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The Risk Creates the Reward: Reputational Returns to Legal and Quality Risks in Online Illegal Drug Trade

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Abstract: Although buyers in unregulated markets depend heavily on reputational information in the absence of state oversight, few studies examine how the riskiness of a good may condition reputational effects on prices. We capitalize on novel data on 10,465 illegal drug exchanges on one online "darknet" illegal drug market and computational text analysis to evaluate how distinct types of *legal* and *quality* risks moderate reputational effects on illegal drug prices. Our results suggest that quality risk considerations are especially acute, where the effect of numeric sales ratings and the sentiment expressed in sales review text are both increased for non-prescription drugs and attenuated for prescription drugs. In contrast, we find limited evidence that legal risks moderate reputational effects on illegal drug prices. These results underscore the importance of quality risks in illegal purchasing decisions, identify quality risk as a determinant of reputational premiums for illegal drug prices, and shed light on how the riskiness of a specific good can guide economic action in unregulated trade settings.

Keywords: risk; reputations; illegal markets; drugs; technology

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THE availability and proliferation of illicit drugs is a substantial social problem. Globally, the number of drug users increased by 26 percent from 2010 to 2022, whereas deaths due to drug use increased by 17.5 percent from 2009 to 2019 (UNODC 2022). During this period, the United States domestically experienced an even sharper increase in drug-related mortality, with a 30 percent increase in overdose deaths from 2019 to 2020 alone, mainly due to opioid and synthetic opioid use (UNODC 2022). The introduction of technologies of emergent clandestine sales platforms, such as online drug markets, has been an important part in the domestic and global expansion of the illegal drug trade. These platforms allow more people in a broad set of locations to access more types of drugs with pseudonymous exchange and anonymous payment from their own homes. As much as 10 percent of the global drug trade is now conducted online, and the percentage of global drug users who report purchasing illegal drugs online increased from 4 percent to 15 percent among surveyed users between 2015 and 2020 (UNODC 2022).

The risks and uncertainties implicit in all exchanges are magnified in online illegal trade. Illegal markets lack formal governmental oversight, meaning that actors cannot rely on contract enforcement and property rights ensured by the state in legitimate trade environments (Beckert and Wehinger 2013; Fligstein 2001). Online platforms increase risks and uncertainty even further (Kollock 1999). Buyers are anonymous and confront substantial information asymmetry due to their inability to inspect products before purchasing. Consequently, a foundational problem in research on illegal markets is how market actors overcome anonymity, high levels of uncertainty, and extreme risk to establish "order without law" in the cooperative tasks of illegal trade (Przepiorka, Norbutas, and Corten 2017).

The high levels of risk posed by illegal online trade provide an ideal case for furthering our understanding of the role of risk and reputation in economic exchange. Prior scholarship recognizes how risk shapes economic action and prices for goods and services (Kollock 1994; Gambetta 2009; Greif 2006; Podolny 2001). A consistent theme in this body of research is that prior studies overwhelmingly treat risk as a characteristic of a complete market environment (Akerlof 1970; Beckert and Wehinger 2013; Duxbury and Haynie 2021; Kollock 1994; Podolny 2001) rather than as a feature of a good or service itself. Departing from this work, we contend that the focus on differences in risk *between* trade environments misses how risk patterns market outcomes *within* trade environments. Specifically, we argue that the riskiness of a good shapes how buyers assess their willingness to pay for a good and the price they are willing to pay.

We build on classic social psychological theories of unregulated markets and third-party endorsements to assess how market risk moderates the effects of reputation (Coleman 1990; Greif 1989, 1993; Kollock 1994, 1999). We conceptualize *legal* and *quality* risks as two sources of risk in illegal trade that condition reputational effects on illegal drug prices. We evaluate the relationship between risk and reputation with novel data on 10,465 illegal drug exchange relationships between 4,891 market actors on the *Silk Road 3.1*, an online "darknet" drug market that specializes in illicit goods, more than 14 months of market activity, and by leveraging computational text analysis to information on third-party reputational effects that may shape illegal drug pricing. In doing so, we address an important puzzle in the literature on online and illegal drug trade.

First, although early studies on online markets document a "reputational premium," where buyers pay higher prices for the same goods to purchase them from high-reputation vendors (Diekmann et al. 2014; Przepiorka et al. 2017), recent studies have found highly heterogeneous evidence that reputations are related to prices or trade partner selection (Duxbury and Haynie 2023; Jiao, Przepiorka, and Buskens 2021; Munksgaard and Tzanetakis 2022). Although some studies find that reputations are associated with higher prices (Diekmann et al. 2014; Przepiorka et al. 2017), others find null effects (Duxbury and Haynie 2023; Munksgaard 2023). Still other studies find that reputations matter most for attracting first-time buyers but their effects disappear once buyers and sellers establish a trade relationship (Norbutas, Ruiter, and Corten 2020; Duxbury and Haynie 2018, 2021). In a meta-analysis, Jiao et al. (2021:9–13) find an overall positive effect of reputation but additionally find substantial evidence of high levels of true effect size heterogeneity. Approximately 41 percent of studies included demonstrate a null or negative effect of good reputations on sales price and 44 percent of studies included demonstrate a null or positive effect of bad reputations on sales price. We examine the possibility that this inconsistent evidence of reputational premiums results from effect heterogeneity, where the reputational premium is most pronounced for risky goods and attenuated for less risky goods.

Second, prior studies have primarily relied on numeric electronic rating systems to conceptualize reputational effects on online markets. However, these numeric reviews may be manipulated or inflated. Recent studies have brought increasing attention to textual comments that supply additional information on product and vendor quality (Macanovic and Przepiorka 2023). These textual reviews provide a separate but concurrent avenue for trade partner evaluation. The heterogeneity of reputational premiums may be due to missing a substantial part of the holistic reputation system that both buyers and sellers use to make decisions on the market. We disambiguate quantitative and qualitative reputations and explore how qualitative reputational effects operating through third-party discursive endorsements may affect prices for risky illegal goods as they operate in parallel to quantitative reputation.

Our results provide several insights into research on risk and reputations in social exchange. First, by finding that the level of risk conditions the importance of reputation effects for illegal drug prices, our findings demonstrate that the level of risk *within* markets contributes to differences in economic success. Second, by disentangling qualitative and quantitative reputation effects on illegal drug prices, our results add to recent studies showing that open discourse and third-party referral effects shape economic outcomes (e.g., Ladegaard 2020; Duxbury and Haynie 2021). Finally, our results provide a rejoinder to inconsistent findings on the "reputational premium" in online markets findings by identifying *when* risk and reputation matter in illegal trade. Collectively, these results advance the current understanding of how risk shapes reputational returns in risky social exchange and carry policy implications for "trust-based" policing efforts designed to reduce online illegal drug trade.

Background

Darknet Markets, Risk, and Reputation

Online darknet markets are websites where primarily illegal goods, such as hacked accounts, counterfeit money, or illicit drugs, are bought and sold on online platforms and may only be accessed through specialized software (e.g., Tor). Most darknet markets operate similar to legitimate e-commerce platforms such as *eBay* (see Haynie and Duxbury 2024). Sellers list their goods for purchase and may include descriptions, pictures, or other material. The goods are indexed, displayed on the market, and are presented in a browsable format. Buyers search for illegal goods, purchase them, and have them delivered to a physical address via a postal service (Aldridge and Askew 2017; Aldridge and Décary-Hétu 2016).

Although online darknet markets resemble their licit counterparts, online illegal trade is subject to significant structural barriers and lacks many characteristics promoting trade in other market environments. Information asymmetry is pronounced due to physical distances that hamper market actors' ability to inspect goods before purchasing (Akerlof 1970; Ladegaard 2020). Trade is anonymous, identities are highly protected, and long-distance, anonymous trade hampers the formation of commitment relations (Brown, Falk, and Fehr 2004; Kollock 1994; Yamagishi, Cook, and Watabe 1998) and trust networks (Cook, Rice, and Gerbasi 2004; DiMaggio and Louch 1998) that facilitate trade in unregulated settings.

Research and theory on social exchange argue that reputational effects are central when uncertainty and risk are high (Kollock 1994; Molm, Takahashi, and Peterson 2000; Podolny 2001). Reputational information alleviates uncertainty by establishing expectations about trade partners' conduct and product qualities. For example, research on premodern trade finds that centralized coalitions circulate information and act as avenues for adjudication of grievances through sharing detailed trade histories (Greif 1989, 1993; Greif, Milgrom, and Weingast 1994; Milgrom, North, and Weingast 1990; Okazaki 2005). Here, reputational information is developed, provided, and disseminated through third-party surveilling institutions.

Prior studies emphasize the importance of reputational effects for prices and cooperation in online illegal drug markets. This research finds that quantitative reputations allow vendors to determine preferential payment modes (Diekmann, Jann, and Wyder 2009; Andrei et al. 2023), leading to more buyer interest and bids for their listings (McDonald and Slawson 2007). Vendors with good reputations are more likely to be selected for a sale (Duxbury and Haynie 2018; 2021; 2023) and are disproportionately selected for repeat sales (Norbutas et al. 2020). Studies also document a "reputational premium," where high-reputation vendors can increase prices for their drugs (Diekmann et al. 2014; Przepiorka et al. 2017). Munksgaard and Tzanetakis (2022) recently found that this reputational premium translates to markets as a whole, where higher levels of generalized trust in online illegal markets are connected to higher prices and more frequent purchasing. Better reputations drive higher prices and better trade conditions in illegal drug markets.

Although prior research emphasizes the importance of reputations in online illegal drug trade (Beckert and Wehinger 2013; Cox 2016; Gambetta 2009; Diekmann et al. 2014; Przepiorka et al. 2017), the current understanding of reputational effects as a solution to the risk inherent in illegal markets has been hampered in two ways. First, although prior research finds that reputations facilitate risky trade, relatively little attention has been directed toward differences in levels of risk *within* illegal markets. Prior studies typically treat risk as a characteristic of illegal market environments (e.g., Duxbury and Haynie 2021; Hardy and Norgaard 2016; Ladegaard 2020; Martin et al. 2020; Norbutas et al. 2020), overlooking the possibility that reputational effects vary *within* illegal markets depending on the risks associated with specific illegal goods. For example, Beckert and Wehinger (2013) conceptualize the risk of illegal exchange as inheriting from the lack of contract enforcement and the threat of state sanctioning and retaliation from other market actors. Similarly, Gambetta (2009) reasons that illegality undermines market actors' ability to trust exchange partners.

Second, prior studies on online illegal trade have focused on *quantitative* reputational effects. Yet, qualitative reputational information is widely circulated in trade environments through open discourse. In addition to numeric sales evaluations, buyers also leave textual comments on vendors' goods through sales evaluations and online message boards. These textual evaluations provide important information on the quality of goods in online trade settings. For example, Kollock (1999) finds that open discourse alleviated risk considerations in the early stages of the online market *eBay* by enabling buyers to circulate information on sellers' communication, promptness of delivery, and product quality. In this regard, open discourse mirrors the widely studied network effect observed in premodern trade environments, where third-party information provides oversight mechanisms that fill the role typically occupied by state surveillance (Greif 2006; Hillmann and Aven 2011).

Although relatively little research examines qualitative reputation within illegal markets, some studies have begun to examine qualitative reputational systems in online trade. For example, Macanovic and Przepiorka (2023) use text mining methods to study moral boundaries in online illegal markets. They find that market actors invest in quantitative reputation systems to establish and entrench moral guidelines surrounding illegal trade. Ladegaard (2020) finds that open discourse provides an important source of technical adaptation, where market actors react to policing interventions by sharing information on website vulnerabilities and strategizing adaptations that will improve future markets' resilience. These studies broadly align with our reasoning by demonstrating that market actors rely heavily on textual content in online mediums to evaluate risks and guide trade practices. Although scholars increasingly look toward qualitative reputation, its effects on sales outcomes are unknown. Furthermore, though quantitative and qualitative reputations exist in the same space, it is unclear if the two systems are used in the same fashion. The theoretical and measurement exclusion of qualitative reputation introduces important endogeneity into models of reputation effects in online markets.

Risk and Reputational Returns in Unregulated Illegal Drug Trade

Despite the importance of risk and reputations for current understandings of risky social exchange and unregulated markets, we know little about how risk may stratify prices *within* illegal markets by increasing or decreasing reputational dependence. We consider how the riskiness of a good may condition the reputational premium assigned to prices. Our core hypothesis is that the returns to reputations will be greater for riskier illegal products—for example, those that pose greater health risks or carry harsher criminal penalties—than less risky products. We focus on illegal prices because prices are essential in determining the viability of illegal trade as a source of revenue, trade decisions, and competition within illegal markets (Beckert and Wehinger 2013; Duxbury and Haynie 2023; Moeller and Sandberg 2019).

Buyers use reputation to mitigate risk in their purchases by the selection of high-quality cooperative trade partners. Also, vendors use reputation to attract high-quality cooperative trade partners and to create long-term trade relationships with return customers (Akerlof 1970; Diekmann et al. 2014; Kollock 1999; Przepiorka et al. 2017). Although deceptive trade practices, such as by not delivering products or delivering low-quality products that are sold at inflated prices, can increase profits in the short run, a good reputation carries long-term returns by expanding client bases, creating long-term trade relationships, and increasing revenue.

Online drug buyers confront both the *legal risk* posed by illegal purchases and the *quality risk* posed by contaminants that may alter drug potency or create adverse health effects. Buyers and sellers are exposed to highly variable *legal* risks depending on the specific drug being exchanged. The severity of a potential criminal punishment represents a variable level of risk within an illegal market. For example, in the United States, at the federal level, trafficking of the least controlled drugs, such as cough medication with limited amounts of codeine, is punishable by no more than one year for a first offense. In contrast, trafficking heroin is punishable by no less than five years at a minimum for a first offense, with larger penalties for larger amounts (Drug Enforcement Agency 2022). Interviews with drug buyers show that sanctioning prospects inform the economic decisions of drug market participants (Moeller and Sandberg 2019).

Moreover, prior studies find that vendors often increase illegal drug prices to offset risks, such as risks posed by international shipping (Décary-Hétu et al. 2016). An extension of this argument is that high-reputation vendors are able to raise prices more than low-reputation vendors in the presence of legal risk because the premium buyers are willing to pay to vendors for riskier substances. Because sanctioning prospects vary according to the drug category, we expect that the positive effect of reputations on illegal drug prices will be greater for drugs that carry relatively severe criminal sanctions.[1]

> Hypothesis 1: The severity of criminal punishments for a drug purchase will increase the effects of quantitative reputation on illegal sales prices.

A second type of risk is related to *product quality*. Quality considerations are central to theoretical accounts of risk and market outcomes (Akerlof 1970; Kollock 1994; Podolny 2010). Quality considerations are amplified in illegal markets because illegal brands lack set standards and can be easily fabricated (Gambetta 2009) and because market actors have few product inspection options before purchasing (Beckert and Wehinger 2013). Quality is also especially salient in drug markets because product tampering can cause severe health consequences. Unscrupulous vendors may dilute their drugs while they maintain the appearance of quality, then dupe buyers into purchasing low-quality drugs for high prices. At times, dilution may be from a benign additive such as sucrose or corn starch or from a harmful adulterant such as strychnine or fentanyl, a synthetic opiate that is cheaper to produce and 50–100 times more powerful than heroin (UNODC 2023).

We focus on a specific quality risk related to prescription drug branding. Branding practices are a widely studied means for distributors to establish the quality of their goods in both legal and illegal markets (Gambetta 2009; Podolny 2010). Pharmaceutical companies provide an easily identifiable brand in drug markets that conveys product quality. For example, prescription "Oxycontin" is more easily identifiable and comes with a clearer quality assurance than "Black tar heroin" because the former was produced by legally regulated pharmaceutical companies before entering the black market, whereas the same is untrue of the latter.

In addition, pharmaceutical branding provides a pathway for buyers to validate a good prior to purchasing. Sellers provided pictures that display packaging or physical attributes of a drug, such as markings, embossing, coloration, or texture, while the same is untrue of non-prescription substances. Therefore, we expect that brand recognition conveys pharmaceutical legitimacy and will help reduce buyers' concerns about product adulteration and potency. As a result, we expect that the effects of reputations on prices will be *greater* for non-prescription drugs as compared to prescription drugs due to heightened concerns about product quality in non-prescription drug exchange.

> Hypothesis 2: Non-prescription drugs will experience a larger quantitative reputation effect on illegal prices as compared to prescription drugs.

In addition to distinguish between levels of risk, we differentiate between types of reputational information. Specifically, we consider how qualitative reputation information is circulated and built through open discourse. Histories of positive textual evaluations are likely to enable sellers to increase prices for illegal goods analogous to the "reputation premium" observed for quantitative reputations in prior research (e.g., Przepiorka et al. 2017). Because buyers are principally concerned with product quality and trustworthiness when conducting illegal exchanges, qualitative reputations provide quality signals regarding vendors' professional etiquette, promptness, communication, discretion, and product quality. Discursive evaluations of past transactions provide buyers with detailed information that can be used to address the various risks they confront. Qualitative reputation signals should be especially influential for riskier purchases, where trust and quality considerations are most salient. Although quantitative and qualitative reputations are both records of past exchange history, they contain different information and are produced by different processes. This may then begin to address the reputation effect heterogeneity that has been noted in prior work. Thus, we expect that quantitative and qualitative reputations will operate concurrently and independently to establish reputational premiums for drug prices and to condition reputational effects on prices for riskier drugs.

> Hypothesis 3a: Qualitative reputations will be positively associated with illegal drug prices.

> Hypothesis 3b: Qualitative reputational effects will be higher for non-prescription drugs and drugs that carry harsher criminal penalties as compared to prescription drugs and those that carry relatively lenient criminal penalties.

In sum, we consider how heterogeneity *within* illegal markets may determine the strength of reputational effects on illegal prices. We predict that the level of risk will moderate the effect of qualitative and quantitative reputations. We now evaluate these possibilities in a novel empirical context—the darknet drug trade—by using comprehensive transaction-level data on illegal drug prices across a wide variety of drugs and computational text analysis to disentangle qualitative reputations from quantitative numeric reputations.

Data and Methods

To examine the operation of darknet illicit markets and the role of reputation and trust in market outcomes, we analyze the market records of the illicit darknet market *Silk Road 3*.1. Data were collected from *Silk Road 3.1* between January 2017 and February 2018.[2] Data were collected using a Python-based web scraper that accessed each vendor's historical transaction records and downloaded each page of records as an HTML file. The HTML files were then parsed, which output individual transaction-level data. This resulted in 10,465 drug sales transactions between 82 vendors and 4,809 buyers.

Silk Road 3.1 provides an ideal data source for two primary reasons. First, the full transaction-level data were openly available on the market as records of each individual vendor. These histories include buyer pseudonym, price paid, numerical transaction rating, drug listing title, which includes drug type (e.g., marijuana and prescription opiate), number of days since the transaction occurred, which provides temporal ordering, and a full-text comment review of the transaction if present. In addition, product pictures were mandated with each sales listing, allowing prescription drug verification. Second, the *Silk Road 3.1* is an iteration of a popular, long-lasting, and established darknet market. Over time, the ownership and staff of the market have changed hands; however, from 3.0 to 3.1, the administration remained stable. The transition of *Silk Road* from 3.0 to 3.1 included an intentional market reset. All records and accounts of *Silk Road* before January 2017 were wiped during website upgrades and maintenance, allowing for a reset of reputational markers for the new market.

Dependent Variables

Our central research interest is how reputation influences vendor long-term market outcomes. To examine vendors' market performance, we evaluate vendors' sales using the price USD for drug transactions[3] (Duxbury and Haynie 2023; Hardy and Norgaard 2016; Holt, Chua, and Smirnova et al. 2013; Munksgaard and Tzanetakis 2022; Przepiorka et al. 2017), or the amount of money that a buyer has spent in a focal drug transaction. The sales price is an effective measure of vendor success and theoretically linked to reputation processes (Diekmann et al. 2014; Przepiorka 2013; Resnick and Zeckhauser 2002; Shapiro 1983). Drugs on the market were purchased using Bitcoin, a decentralized digital cryptocurrency, and the price in USD was listed within the transaction record based on the exchange rate from Bitcoin at the time of purchase. Due to the high skewness of the price variable, we log transform the variable for statistical analysis.

Although prior studies standardize prices by sales purchase size (i.e., the gram), we focus on prices for two key reasons. First, prices have a direct relationship to vendor revenue, and thus bear more explicitly on our interest in vendors' long-term success. Second, our focal interest is in buyers' decisions to entrust vendors without immediate guarantees that their goods will be delivered. The monetary value of a purchase is a more meaningful standardized value because buyers' assessment of risk is informed by the amount invested in a transaction as a whole, not standardized to a specific scale.[4] Thus, we follow prior studies on sales price to treat the log price as the dependent variable (Duxbury and Haynie 2023). As we elaborate below, we also control the size of the purchase in all analyses, so differences in purchase size are held constant in our model. We report sensitivity analyses that examine price per gram, which is shown in Appendix B in the online supplement.

Quantitative Numeric Reputations

The goals of our analysis are to evaluate whether public expressions of reputation in trade relationships help to establish perceptions of vendor trustworthiness that translate into long-term success as sales price increase and to evaluate the moderating effect of levels of risk on the relation between reputation and illegal drug prices. We construct our measures of quantitative reputation through the quantitative sales ratings left by buyers, which range from –5 to 5, hereafter referred to as numeric reputation. We use the effective percent positive (EPP) metric, which is the ratio of positive reviews to all reviews (Elfenbein, Fisman, and McManus 2019; Nosko and Tadelis 2015; Tadelis 2016) for each seller to represent their numeric reputation. EPP is a measure of review quality designed to consider the saturation of positive reviews on online illegal markets, where most buyers rate transactions as "5-star" exchanges (Norbutas et al. 2020; Przepiorka et al. 2017).[5] Consistent with prior studies, we set the threshold for a positive review at five stars[6] (Przepiorka et al. 2017; Norbutas et al. 2020). The measure is lagged by one month to ensure the correct temporal order of variables. Numeric reputation is multiplied by 100 to aid in substantive interpretation, such that the coefficient may be interpreted as the effect of a one percent change in numeric reputation on illegal drug prices.

Qualitative Discursive Reputations and Sentiment Analysis

We use sentiment analysis to quantify the sentiment expressed in full-text public sales evaluations to test hypothesis 3 on the effect of discursive reputation information on illegal prices. Sentiment analysis is a computational text analysis technique that examines the tone of a given text, whether the language is positively or negatively oriented. We use a lexicon approach, using the AFINN sentiment lexicon (Nielsen 2011), which assigns scores to each snippet of text through reference to a dictionary of sentiment words with corresponding numerical values.[7] We use the AFINN lexicon to assign sentiment scores to text strings. The AFINN dictionary rates negative and positive words on a scale from –5, typified by profanity or slurs, to +5, typified by words such as "breathtaking" or "outstanding." The primary strength of the AFINN lexicon is that it incorporates the emotional charge of language, whereas other popular lexicons do not (e.g., Hu and Liu 2004). The scores for each word are then aggregated to the transaction level to measure the tone of a sales review. This procedure assigns a numeric score to each transaction, where higher values indicate that a focal transaction reflects a higher quality evaluation. Sales with no textual review are assigned a score of 0, as they contain no positive or negative textual content.[8] These sales are retained because they represent a buyer's decision not to leave a textual review, which is a meaningful market behavior.

Although a primary strength of the AFINN lexicon is that it provides weights to each word, lexicon approaches are limited in that they do not incorporate domain-specific language and are sensitive to shifter words, such as "not" or "never," which substantively modify the positive or negative score of the sentiment word that follows them. We addressed these weaknesses in two ways. First, we supplement the AFINN dictionary by incorporating language commonly used in darknet drug markets identified through a manual examination of the textual reviews. For example, a key concern for many buyers is receiving their drugs in the mail after purchase. Accordingly, our lexicon incorporates "receive" and "received," as well as the misspelling "receiveid," to measure this positive attribute of a sale. We also added a litany of domain-specific words frequently used to convey positive vendor trade practices.[9]

We determine sentiment weight by its relative sentiment attributes within the market domain and the AFINN sentiment scale. For example, we assign a score of 3 to the word receive, the same scoring as the word "good." Successful reception of a package signifies transaction success, whereas never receiving a package signifies transaction failure. However, it signifies neither the positive attributes of a +4, such as "exuberant," nor the negative attributes of a –4, such as "fraud." Second, we adjust sentiment scores by accounting for shifter words when present. Each sentiment word is inspected for a shifter word preceding it. If a shifter word is present, we reverse the sign of the sentiment score.[10]

To create vendor-level measures of textual reputation, we compute a measure analogous to the EPP as the proportion of positive sentiment evaluations to all evaluations within each individual month, hereafter referred to as discursive reputation. We lag each value by one month to ensure the correct temporal order of variables. The discursive reputation measure includes information on the sentiment scores of all textual reviews provided in the prior month.[11] Higher values indicate that a vendor receives more positive language in their sales evaluations, reflecting third-party endorsement for future purchasers. Discursive reputation is multiplied by 100 to aid in interpretation.

Market Risks

We create two measures to capture different forms of risk: legal risk and product quality risk. We operationalize *legal risk* as the possible sanctions that a market actor would incur if their drug order were apprehended by law enforcement. Due to the international nature of *The Silk Road 3.1*, we operationalize legal risk for drugs by their schedule within the United Nations Single Convention on Narcotic Drugs of 1961, its amendment in 1972, and the Convention on Psychotropic Substances of 1971, as they were in effect during the sampled time frame (United Nations 2016, 2017). The United Nations Commission on Narcotic Drugs schedules are a set of international conventions and statute designations of drugs set by international treaty. The conventions rank drug risk on a scale of 1–4[12] and lay out legal standards, enforcement mandates, and oversight of drugs to member nations. Our model includes drug schedule[13] as a reverse-coded categorical variable such that higher values indicate higher risk. Unscheduled drugs are coded as the reference category. One limitation in using U.N. codes is that countries vary considerably in the penalties for drug purchasing and may meaningfully depart from U.N. scheduling criteria. To address this possibility, we also report results from a sensitivity analysis that only examines a subset of domestic drug exchanges within the United

States and uses scheduling categories from the U.S. Drug Enforcement Agency as an alternative measure of legal risk.

Second, we operationalize product quality risk as a dichotomous variable that denotes whether a good is a prescription drug or not. Prescription drugs provide a quality heuristic through their branding and through the ability to check vendor-provided documentation against confirmed references. Prescription drugs provide a pathway for ensuring product quality and rely on trust to a lesser degree. We expect that the positive effect of reputation will be larger for drugs that are much more difficult to examine for quality (e.g., heroin and methamphetamine) than for drugs that have the easy-to-use quality heuristic of professional pharmaceutical manufacturing (e.g., valium and oxycodone).

To test hypotheses on the moderated role of risk, we include an interaction term between each of our reputational measures and each measure of legal and quality risks. We expect that the coefficients for each interaction term will be positive, reflecting that the returns to qualitative and quantitative reputations are greater for legally riskier drugs and drugs with higher quality risk.

Controls

We incorporate several control variables to account for possible confounding explanations.[14] Buyers may be attracted to vendors who have been active on the market for a longer period of time. The duration of activity may communicate vendor stability and legitimacy. We control for this by including the number of months a vendor has been active on the market. Repeated exchange may impact vendor revenue and the effect of reputation by building trust between exchange partners (Décary-Hétu and Quessy-Doré 2017; Duxbury and Haynie 2021, 2023). We control for this with a dichotomous variable denoting whether a transaction is an initial first-time purchase or whether the transaction is a repeated purchase between the buyer and seller. Individual transaction sales price may be affected by the size of the order, where larger orders demand higher values (Andrei and Veltri 2024; Andrei et al. 2023; Munksgaard and Tzanetakis 2022). To account for this, we control for size in grams of the transaction.[15] Product diversity may impact vendors' ability to charge more for their products by expanding vendors' consumer base. Furthermore, specific drugs may also have their own sales characteristics, such as typical transaction prices. We control for this with a vector of indicator variables for the *type* of drug being sold, which is composed of the following drug groups on *Silk Road 3.1*: marijuana, prescription opioids, heroin, prescription stimulants, methamphetamine and speed, cocaine, MDMA/ecstasy, psychedelics, dissociatives, and an "other" category composed of infrequently purchased drugs such as anabolic steroids and abortifacients.

There may be effects of stated vendor location on price, such as whether vendor location is disclosed and where that location is situated in the world (Décary-Hétu et al. 2017; Norbutas et al. 2020). We include geographic location with the United States as the reference category. Finally, it is possible that unmeasured or unmeasurable attributes of vendors or time periods may cause variations in drug prices. To account for potential unobserved heterogeneity, we include vendor-level fixed effects. We also include a vector of month-fixed effects to purge the estimates of time trends and any unobserved period effects.[16]

Analytic Strategy—Two-Way Fixed-Effect Models

We begin with model 1, which acts as our baseline model and includes market and vendor characteristic controls (prescription indicator, schedule factor variable, drug type factor variable, repeat sale indicator, time fixed effects, vendor location, vendor time active on the market, and vendor fixed effects) to establish their effect on vendor outcomes. Our model holds constant the number of sales within vendors, within month. This takes into account the number of sales that vendors make and the average price of a vendor's sales within an individual time period of the market. Model 2 introduces numeric reputation and discursive reputation to assess their effect on drug prices. Model 3 tests international drug schedule interactions with both reputation terms to assess the moderation of reputation by legal risk. Model 4 tests the interaction of the prescription indicator term with both reputation terms to assess reputation moderation by adulteration risk.[17,18]

Descriptive Results

Table 1 reports the descriptive statistics. Consistent with past research on the darknet drug trade, numerical ratings are highly positive (Cox 2016), with an average numeric reputation of 87, indicating that 87 percent of cumulative sales as of the prior month were rated as five out of five stars. The average discursive reputation is also positive, but it is reduced substantially by the large number of neutral evaluations. This likely reflects the marginally higher effort to write a sales review than ranking a transaction numerically. In addition, the differences in the descriptive characteristics of numeric and discursive reputations support separating the two systems. More tightly controlled substances are the most common on *Silk Road 3.1*, with the vast majority of sales being schedule 1 and schedule 2 substances. Cocaine, marijuana, MDMA/ecstasy, and psychedelics are the largest categories of drugs sold. Prescription drugs are a minority but still a substantial category of drugs traded on the market, making up approximately 10.7 percent of sales among primarily opiate, stimulant, and dissociative categories.

Bivariate correlations of our primary explanatory variables suggest a relationship between reputations and the price charged by vendors. Numeric reputation correlates with sales price at –0.34, whereas discursive reputation correlates with sales price at 0.35. Although perhaps surprising, the negative correlation of numeric reputation is consistent with recent studies finding inconsistent evidence of the relationship between numeric reputations and prices (Jiao et al. 2021; Munksgaard and Tzanetakis 2022). Consistent with the importance of differentiating between quantitative and qualitative reputations, our key measures of numeric and discursive reputations are inversely correlated at –0.13.

Table 1: Descriptive statistics, *Silk Road 3.1* darknet drug market January 2017 to February 2018.

Variable	Mean (SD) or N	Range
Price $USD	235 (478)	5–21,002
Discursive EPP	15 (17)	0–100
Numeric EPP	87 (11)	0–100
Log cumulative sum of negative ratings	4.72 (1.42)	0–7.29
Log sum of positive ratings	5.28 (1.43)	0.69–7.91
Repeat sales	5,994	
Months active on market	4.94 (2.44)	2–11
Size in grams	6.63 (39.23)	0.0001–1814
Prescription drug sales	1,052	
Drug schedule, UN		
Unscheduled	186	
Schedule 4—low risk	445	
Schedule 2—medium risk	4,637	
Schedule 1—high risk	5,197	
Drug type		
Marijuana	1,830	
Prescription opiate	404	
Heroin	591	
Methamphetamine and speed	504	
Prescription stimulants	99	
Cocaine	3,499	
MDMA/ecstasy	1,703	
Psychedelic	1,256	
Dissociative	531	
Other	48	
Vendor sale location		
United States	1,817	
Canada	369	
Netherlands	2,967	
United Kingdom	1,118	
Europe	640	
France	336	
Spain	138	
Unknown	2,810	
Worldwide	200	
Other	70	

Fixed-Effect Results

Models 1–4 in Table 2 show the results of fixed-effect regressions on the effects of reputation and risk on drug prices. Model 1 presents a baseline model of market and vendor characteristics. The main effect of our prescription drug indicator is positive but non-significant, suggesting that baseline prices for prescription drugs do not differ from non-prescription drugs at statistically significant levels. Consistent with price inflation for more risky goods (e.g., Décary-Hétu et al. 2017), higher U.N. scheduling categories are linked to price increases. Results also provide evidence that prices are higher for sellers located in certain countries (Cunliffe et al. 2017; Munksgaard and Tzanetakis 2022) and that some substances are costlier than others (Munksgaard and Tzanetakis 2022). The positive coefficient for time on the market indicates that sellers can charge higher prices the longer they are active.

Regarding reputational effects, model 2 introduces our key measures of numeric and discursive reputations. The effects of these measures are non-significant when included independently. Although perhaps again surprising, these results align

Table 2: Fixed-effect models of drug transactions *Silk Road 3.1* January 2017 to February 2018.

	Model 1 Baseline	Model 2 Reputation	Model 3 Legal Interactions	Model 4 Rx Interactions	Model 5 USA to USA
Numeric reputation		−0.001	−0.003	−0.000	−0.087
		(0.001)	(0.005)	(0.001)	(0.05)
Discursive reputation		0.000	−0.001	0.001	−0.014
		(0.001)	(0.003)	(0.001)	(0.012)
Non-prescription	−0.434*	−0.433*	−0.390*	−1.182***	−3.620**
	(0.193)	(0.193)	(0.193)	(0.305)	(1.166)
U.N. schedule, low risk	0.158	0.157	0.832	0.149	
	(0.082)	(0.082)	(0.439)	(0.082)	
U.N. schedule, medium risk	0.796***	0.798***	0.174	0.805***	
	(0.138)	(0.138)	(0.412)	(0.139)	
U.N. schedule, high risk	0.847***	0.850***	0.761	0.860***	
	(0.151)	(0.151)	(0.403)	(0.152)	
DEA schedule, medium risk					−4.388
					(3.197)
DEA schedule, high risk					−0.667
					(2.108)
Months active on market	0.157***	0.161***	0.147***	0.148***	−0.113
	(0.039)	(0.039)	(0.039)	(0.039)	(0.267)
Opiate	0.388*	0.388*	0.347	0.382*	−1.280
	(0.188)	(0.188)	(0.188)	(0.188)	(0.880)
Heroin	0.132**	0.130**	0.141**	0.128**	
	(0.048)	(0.048)	(0.048)	(0.048)	
Meth	0.002	0.002	0.002	0.002	1.778*
	(0.074)	(0.074)	(0.074)	(0.074)	(0.734)
Rx stimulants	0.486*	0.483*	0.559*	0.339	
	(0.231)	(0.231)	(0.232)	(0.232)	
Cocaine	0.620***	0.619***	0.624***	0.620***	0.993
	(0.071)	(0.071)	(0.072)	(0.071)	(0.737)
MDMA/ecstasy	−0.054	−0.055	−0.050	−0.055	0.032
	(0.038)	(0.038)	(0.038)	(0.038)	(0.379)
Psychedelic	−0.183***	−0.186***	−0.187***	−0.188***	0.494
	(0.051)	(0.051)	(0.051)	(0.051)	(0.406)
Dissociative	0.156	0.158	0.163	0.118	0.195
	(0.215)	(0.215)	(0.221)	(0.217)	(0.706)
Other	0.127	0.127	0.192	0.111	
	(0.294)	(0.294)	(0.295)	(0.294)	
Repeat sale	0.024	0.023	0.024	0.016	−0.430**
	(0.037)	(0.037)	(0.037)	(0.037)	(0.132)
Cumulative sales	−0.000*	−0.000*	−0.000*	−0.000*	−0.007
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
Canada	−0.435***	−0.435***	−0.485***	−0.428***	
	(0.101)	(0.101)	(0.101)	(0.100)	
Netherlands	−0.637***	−0.639***	−0.683***	−0.665***	
	(0.065)	(0.065)	(0.066)	(0.065)	
United Kingdom	0.021	0.020	−0.019	0.003	
	(0.075)	(0.075)	(0.076)	(0.075)	
Europe	−0.948***	−0.948***	−1.005***	−0.975***	
	(0.105)	(0.105)	(0.106)	(0.105)	
France	0.102	0.102	0.040	0.091	
	(0.123)	(0.123)	(0.123)	(0.123)	
Spain	−0.626	−0.623	−0.672	−0.636	
	(0.738)	(0.738)	(0.736)	(0.737)	
Unknown	−0.503***	−0.504***	−0.560***	−0.521***	
	(0.078)	(0.078)	(0.078)	(0.078)	
Worldwide	−0.948***	−0.949***	−0.978***	−0.952***	
	(0.184)	(0.184)	(0.184)	(0.183)	
Other	−0.281	−0.286	−0.392	−0.242	
	(0.229)	(0.229)	(0.238)	(0.235)	
Size in grams	0.005***	0.005***	0.005***	0.005***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-prescription × discursive reputation				0.008***	
				(0.002)	
Non-prescription × numeric reputation				0.007*	
				(0.003)	

Table 2: (Continued)

U.N. schedule, low risk × discursive reputation			-0.014^{**}		
			(0.004)		
U.N. schedule, medium risk × discursive reputation			0.002		
			(0.004)		
U.N. schedule, high risk × discursive reputation			0.003		
			(0.004)		
U.N. schedule, low risk × numeric reputation			−0.005		
			(0.005)		
U.N. schedule, medium risk × numeric reputation			0.006		
			(0.005)		
U.N. schedule, high risk × numeric reputation			−0.000		
			(0.005)		
DEA schedule, medium risk × discursive reputation					0.019
					(0.018)
DEA schedule, high risk × discursive reputation					−0.000
					(0.009)
DEA schedule, medium risk × numeric reputation					0.079
					(0.042)
DEA schedule, high risk × numeric reputation					0.047
					(0.027)
Akaike Information Criteria (AIC)	23131.07	23134.23	23089.85	23111.81	
Bayesian Information Criteria (BIC)	23392.28	23409.95	23409.1	23402.04	
Within R^2	0.3857	0.3858	0.3891	0.3873	0.4598
Constant	5.543^{***}	5.630^{***}	5.907^{***}	5.545^{***}	4.953^{*}
	(0.267)	(0.300)	(0.477)	(0.301)	(2.183)
Observations	10,465	10,465	10,465	10,465	551

Note: Standard errors in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

with the heterogeneous evidence of a reputational premium on prices in both legal and illegal online market settings (Diekmann et al. 2014; Jiao et al. 2021; Munksgaard and Tzanetakis 2022).

We now explore the possibility that the riskiness of a drug listing conditions the effect of reputations on prices. Model 3 includes interactions between both numeric and discursive reputation variables with the U.N. drug schedule. In contrast to expectations, interactions between reputational measures and legal risk are non-significant or incoherent. The interaction of numeric reputation with legal risk is across all levels non-significant. Furthermore, low-risk drugs are subject to a marginally lower numeric reputation premium as reputation increases. Although medium-risk drugs have a higher premium than unscheduled drugs, this benefit again *decreases* for high-risk drugs. The interaction of discursive reputation with legal risk is similarly incoherent. The premium granted by an increase in discursive reputation is lower for low-risk drugs than unscheduled drugs. Furthermore, the premium for an increase in discursive reputation for both medium-risk drugs and high-risk drugs is not statistically significantly different than unscheduled drugs. We find that a reputation premium does not increase as legal risk increases.

Model 4 tests the hypotheses on quality risk by including an interaction between the reputational measures and the prescription drug indicator variable. In line with expectations, the interaction between discursive reputation and the prescription drug indicator variable is positive and significant, indicating that reputations boost illegal prices more for non-prescription drugs as compared to prescription drugs. Also consistent with expectations, positive numeric evaluations benefit non-prescription drugs less than non-prescription drugs. In line with our

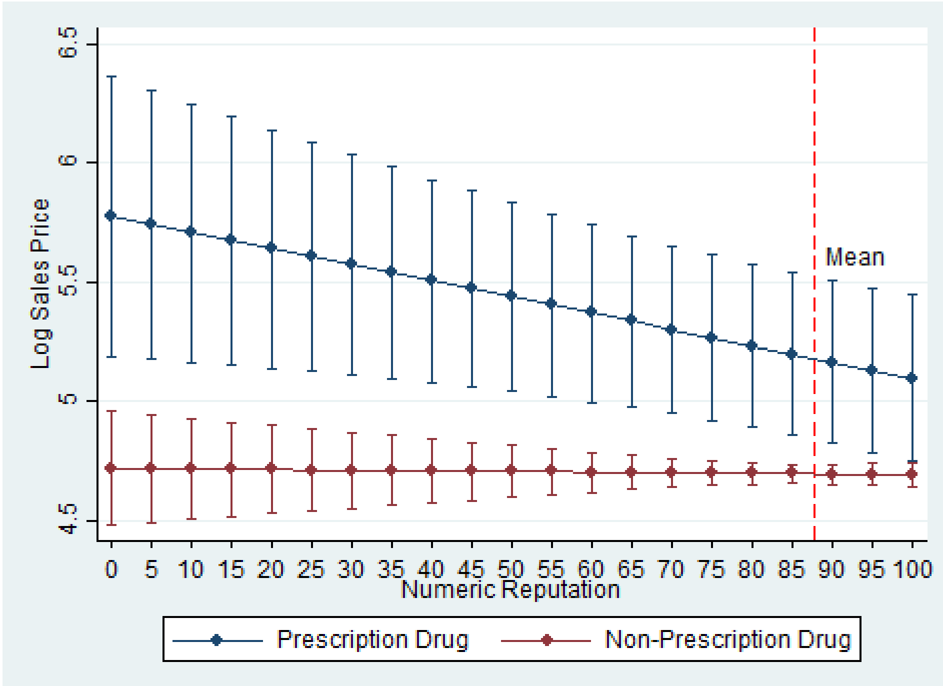

Figure 1: Marginal predictions of prescription indicator on log of sales price by quantitative numeric reputation, *Silk Road 3.1* January 2017 to February 2018.

hypotheses, these results support the argument that the reputational premium for non-prescription drugs is higher than that for prescription drugs.

Figures 1 and 2 report the marginal predictions.[19] These plots make visible the price gap produced by the interaction of product quality risk and both forms of reputation, as well as where this gap occurs on the reputation spectrum. Figure 1 shows how the effect of numeric reputation varies across levels of product quality risk. Prices decline for prescription drugs as numeric reputations increase but increase for non-prescription drugs. When the numeric reputation is 10 points below the mean, for example, the average price of a non-prescription drug is roughly \$69 USD cheaper than a prescription drug (exp(4.69) = \$108 USD vs. exp(5.18) = \$177 USD). Increases in reputational effects for non-prescription drugs are even starker when considering discursive reputation. Here, on average, non-prescription drug prices are \$82 USD lower compared to prescription drug prices when the discursive reputation is 10 points below the mean, but \$22 USD higher when the discursive reputation obtains its maximum observed value. These results align with the reasoning that the reputational premium on drug prices is greater for non-prescription drugs than prescription drugs, where product quality is uncertain.

Sensitivity Analysis: Legal Risk in the United States

Primary findings support arguments of a reputational premium for quality risks related to non-prescription drugs but do not support hypotheses on reputational

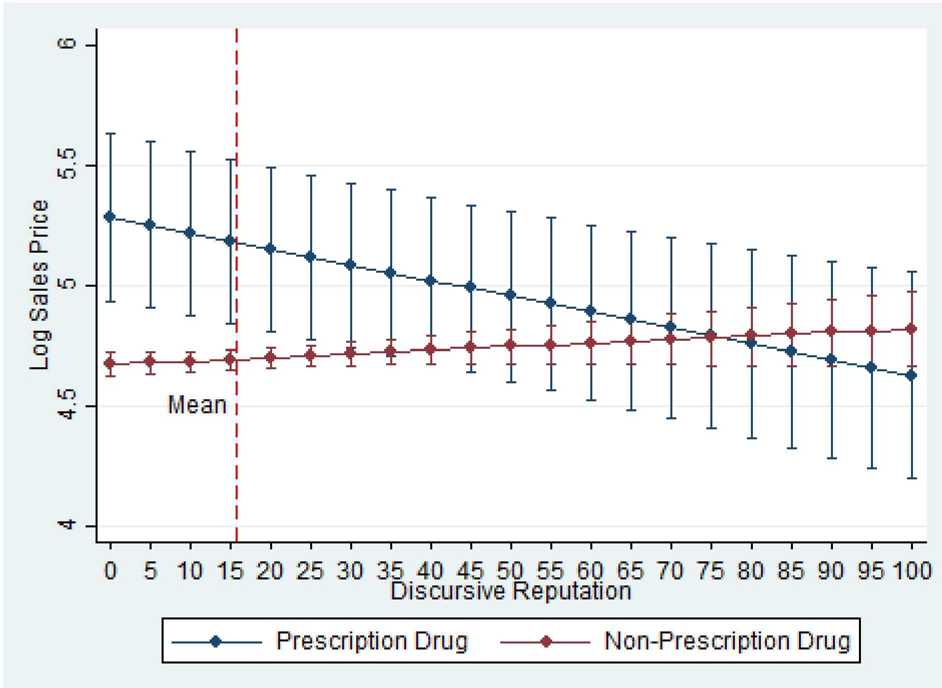

Figure 2: Marginal predictions of prescription indicator on log of sales price by qualitative discursive reputation, *Silk Road 3.1* January 2017 to February 2018.

premiums for legal risk. One possible explanation for our finding is that U.N. scheduling may be too heterogeneous between nations or buyers may have too little information on U.N. scheduling policies to inform purchasing behavior. To consider this possibility, we conducted sensitivity analyses using the subset of domestic drug transactions within the United States and by using Drug Enforcement Agency (DEA), rather than UN, scheduling to operationalize legal risk. The benefit of this analysis is that it holds constant between-nation variation in scheduling policies and information availability to only examining drug exchanges within a single country.[20]

Model 5 in Table 2 assesses the possibility of localized legal risk as a moderator of the effect of reputation on drug price. Although medium-risk drugs benefit more from discursive reputation than low-risk drugs, high-risk drugs benefit less from discursive reputation than low-risk drugs. Similarly, neither medium-risk nor high-risk drugs benefit more from numeric reputation than low-risk drugs. Furthermore, beyond significance, the coefficient for high-risk drugs is smaller than that of medium-risk drugs. These results testing the relationship of risk and reputation with national level drug scheduling run counter to the predicted relationship.

In sum, results partially support expectations on risk, reputation, and market success. Although we find strong and distinct effects of discursive and numeric reputational results on prices for non-prescription drugs, we find null evidence of reputational returns to legal risk internationally or within the United States.

These results broadly suggest that quality risks pattern reputational effects in online illegal drug markets and highlight the importance of disentangling qualitative and quantitative reputational dynamics in risky trade settings.

Discussion

Classic theory on risk in social exchange (Akerlof 1970; Kollock 1994) suggests that reputation is a key tool in solving trust issues in unregulated markets. We build upon this theory and argue that risk variation affects the use of both quantitative and qualitative reputations as a determinant of prices within illegal drug markets. We examine this process using 10,465 drug transactions from *Silk Road 3.1*, a large darknet drug market, from January 2017 to February 2018. We find that both numeric and discursive reputations increase prices for non-prescription drugs. Still, we find limited evidence that more strictly scheduled drugs condition reputational effects on illegal drug prices.

Findings have implications for scholarship on risk, reputation, and trade, as well as policy implications for intervention in the modern drug crisis. Our results on the conditional effects of reputation systems inform the debate on reputation effect heterogeneity observed in prior studies on online markets. Although some studies find that reputations and status increase prices (Diekmann et al. 2014; Podolny 2010; Przepiorka et al. 2017), others report null evidence of reputational effects in both regulated and unregulated trade (Jiao et al. 2021; Munksgaard and Tzanetakis 2022). We argued that one reason for this heterogeneity is that prior studies have not considered how reputations have a *conditional* relationship with the type of good being distributed.

In support of this argument, we find that quality risks are especially salient in determining the prices paid for illegal drug listings in darknet markets. Both quantitative and qualitative reputational information increases the prices for non-prescription drugs lacking brand-name quality assurances. These results align with our reasoning on the conditional reputational returns to risky trade and broadly suggest that variation in levels of risk *within* markets is an important determinant of market outcomes.

Findings also underscore the importance of disentangling quantitative and qualitative reputational information. Although prior studies emphasize the importance of reputations in online markets (Diekmann et al. 2014; Przepiorka et al. 2017), relatively less attention has been directed to how qualitative reputations accrued through textual discourse guide economic action. As suggested in prior work on premodern trade (Greif 1989, 1993), qualitative reputation affects market outcomes. In the case of darknet drug trade, we find that discursive reputational information is linked to higher prices for non-prescription drugs, even when quantitative reputations are controlled.

Although our null findings on the effects of legal risk on illegal drug prices depart from expectations, they are consistent with criminological research on deterrence (Becker 1968; Nagin 2013). Deterrence theory separates the severity, speed, and certainty of punishment as causes of risk perceptions (Decker and Wright 1993; Jacobs 2010). Prospective punishments have the greatest effect on risk perceptions when they are fast and certain. However, punishment *severity* has been found to have inconsistent effects on criminal risk perceptions and decision-making (Chalfin and McCrary 2017; Nagin 2013). Because both our legal risk measures rely heavily on the severity of prospective sentence lengths, they may do little to affect buyers' risk perceptions of participating in illegal trade. Future research can address this limitation by incorporating measures of legal risk that more explicitly capture the speed and certainty of a potential criminal sanction to overcome this issue.

More broadly, our results support the argument that the riskiness of illegal goods moderates reputational premiums for that good. However, this moderation is conditional on the type of risk that is encountered. Our findings show that the strength of reputational premium for illegal drug prices varies, in part, on whether buyers can use brand information to alleviate concerns about drug quality. These findings offer a contribution to the sociology of markets by illustrating how the quality risk of a good should be conceptualized in addition to the riskiness of a trade environment.

Our results also provide empirical insights for policy interventions designed to disrupt online drug distribution. Recent work advocates "trust-based" policing interventions that seek to undermine reputations on online drug markets (Duxbury and Haynie 2018, 2020). Results on the positive effects of discursive and numeric reputations bolster the evidentiary basis for these recommendations. Policymakers should consider the set of third-party endorsements that buyers and sellers engage with as potential pathways to intervene in and disrupt these emergent and growing vectors of drug exchange.

Although our observational digital trace data allow for the measurement of a previously difficult-to-observe exchange process, we are unable to assess incomplete transactions, which would allow for the estimation of sales likelihoods and vendor-level preferential attachment. Future research should examine these other measures of success and how they are impacted by risk and reputation, beyond only the sales price premium that we assess.

In sum, our study examines the use of multiple types of reputation as a mechanism to manage trade and cooperation across multiple types of risk in a high-risk, online, darknet drug market. Our results show that vendors benefit more from reputation when they sell drugs that are at higher risk of adulteration than for drugs that are prescriptions that are manufactured in tightly controlled environments and checkable against public references. On the other hand, we find that legal risk and reputation have no coherent or meaningful interaction. Understanding how reputation and risk interact in this illicit market is an important component in understanding how trust operates in unregulated markets, how illicit markets operate, and understanding the processes that drive modern illicit drug exchange.

Notes

1 Prior research has reported results that are broadly consistent with the reasoning. For example, Décary-Hétu, Paquet-Clouston, and Aldridge (2017) find that vendors typically charge higher prices for international shipments due to the heightened threat of detection at the relatively harsher sanctions assigned to international as compared to domestic

drug shipments. We expect an analogous process for distinct drug types, where the severity of a potential punishment will increase the reputational premium for illegal drug prices.

2 Silk Road 3.1 briefly shut down for the month of July 2017. While the website remained offline, no market activity occurred and as such July 2017 is excluded from our data. In addition, few sales occurred in January 2017. To retain these data, January and February 2017 were merged together.

3 The two most common measures for vendor success in observational data are sales price and preferential attachment. We choose sales price due to the close theoretical ties between sales price and reputation.

4 We note that our unit of analysis makes our analysis distinct from prior studies. Prior studies on prices that use price per gram typically evaluate sales *listings* (see Munksgaard and Tsanetakis 2023; Przepiorka et al. 2017), rather than price per *sale*. Because the price of listings cannot account for buyers' decisions to spend more or less money on a good, it makes sense to standardize by the size of a listing. However, because our analysis examines the amount of money buyers choose to spend, standardizing by purchase weight necessarily sacrifices information on buyers' decisions to entrust vendors with differing reputations with higher or lower amounts of money.

5 A second benefit of the EPP measure is that it accounts for threat of retaliation, such as refusing to reship or refund purchases when a buyer leaves a negative review (e.g., see Appendix A in the online supplement).

6 Here, 9,823 transactions, 90.7% of transactions collected, have a perfect five star out of five rating. This distribution is common within online market systems (Cox 2016).

7 Although lexical approaches have been critiqued for using limited social context, they have been shown to perform exceptionally well in online sales reviews because the nature of discourse is limited to the transaction itself and review text tends to be straightforward (Liu 2015).

8 Approximately 70% of reviews contain no textual review. These sales are retained because they represent a buyer's decision not to leave a textual review, which is a meaningful market behavior.

9 In addition, we add the words: fast, quality, timely, discreet, trustworthy, the misspelling "trut," quick, quickly, reliable, bueno, scammer, professional, legit, legitimate, prompt, and arrived.

10 In total, we identify 261 of 3316 words within 241 transactions that are shifted.

11 Sellers' listings only provide the six most recent reviews per page. To access older reviews, buyers have to scroll through additional pages. This is in contrast to numeric reputation, which is collated, summed, and clearly presented to buyers for all drug listings and at the top of vendors' homepages. Therefore, we only include the prior month of sales reviews in our measure of discursive reputation to account for high search and time costs involved in seeking out and reading older comments.

12 The United Nations Single Convention on Narcotic Drugs of 1961 and its 1972 amendment designates 4 as the highest scheduling and level of risk for a drug, 1 as the second highest scheduling and level of risk for a drug, and 3 as the lowest level scheduling and level of risk for a drug. The Convention on Psychotropic Substances of 1971 designates 1 as the highest level of scheduling and risk for a drug, and scales to 4 as the lowest level of scheduling and risk for a drug. The reverse-coded combined scale of both conventions standardizes coding as an unscheduled reference for the least risky category and high for the riskiest and most controlled substances.

13 Very few transactions of schedule 3 substances, only 21, occurred on *Silk Road 3.1* during the observed time period. Schedule 3 transactions that did occur were purchases of tramadol and suboxone, low-potency prescription opioids, and were merged into schedule 2 because schedule 2 contained the other prescription opioids.

14 Models have additionally been tested for the inclusion of the cumulative sum of positive sales evaluations and the cumulative sum of negative sales evaluations, which are the standard measures of reputation (e.g., Diekmann 2014, cite) that incorporate the building of reputation. Inclusion does not meaningfully change results.

15 Here, 432 observations were dropped from analysis as size in grams could not be clearly identified from the listing. In addition, we check alternative specifications of the model including using log price per microgram as our dependent variable (for discussion of size in micrograms variable, see Appendix B in the online supplement).

16 We verified this specification against a vector of time indicator variables and polynomial time specifications. The factor specification minimized both AIC and BIC, reflecting best model fit.

17 We test an additional model that includes interactions of both risk measures and both reputation measures. This model decreases AIC and increases BIC, while at the same time does not produce a substantial improvement in R^2, which suggests model overfitting.

18 We test the sensitivity of the results for the inclusion of interactions of reputational measures with sales quantile to test for effects of when a sale occurs within a vendor's history, controls for log number of positively rated sales and log number of negatively rated sales, which are the standard measures of reputation in online peer-to-peer markets. These models have no substantive effect on our results (see Appendix C in the online supplement).

19 Marginal plots of the effect of prescription status across risk reproduce the coefficients estimated in model 4. Marginal predictions are calculated as observed. See Appendix D in the online supplement for marginal predictions on U.N. scheduling.

20 We identify these sales through explicit claims in vendor profiles that they are located in the United States and sell only to domestic buyers.

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