.0207**	0.0129
					(0.0082)	(0.0086)
Seller Fixed Effects	No	Yes	No	Yes	No	Yes
N	1,636	1,636	1,636	1,636	1,621	1,621
R^2	.98	.99	.98	.99	.99	.99

Notes: Reported models estimate the effect of reputation on methamphetamine price and correspond to Columns 6 and 7 of Table 4c, but specify reputation using only measures of seller-level reputation. Columns 1 and 2 use a dummy variable for whether a seller has any negative reviews (akin to the item-level dummy employed in other models) and report results with and without seller fixed effects, respectively. Columns 3 and 4 specify reputation as the log of positive and log of negative seller reviews. Columns 5 and 6 include only the log of total seller transactions to investigate the sufficiency of seller experience as a signal of quality.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level.

Table 8.11: The Role of Reputation – Finalized Early Samples

	Marijuana		Speed		Meth	
Independent Variable	(1)	(2)	(1)	(2)	(1)	(2)
Log(Quantity)	0.7335***	0.7293***	0.8027***	0.8353***	0.8948***	0.8959***
	(0.0297)	(0.0315)	(0.0291)	(0.0171)	(0.0145)	(0.0126)
Any Negative Reviews	-0.0406	-0.0620**	-0.0969**	-0.0955***	-0.0472**	-0.0352*
	(0.0367)	(0.0291)	(0.0378)	(0.0310)	(0.0233)	(0.0192)
Seller % Favorable	0.0108*	0.0111**	0.0341***	0.0010	0.0128**	-0.0056
	(0.0061)	(0.0052)	(0.0085)	(0.0118)	(0.0053)	(0.0081)
Premium Strains	0.1312***	0.0928***	--	--	--	--
	(0.0358)	(0.0363)				
Location, Time, and Textual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Seller Fixed Effects	No	Yes	No	Yes	No	Yes
N	4,314	4,314	859	859	626	626
R^2	.85	.91	.96	.98	.99	.99

Notes: Reported models correspond to Columns 1 and 2 of Table 6 – full models for marijuana, speed, and meth with and without seller fixed effects – computed for transactions finalized early. Finalizing early released funds to the vendor as soon as the order was placed, ensuring the observed price is the true purchase price. Further, the avoidance of escrow eliminated any possibility for arbitration and preserves a pure uncertainty environment. Models regress the log of U.S. dollar price on log quantity, reputation measures, and differentiating item characteristics and include time and route controls (Column 1) along with seller fixed effects in Column 2.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level.

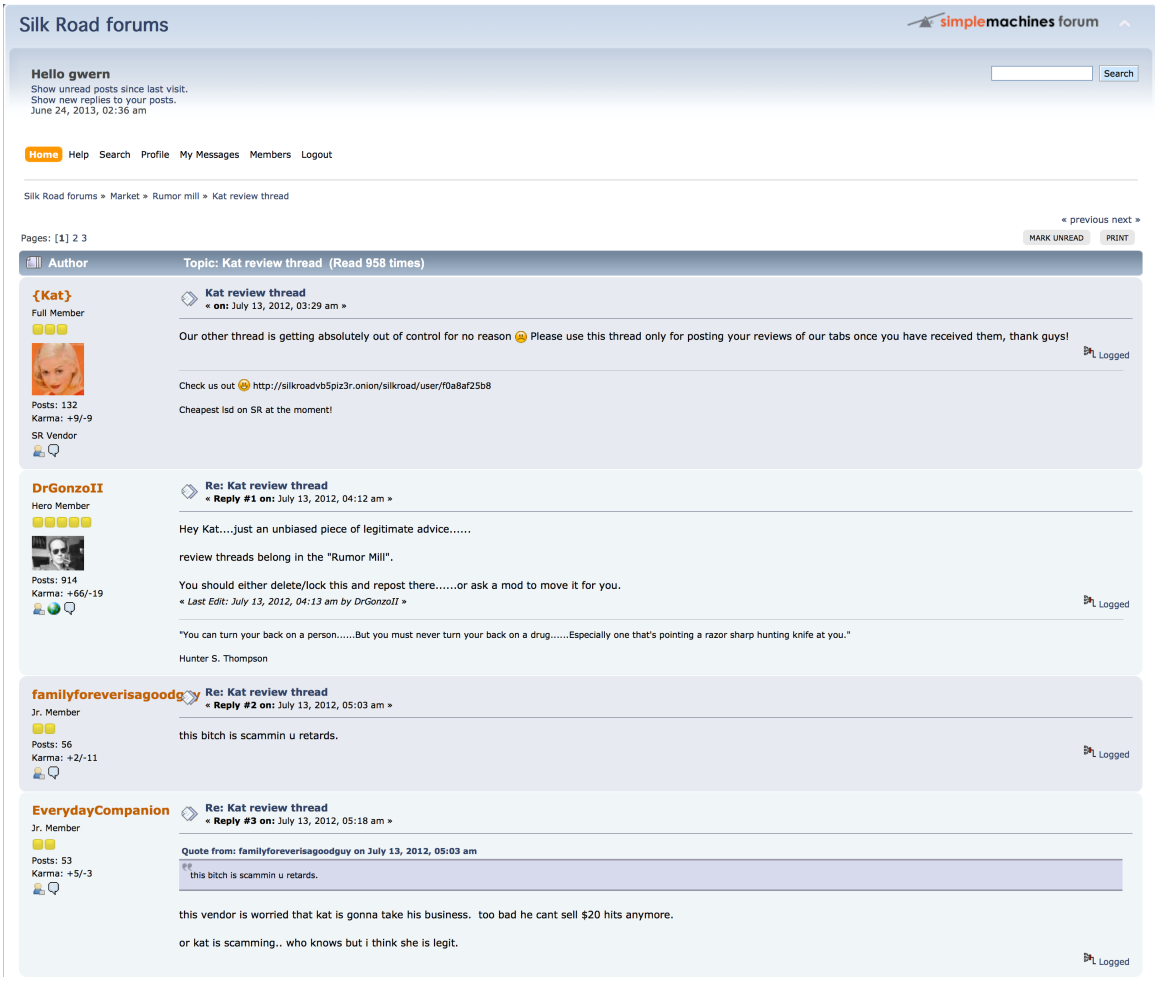


Figure 8.1: Forum thread, July 2012. Source: antilop.cc/sr

SIGNAL HETEROGENEITY: SELLER AGE

One alternative explanation for the prior results relates to seller development over time. It may take time for vendors to adapt to the Silk Road market environment and "learn the ropes" – in which case they would gradually improve in performance over time and observe higher prices later on as a result. If negative reviews generally come early in a seller's life, then the above models would be incorrectly attributing this effect of seller learning to negative feedback.

Table 9.1 tests this hypothesis by allowing for signal heterogeneity by seller age. Rather than determine an arbitrary definition of a "new" seller, I use the site's own definition of a novice seller. One feature available to senior sellers on the Silk Road was the ability to finalize a sale early, a scenario in which consumers could release funds from escrow before receiving the item. This process was thought to expedite repeat transactions between buyers and sellers. However, as the release of funds negated any possibility for site intervention in the case of a dishonest seller, the site specified that only sellers with greater than 35 transactions and 1 month of activity could require buyers to finalize a sale early.[1] This official definition of a "new" seller is used to specify three additional reputation variables. First is a binary dummy equal to one if the seller satistifies this definition of new, and equal to zero otherwise. Next, interaction terms between new sellers and each of the reputation variables (the negative review indicator and seller percent favorable rating) are included to allow for the effect of reputation to differ across item and seller-level margins between new and senior sellers.

Table 9.1 yields no evidence of price penalties for new sellers. Coefficients for the new seller indicator return statistically insignificant estimates in 5 of 6 cases, and

[1] In addition ot the site's arbitrary definition, I test three alternate definitions: fewer than 5, 10, or 20 transactions. Results are unchanged relative to the site's definition.

estimates a major new seller price penalty of -86% for column 2 of amphetamine models.[2] Looking to interaction terms, no evidence of signal heterogeneity displays itself. Signs on estimates flip from model to model, and are generally indistinguishable from zero. Models do not consistently estimate a new seller inexperience penalty upon entering the market, and negative reputation does not appear to disproportionately harm new vendors. If, as earlier hypothesized, senior sellers were required to gradually discount prices to combat market entry, then such price-cutting behavior would attenuate any inexperience penalty for entering vendors.

[2]This sizable estimate for amphetamines may be a result of market concentration. 3 overseas vendors hold nearly $\frac{2}{3}$ of the amphetamine market; in this case the effect is likely driven by the comparison of three primary vendors against their new, inexperienced selves.

Table 9.1: The Impact of Seller Age on Drug Prices

	Marijuana		Speed		Meth	
Independent Variable	(1)	(2)	(1)	(2)	(1)	(2)
New Seller	-0.6799	-0.5696	0.0076	-1.9877**	0.3415	0.3024
	(0.8872)	(0.7288)	(1.4554)	(0.9942)	(0.5312)	(0.4257)
Any Negative Reviews	-0.0848**	-0.0911***	-0.0957**	-0.1081***	-0.0049	-0.0324**
	(0.0375)	(0.0330)	(0.0404)	(0.0320)	(0.0168)	(0.0131)
New Seller x Any Neg	0.0131	0.0656	0.01226	0.1008	-0.0049	0.0025
	(0.1056)	(0.0589)	(0.1057)	(0.0862)	0.0333)	(0.0249)
Seller % Favorable	-0.0063	0.0083	0.0483***	-0.0066	0.0218***	0.0057
	(0.0075)	(0.0074)	(0.0117)	(0.0862)	(0.0037)	(0.0053)
New Seller x Seller %	0.0056	0.0054	-0.0002	0.0206**	-0.0043	-0.0032
	(0.0089)	(0.0074)	(0.0153)	(0.0102)	(0.0055)	(0.0044)
Seller Fixed Effects	No	Yes	No	Yes	No	Yes
N	12,305	12,305	2,091	2,091	1,636	1,636
R^2	.82	.88	.95	.97	.98	.99

Notes: Models regress the natural log of U.S. dollar price on log quantity, reputation measures, and differentiating item characteristics and include time and route controls (Column 1) along with seller fixed effects in Column 2. Reported models correspond to Table 5: full models for marijuana, speed, and meth with and without seller fixed effects, with the addition of a new seller indicator and interactions of new sellers with negative reputation and new sellers with seller % favorable. The new seller indicator evaluates to one until a seller has operated for greater than one month and conducted at least 35 transactions (as used by Silk Road).

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level.

CONCLUSION

Although a large number of studies have estimated the value of reputation on conventional web-based markets, few have been able to comment on its value in the absence of formal contracting and legal institutions. Those that have approached reputation in black market environments have faced either limited extension of results to other market structures or an inability to control for relevant sources of price variation. I use novel data from the first deep web market, Silk Road, to estimate the value of reputation in the face of heightened uncertainty and considerable social distance. Market institutions on the site were designed to mirror those of established legal web markets, and I am able to take advantage of these similarities to directly approach the question of how the value of reputation changes as uncertainty and information asymmetries increase.

Using variation in both item and seller-level reputation, I find compelling evidence of a "bad-news" learning environment. Silk Road consumers utilize negative reviews as the primary signal of vendor honesty and quickly respond to past dishonesties. Item listings for marijuana, amphetamine (speed), and methamphetamine (meth) suffer price discounts between 3 and 11% when their reputations become tarnished and they receive negative reviews. Vendor ratings are found to have some value as a signal, primarily proxying for permanent seller quality rather than capturing personality or behavioral changes. Further, I find little evidence that new vendors suffer from an "inexperience tax" and find no support for heterogeneity in reputation signals according to vendor age.

Marijuana models reveal consistent evidence of strain as an important means of quality differentiation. Named strains act as a proxy for less readily-identifiable determinants of marijuana quality, and strains known for high-potency receive premium prices to reflect that potency. Recognized high-quality strains enjoy an 8-9% price premium over lower quality marijuana. Further, findings suggest that only high-quality sellers were able to acquire

and market high-quality strains on Silk Road, with lower quality vendors peddling more questionable goods. During its existence, Silk Road gained a reputation for high-quality, boutique product and model results provide empirical evidence of this perception.

This paper provides novel evidence to suggest that, in the absence of formal contract enforcement, reputation can serve as a mechanism for quality signaling through which consumers can gather considerable information. Through the use of effectively designed reputation systems, users are able to overcome issues of social distance and asymmetric information, preventing market failure. This study confirms the importance of socially-driven information systems in facilitating the development and success of modern markets and methods of exchange.

APPENDICES

APPENDIX A

THE TOR NETWORK

Tor, an acronym for The Onion Router, was launched in 2002 as a means for anonymously interacting with “web browsers, instant messaging clients, and more” (htw). Tor prevents traffic analysis through onion routing, where user traffic is routed through a randomized network of relay systems. The network is extended one step at a time, and each encrypted connection is independent from other connections to ensure no individual relay ever knows the complete path the data travels. Figures 1 through 3 provide a visual description of this process. In 2004 Tor launched hidden services, allowing websites to operate exclusively within the Tor network. Hidden services are only accessible through Tor browsers and are reached through an onion address (equivalent to a web url). Hidden service connection is encrypted on both ends, preventing eavesdropping and hiding server information.

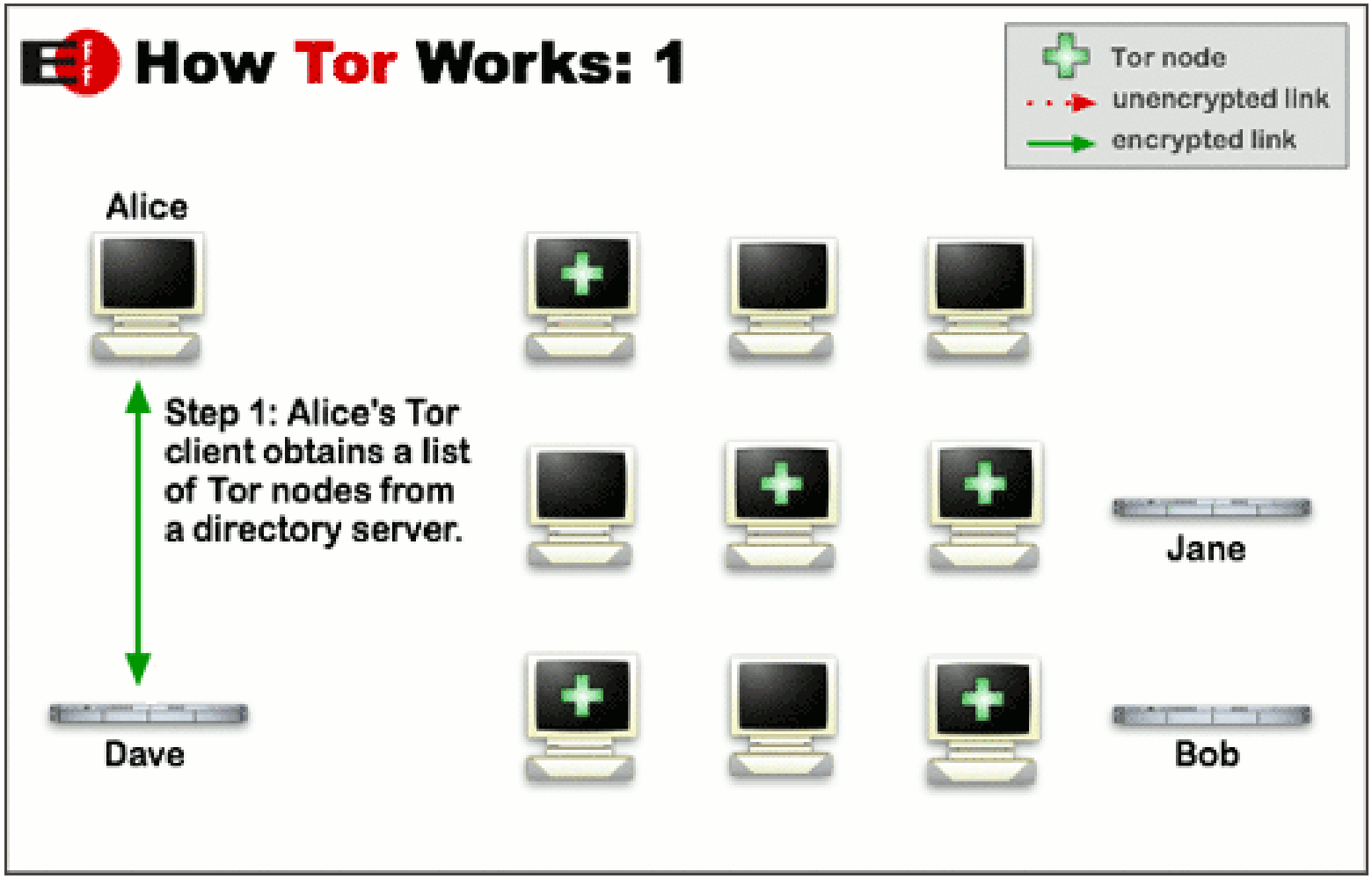


Figure A.1: How Tor Works – 1

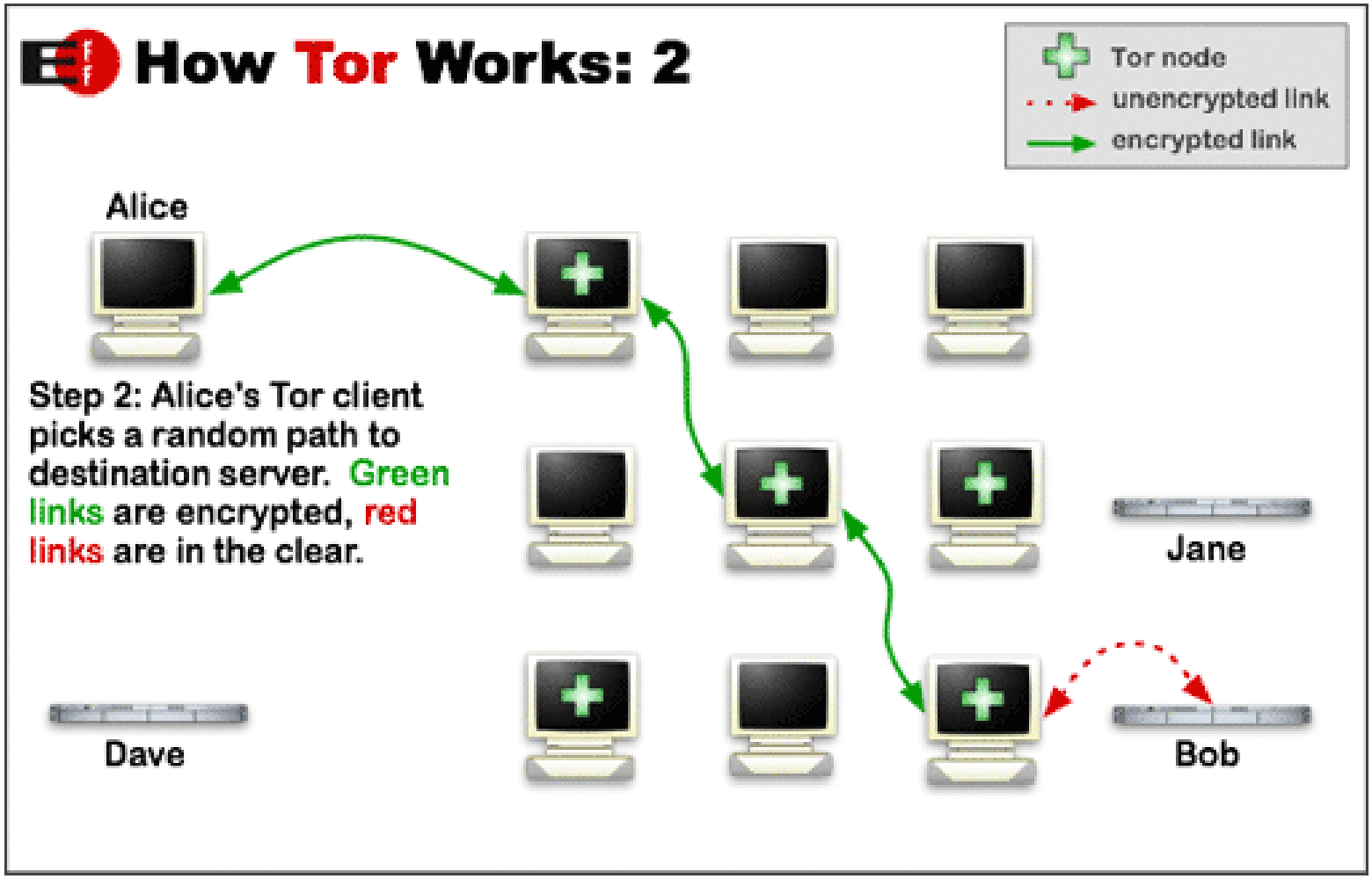


Figure A.2: How Tor Works – 2

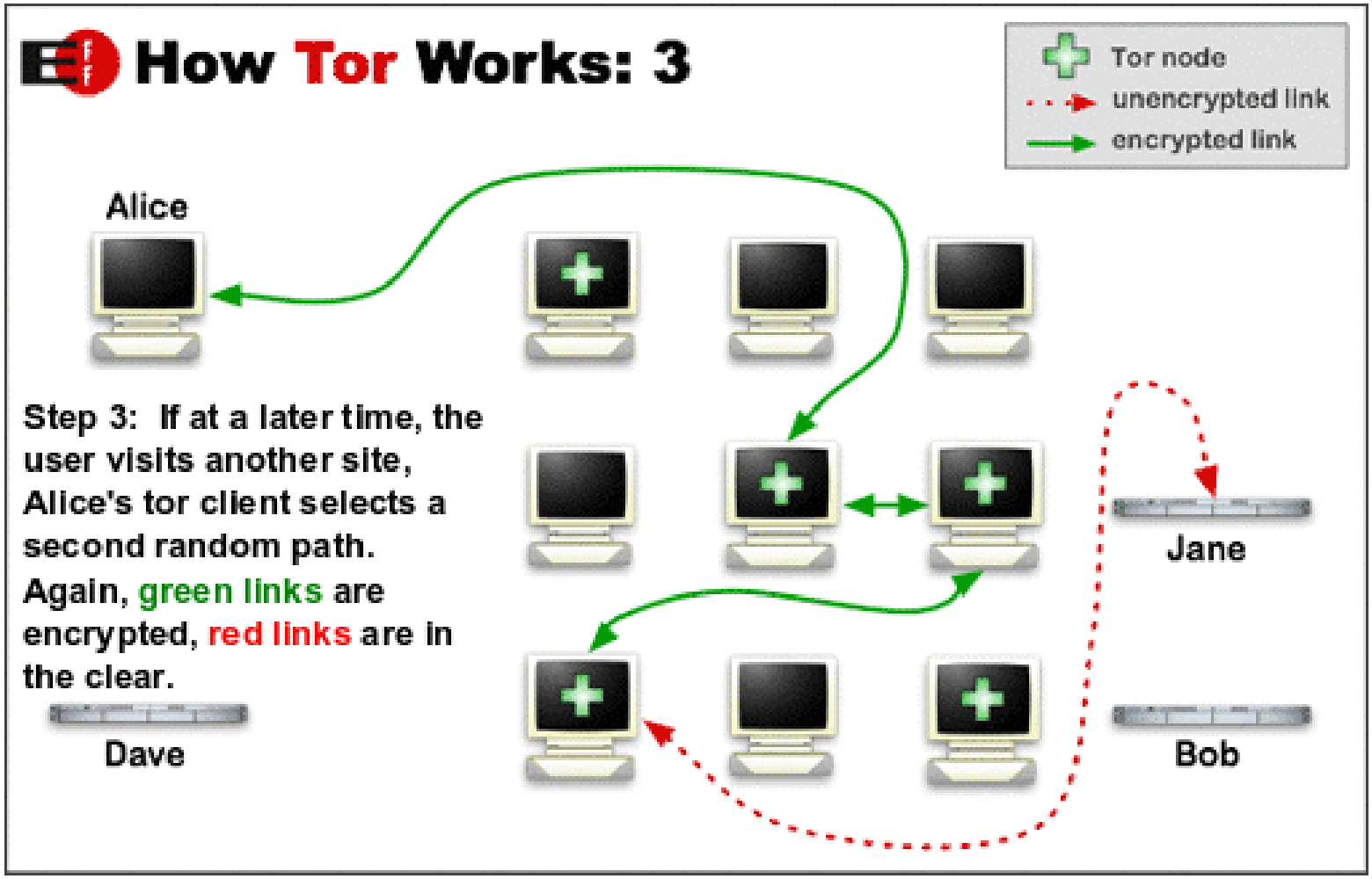


Figure A.3: How Tor Works – 3

APPENDIX B

BITCOIN

Bitcoin is a pseudo-anonymous, open-source cryptocurrency released in 2009. Bitcoin is a decentralized currency, operating independently from a central bank or government authority (coi, 2015). Bitcoins are based on addresses, held within personal Bitcoin wallets. Bitcoins are created through a process called "mining" that simultaneously creates new currency and confirms current transactions. Bitcoin "mining" involves computers searching for solutions to crytographic hash functions. Each new function allows current transactions to be confirmed and added to the archive of past transactions; the miner who solves for the correct function is rewarded with a bundle of new Bitcoin addresses.

Bitcoin was the first digital currency to overcome the challenge of unique use by utilizing a public ledger known as the "block chain" through which all transactions and balances could be verified at any time. The block chain operates as a public ledger, allowing peer confirmation of individual transactions through the mining process. Appendix Figure B.1 provides an overview of how Bitcoins originate, how individual wallets are used, and how transactions are publicly verified (Romero and Palacio, 2012).

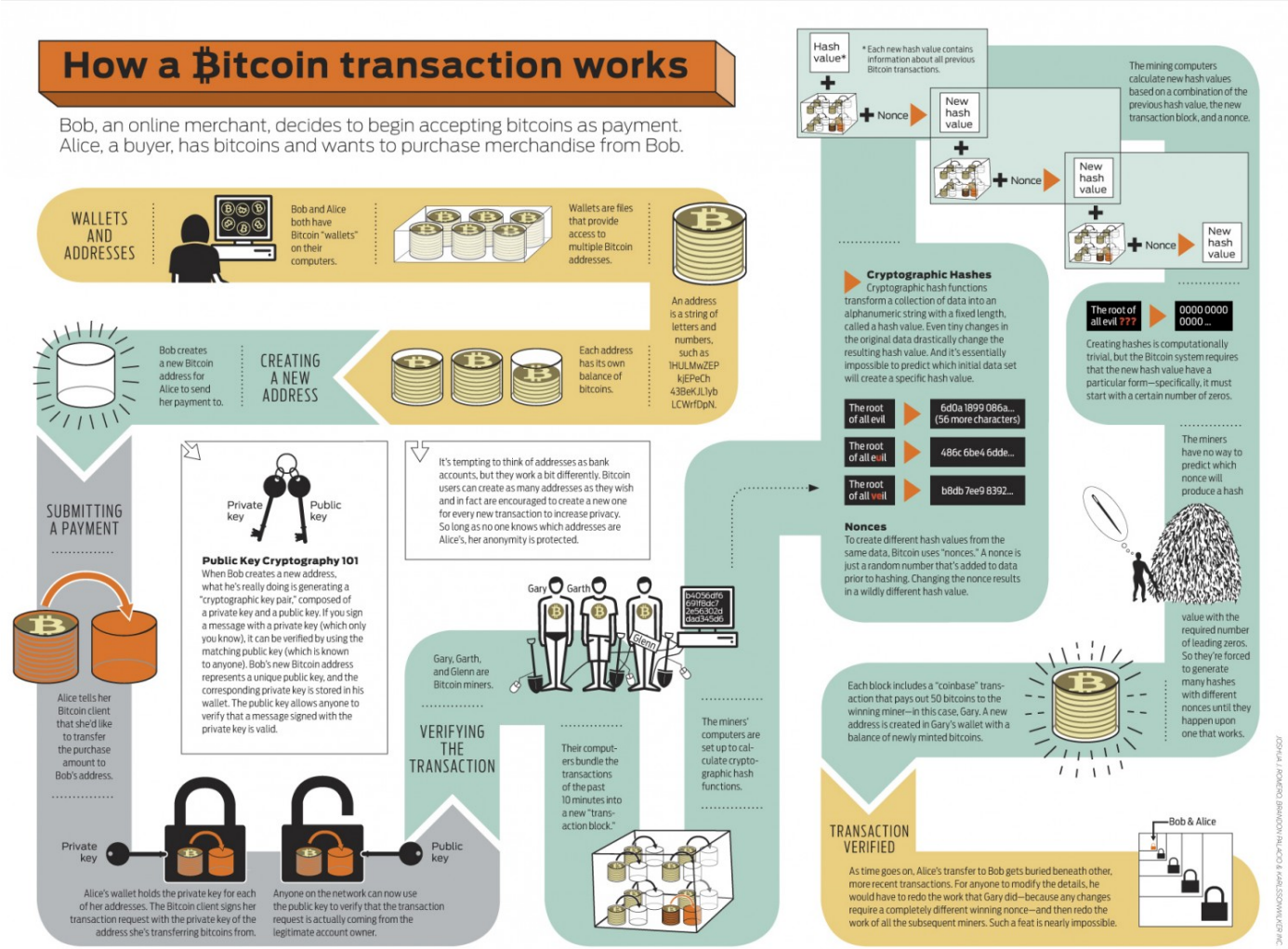


Figure B.1: How Bitcoin Works

APPENDIX C

MARIJUANA ON SILK ROAD

Prices: Street vs. Silk Road

Prior works suggest that marijuana prices on Silk Road were consistently higher than prevailing street prices (Barratt et al., 2013; Mahapatra, 2013). Can a premium be observed in this sample, and if so, is the premium particular to one quality type? Table C1 reports three different Silk Road average prices for February through July 2012 and compares them to street prices for the same time period.

The first row compares the average price for all Silk Road marijuana transactions to the *High Times* average price index for the 6 month observation period. During this time, the average Silk Road listing sold at a price of $442 per ounce (28.5 grams) while transactions on the street only averaged $329 per ounce. As a result, Silk Road marijuana received an additional $112 per ounce, a 34% premium.[1]

To further break down the Silk Road price premium, the following rows report average prices (and premiums) for high and low-quality strains. The second row reports prices for high-quality marijuana on Silk Road relative to prevailing street prices for high-quality strains. Reported Silk Road prices correspond to domestic United States observations where the premium strain indicator evaluates to one. The final row reports similar measures for low-quality marijuana – where the Silk Road strain indicator evaluates to zero. Street prices correspond to the *High Times* Price Index for "kind" (high-quality strains) or "mids" (medium-quality strains).[2]

[1] Breaking the premium down to the monthly level, marijuana on Silk Road received a sizable premium relative to prevailing street prices in every month – ranging from 22.5% in June up to a 41% premium in February.

[2] In total, *High Times* reports four price indices: a "kind" high-quality index, a "mids" medium-quality index, a "schwag" low-quality index, and an overall monthly average. Prices for "schwag" are dramatically lower than that for higher grades and range from $79 in March to $108 in June. In effect, the comparison presented here suggests that "low-quality" marijuana on Silk Road is most comparable to (and even higher priced than) medium-quality products available on the street.

The calculated means indicate that both quality types observe a premium, although the premium for low-quality strains is notably larger. High-quality strains on Silk Road command a 14% premium ($104 per ounce) over comparable product on the street, while low-quality strains receive premiums of 45% ($128 per ounce).[3]

One possible explanation for the higher Silk Road prices is a consumer preference for mitigating transaction risk. According to Ba and Pavlou (2002), price discounts serve "as compensation for buyers for bearing higher than average risk." At the time, purchasing drugs off Silk Road was viewed as less-risky than purchasing on the street; consumers avoided face-to-face interactions that increased the likelihood of arrest, identification, or physical harm. If consumers viewed street purchases as bearing higher transaction risks, then the observed Silk Road premium is likely picking up the willingness-to-pay for reduced transaction risk. The larger premium for low-quality products supports this interpretation: low-quality products are those more likely to be purchased in sketchy back alleys where transaction risk is highest.

To investigate whether structural differences existed between listings for different quality marijuana strains, I present descriptive statistics split according to the premium strain quality indicator. Table C2 presents descriptive statistics for the entire marijuana sample in Column 1 (identical to descriptive statistics for marijuana in Tables 1a, 1b, 1c, and 2a), only high-quality strains in Column 2, and low-quality strains in Column 3.[4] Of first note is that high-quality strains were not dramatically higher priced; high-quality strains received only a $2.50 premium per gram ($70 per ounce) on average relative to

[3] At the monthly level, the premium for high-quality product on Silk Road ranges from a low of $39 per ounce (a 9.4% premium) in March 2012 to a high of $89 (21.2%) in June. In contrast, the minimum premium for low-quality product is $103 per ounce (35.6%) in February – with a maximum of $168 (60.2%) in April.

[4] To allow for price premiums to high-quality strains, I employ a quality indicator as constructed by Anderson et al. (2013). Anderson et al. (2013) follows Jacobson (2004) and codes 8,271 marijuana transactions reported in *High Times* as either high-quality or low-quality according to the specified strain. I employ their strain list and update it for strains persent on Silk Road from January through July 2012 that were not included in the original list.

prices for lower quality strains. High-quality listings sold in lower volumes – 9 grams in comparison to 13 for low-quality – for roughly equivalent lot prices. Listings for high-quality marijuana had fewer negative reviews, but also fewer transactions – yielding identical average feedback ratings for both quality types. Similar proportions of products in each category were grown organically or hydroponically (though more low-quality marijuana was grown indoors), sold only domestically, or finalized early.

If listing characteristics were not structurally different between high and low-quality marijuana listings, perhaps sellers active in each quality type were inately different. Table C3 presents descriptive statistics for marijuana sellers, broken down by quality type. Again, vendors of high and low-quality marijuana do not appear particularly different along any notable margin. In terms of their reputations, vendors active in the high and low-quality market segments appear comparable along percent favorable ratings and cumulative negative reviews. Both types of sellers list similar numbers of items (between 12 and 13), and nearly all are for marijuana. Both categories have similar shares of new sellers and sellers with comparable numbers of lifetime transactions. The only margins along which sellers of high-quality marijuana differ are that they tend to be slightly younger (94 days active, versus 104 for sellers of low-quality product) and fewer in number.

Signal Heterogeneity: Strain Quality

Structurally, sellers of high and low-quality marijuana appear similar, yet vendors of high-quality marijuana exhibit a lower rate of negative reviews. Is the lower incidence of negative reputation merely a result of high-quality product, or do the signaling characteristics of reputation function differently for high and low-quality strains?

To investigate potential signal heterogeneity along quality lines, Table C4 presents results for marijuana models that include an interaction term between the negative review and premium strain indicators. *Strain x Any Negative* evaluates to one only for premium

strains that have acquired negative reviews, and is otherwise equal to zero. Column 1 presents results without seller fixed effects, while Column 2 includes them. In either case, no evidence of signal heterogeneity presents itself. Coefficient estimates for *Strain x Any Negative* are statistically insignificant and indistinguishable from zero. Coefficients on reputation measures and premium strains remain unchanged from previous models. The results in Table C4 confirm that Silk Road listings for high-quality marijuana strains received fewer negative reviews due to an accurate representation of the higher grade products, and the observed price premium reflects this difference in quality.

Table C.1: The Price of Marijuana on Silk Road Versus the Street

Month	Silk Road Price ($/Oz)	Street ($/Oz)	$ Difference	% Premium
All Listings	$442	$329	$112	34.0%
High-Quality	$476	$417	$104	14.1%
Low-Quality	$411	$281	$128	45.2%

Note: The above table reports average prices of marijuana (U.S. dollars per ounce) from February to July 2012 by transaction type. Silk Road prices report the arithmetic monthly average for transactions used in this paper's empirical analysis. Street prices correspond to the mean of monthly average prices as reported by a *High Times* U.S. price index. The difference reports the premium (or discount) Silk Road listings realized relative to street prices, followed by the percent premium. Row 1 reports an average price for all marijuana on Silk Road versus the average *High Times* index, row 2 only for high-quality named strains on Silk Road versus the high-quality "kinds" index, and row 3 only for low-quality Silk Road versus the "mids" index.

Table C.2: Descriptive Statistics by Strain Quality – Listing Characteristics

	All Strains	High-Quality	Low-Quality	
Variable	Mean (S.D)	Mean (S.D.)	Mean (S.D.)	Description
Price USD	109.97 (208.15)	106.91 (188.96)	112.10 (220.52)	Price, USD
Quantity	11.20 (31.29)	9.05 (22.29)	12.70 (36.19)	Quantity, grams
Price per Gram USD	15.27 (6.12)	16.72 (5.60)	14.25 (6.26)	USD per gram
Price per Ounce USD	432.77 (173.61)	474.11 (158.89)	403.95 (177.58)	USD per ounce
Bulk Listing	0.05 (0.23)	0.05 (0.21)	0.06 (0.24)	=1 if quantity > 1 ounce (28.35g), =0 otherwise
Feedback Rating	4.92 (0.47)	4.92 (0.47)	4.92 (0.47)	Average numeric feedback rating
Prior Negative Reviews	0.66 (1.90)	0.58 (1.30)	0.71 (2.22)	Count of prior negative reviews
Any Negative Reviews	0.25 (0.44)	0.28 (0.45)	0.24 (0.42)	=1 if listing has any negative reviews, =0 otherwise
Bio/Hydro	0.07 (0.25)	0.06 (0.24)	0.07 (0.26)	=1 if product is advertised as bio/organic or as grown hydroponically, =0 otherwise
Indoor	0.04 (0.19)	0.01 (0.08)	0.06 (0.24)	=1 if product is advertised as grown indoors, =0 otherwise
Domestic Only	0.55 (0.50)	0.57 (0.50)	0.55 (0.50)	=1 if item only ships within country of origin, =0 otherwise
Prior Transactions	81.54 (106.98)	37.41 (51.78)	49.29 (67.94)	Character length of textual feedback
Finalized Early	0.35 (0.48)	0.33 (0.47)	0.36 (0.48)	=1 if feedback mentions finalizing early, =0 otherwise
N	12,305	5,054	7,251	Observations

Notes: The above table reports transaction and listing characteristics for marijuana listings on Silk Road through July 24, 2012. Strains are classified as high or low-quality following Jacobson (2004) and Anderson et al. (2013) using actual street prices published in *High Times*.

Table C.3: Descriptive Statistics by Strain Quality – Vendor Characteristics

	All Strains	High-Quality	Low-Quality	
Variable	Mean (S.D)	Mean (S.D.)	Mean (S.D.)	Description
Seller Age	99.64 (78.79)	93.87 (75.53)	103.66 (80.74)	Seller age, days
New Seller	0.12 (0.32)	0.13 (0.34)	0.11 (0.31)	=1 if seller has fewer than 35 lifetime transactions and is younger than 1 month, =0 otherwise
Seller Transactions	295.68 (296.91)	287.99 (306.66)	301.03 (289.83)	Count of prior seller transactions
Multiple Categories?	0.04 (0.21)	0.05 (0.22)	0.04 (0.20)	=1 if seller also participates in non-marijuana categories
Items by Seller	18.51 (18.46)	11.79 (11.07)	12.99 (14.48)	Number of items currently listed across all categories
In-Category Items	12.41 (0.25)	11.72 (11.07)	12.89 (14.53)	Number of current marijuana listings
% Favorable Rating	98.64 (2.09)	98.64 (2.42)	98.59 (2.10)	Percent favorable rating across all of a seller's items
Negative Seller Reviews	6.05 (10.10)	6.23 (10.37)	5.92 (9.90)	Count of negative reviews accrued across all of a seller's items
Sellers	240	139	179	Total number of unique sellers active in market
N	12,305	5,054	7,251	Observations

Notes: The above table reports seller characteristics for marijuana listings on Silk Road through July 24, 2012. Strains are classified as high or low-quality following Jacobson (2004) and Anderson et al. (2013) using actual street prices published in *High Times*.

Table C.4: Reputation and Marijuana Strain Quality

Independent Variable	(1)	(2)
Premium Strains	0.0865*	0.0551
	(0.0492)	(0.0414)
Any Negative Reviews	-0.0742*	-0.1052***
	(0.0444)	(0.0398)
Strain x Any Negative	-0.0012	0.0377
	(0.0786)	(0.0488)
Seller % Favorable	-0.0025	0.0108***
	(0.0046)	(0.0044)
Location, Time, and Textual Controls	Yes	Yes
Seller Fixed Effects	No	Yes
N	12,305	12,305
R^2	.82	.88

Notes: Reported models correspond to Columns 6 and 7 of Table 4a with the addition of an interaction term between the premium marijuana strain indicator and negative reputation measure. Models regress the log of U.S. dollar price on log quantity, reputation measures, and differentiating item characteristics and include time and route controls (Column 1) along with seller fixed effects in Column 2.

*Significant at 90% level; **Significant at 95% level; ***Significant at 99% level.

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