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Research Paper

Uncertainty and risk: A framework for understanding pricing in online drug markets

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ABSTRACT

Background: The pricing of illicit drugs is typically approached within the risks and prices framework. Recent sociological and economic studies of prices in online drug markets have stressed the centrality of reputation for price formation. In this paper, we propose an account of price formation that is based on the risks and prices framework, but also incorporates internal social organization to explain price variation. We assess the model empirically, and extend the current empirical literature by including payment methods and informal ranking as influences on drug pricing.

Methods: We apply our model to estimate the prices of cannabis, cocaine, and heroin in two online drug markets, cryptomarkets (n = 92.246). Using multilevel linear regression, we assess the influence of product qualities, reputation, payment methods, and informal ranking on price formation.

Results: We observe extensive quantity discounts varying across substances and countries, and find premia and discounts associated with product qualities. We find evidence of payment method price adjustment, but contrary to expectation we observe conflicting evidence concerning reputation and status. We assess the robustness of our findings concerning reputation by comparing our model to previous approaches and alternative specifications.

Conclusion: We contribute to an emerging economic sociological approach to the study illicit markets by developing an account of price formation that incorporates cybercrime scholarship and the risks and prices framework. We find that prices in online drug markets reflect both external institutional constraint and internal social processes that reduce uncertainty.

Introduction

The study of drug prices has traditionally been shaped by the risks and prices framework (Ritter, 2006), but recent work by criminologists and sociologists have drawn attention to the relevance of social organization in the study of drug prices (Beckert & Wehinger, 2013; Moeller & Sandberg, 2019). In this paper, we draw on both approaches to study the pricing of drugs within illicit online markets. These platforms offer unique institutional contexts including contracts, formalized sanction, and dispute resolution to support illicit commerce, and we assess the influence of these uncertainty reducing social processes on drug prices.

Illicit online drug markets, hereafter cryptomarkets (Martin, 2014), have become both part of popular culture and have attracted the attention of drug policy scholars, criminologists, sociologists and economists (see Martin, Cunliffe, & Munksgaard, 2019, for an overview). They primarily supply retail drug markets, the "last mile" of drug distribution (Demant, Munksgaard, Décary-Hétu, & Aldridge, 2018; Dittus, Wright, & Graham, 2018). These platforms operate in a state of "open secrecy" (Ladegaard, 2020), in which the platform is anonymous but open to buyers and sellers (Aldridge & Décary-Hétu, 2016). More generally, cryptomarkets are one manifestation of a growing trend in which actors adopt digital tools to facilitate the distribution of illicit goods and services (see for example Demant, Bakken, Oksanen, & Gunnlaugsson, 2019; Hutchings & Holt, 2015; Soska & Christin, 2015; Tzanetakis, 2018a).

Prices are both theoretically interesting and relevant for drug- and crime control policy. In the study of illicit online markets, scholars have emphasized the centrality of reputation systems to price formation (Hardy & Norgaard, 2016; Przepiorka, Norbutas, & Corten, 2017), whereas country-level variation has received less attention (Cunliffe, Martin, Décary-Hétu, & Aldridge, 2017). Moreover, no studies have examined the influence of two key mechanisms, escrow systems which in-

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troduce contracts to illicit markets, and informal status rankings by administrators (Odabaş, Holt, & Breiger, 2017). In this paper, we propose a framework for how sellers set prices in illicit online markets. We argue that a set of uncertainty reducing social practices support the exchange of goods in these markets, but that price formation remains restricted by the formal institutional constraint of drug policy and enforcement. The added value of this approach is that it is both enlightening with regards to the social organization of illicit online markets and produces policy relevant results.

In the following three sections, we present our theoretical framework, which combines criminological, economic and sociological perspectives on illicit markets. Hereafter we summarize our model of price formation. We then present data, analytical approach, and the analysis. We conclude the paper with a discussion of our findings and their implications for theory and further research.

How are illicit drugs priced?

Research on traditional drug markets and prices has been shaped by the risks and prices framework, which argues that risk functions as a “tax” levied onto each transaction (Reuter & Kleiman, 1986). Market actors in the drug economy are compensated for the relative risk posed by both law enforcement (e.g. incarceration) and peers (e.g. fraud). Consequently, the price of drugs is often higher than gold or silver (Reuter & Caulkins, 2004). Drug prices are therefore a function of state induced risk towards market actors. Moeller and Sandberg (2019) argue that the risks and prices approach is compatible with institutional strands of economic sociology, which highlight the role of the state in producing “stable worlds of exchange” (Fligstein, 2001). Contrary to licit markets, however, this relation is reversed, and the state actively produces disorder through the absence of regulation, courts, and contracts, and its enforcement of law (Beckert & Wehinger, 2013).

Drug prices vary extensively across countries as those involved in trafficking must be compensated. Boivin (2014) argues this is a function of border enforcement and interdiction, which leads to both product seizures and increased risk of arrest (see also (Caulkins, Burnett, & Leslie, 2009)). Within countries extensive variation in prices is also observed. Caulkins and Padman (1993) find that prices seem to increase as competition decreases and distance to the source of production increases. Mahamad, Wadsworth, Rynard, Goodman, and Hammond (2020) observe illegal cannabis prices varying between Canadian states, and Moeller (2012) finds variation within one city. Non-state actors and institutions, such as gangs (Levitt & Venkatesh, 2000), or the Mafia (Reuter, 1984) can support stability in illicit markets through sanctions, informal social control, and dispute resolution. Consequently, they may also influence price formation. For example, the insurgent group FARC-EP instituted price control on drug trafficking in its territories (Gutierrez & Thomson, 2020).

Information asymmetry and product uncertainty are also crucial factors in price formation (Akerlof, 1970). When state regulation is absent, buyers have imperfect information about product quality (Beckert & Wehinger, 2013; Ben Lakhdar, Leleu, Vaillant, & Wolff, 2013), and pricing tends to be more reflective of perceived, rather than actual, potency (Ben Lakhdar, 2009). In addition, predation and fraud among market actors poses another problem for the participants of illicit markets (Naylor, 2003). A solution may be to embed exchange in social networks, which are also argued to reduce price (Moeller & Sandberg, 2019). Moreover, the social embeddedness of exchange within relationships and networks also influences pricing (Dwyer & Moore, 2010).

Another source of variation in drug pricing is quantity or “bulk” discounts (Caulkins & Padman, 1993). Scholars have observed that price tends to decrease sharply as quantity increases (e.g. Moeller & Sandberg, 2019; Caulkins, 1994; Giommoni & Gundur, 2018). At the retail level, discounts may reflect the lower exposure to risk and the absence of middle-men (Moeller & Sandberg, 2017). As with prices, these quantity discounts also tend to vary across and within countries. Ben Lakhdar et al. (2013) observe variation between French cities (see also Mahamad et al., 2020), and Moeller, Munksgaard, and Demant (2021) observe lower quantity discounts for cannabis in Sweden than in past research on other countries.

Summing up, according to the risks and prices framework, drug prices are predominantly a function of their legal classification and subsequent law enforcement. While risk is a crucial factor in the formation of prices, the drug trade remains embedded in social relationships. Empirically, drug prices are observed to vary across and within countries, even within local markets. Information asymmetry, perceptions of quality, and social relations are factors that influence pricing at the micro-level, whereas enforcement, distance from the source, and borders influence price at the macro-level.

Illicit online markets

The past decade has seen explosive growth in illicit online commerce, fraud and drugs in particular (e.g., Elbahrawy, Alessandretti, Rusnac, Teytelboym, & Baronchelli, 2020; Hutchings & Holt, 2017). Online drug markets come in a variety of forms, including simple web-shops, forums, social media markets and innovatively organized platform economies (Martin et al., 2019). The latter type, cryptomarkets, have grown from a niche market into an integrated part of the international drug trade, catering primarily to an audience of end-users and smaller-scale suppliers in Europe, North America and Oceania (Demant et al., 2018; Tzanetakis, 2018a). Although these markets allow the trade of other goods and services, supply and demand are predominantly for illicit drugs (Soska & Christin, 2015). Platforms are organized similarly to licit platform economies, but rely on a set of techonolgies, namely Tor and cryptocurrencies. These allow the overt exchange of illicit goods between anonymous users under a high degree of security from law enforcement (Aldridge & Décary-Hétu, 2016). Compared to the traditional drug trade, sellers are able to publicly offer all types of drugs and can include detailed information on drug classes, weight, price, qualitites, payment system, countries of origin and destination (Tzanetakis, Kamphausen, Werse, & von Laufenberg, 2016).

Administrators play a crucial role in these markets (Lusthaus, 2012). Odabaş et al. (2017) argue that platform administrators support exchange and stability through processes of authentication and mediation. Mediation consists of dispute resolution and escrow systems, whereas authentication is provided through product verification and the ranking of sellers. Administrators allow sellers to offer goods on the platform in exchange for a commission, and in turn they provide several services: Sellers are differentiated through reputation systems and rankings, reducing both search costs and information asymmetry (Paquet-Clouston, Décary-Hétu, & Morselli, 2018; Przepiorka et al., 2017).

Dispute resolution systems allow conflict resolution through mediation by a moderator (Morselli, Décary-Hétu, Paquet-Clouston, & Aldridge, 2017). The power to mediate depends on escrow systems, in which the administrator acts as a mediator to exchanges. Different modes of payment exist and with each comes a different type of mediation (see Tzanetakis et al., 2016). Sellers may offer payments through centralized escrow, in which the marketplace releases funds after the product has arrived. They may also require early finalization, payment upon ordering. Finally, decentralized, also known as multisignature escrow, distributes three keys to the administrator, buyer and seller. The funds can only be released using two of the three keys. Each mode involves varying labor costs and risks (Moeller, Munksgaard, & Demant, 2017).

The relative ease with which sellers can enter and exit the market poses a problem, since opportunistic sellers can defraud buyers and exit the market with few repercussions (Moeller et al., 2017). Escrow systems, in combination with vendor bonds, reduce the incentives for opportunism. Scholars also document the relatively high payoffs through sales and premiums that come with accumulating reputation (Martin, Cunliffe, Décary-Hétu, & Aldridge, 2019; Przepiorka et al., 2017). Entry costs therefore entail the accumulation of repeat buyers and reputation, along with a bond.

Cryptomarkets, and illicit online markets more generally, therefore allow the resolution of coordination problems, namely those rooted in predation, fraud and information asymmetry, in novel ways compared to traditional illicit markets (Tzanetakis, 2018b; Bakken, Moeller, & Sandberg, 2018). The institutional features, reputation systems, rankings, escrow, and dispute resolution, aim to reduce the transactional uncertainty that distinguishes illicit markets.

Drug pricing in illicit online markets

Illicit online markets are unique environments and we consider studies which have examined the pricing of illicit goods online. In the scholarship on cryptomarkets, two tendencies may be observed in the literature. One strand of research is concerned with the reputation system, and another with country-level variation. Within the literature on drug prices in cryptomarkets, scholars have been particularly interested in reputation systems, but we suggest that modes of payment (e.g. escrow) and status rankings may also influence price setting.

Reputation systems allow buyers to rate and comment after a purchase, typically using a 5-star scale (Martin, 2014). In traditional illicit markets, reputation propagates through social networks and supports stability by establishing the credibility of some sellers above others (Denton & O'Malley, 1999; Dickinson & Wright, 2015). Reputation systems distinguish themselves from reputation in its traditional sense, because they are not contingent on social networks. Consequently, they may be conceived of as anonymous, rather than networked, reputation (Glückler & Armbrüster, 2003). They may still reduce information asymmetry and sanction dishonest actors (Diekmann & Przepiorka, 2019), although Moeller et al. (2017) point out that sellers may inflate their own feedback as well as act opportunistically later. In contrast to licit online markets, evidence of a positive association between reputation and price is mixed for illicit online markets (e.g. Diekmann, Jann, Przepiorka, & Wehrli, 2014). Przepiorka et al. (2017) observe that sellers respond to positive reputation by increasing prices while decreasing it on negative feedback. Hardy and Norgaard (2016) analyze cannabis prices in the US but do not observe parameter estimates consistent with this thesis. Espinosa (2019) observes a tendency in the expected direction, but parameter estimates are not consistently significant in the expected direction. Červený and van Ours (2019) find no effects of positive feedback. Finally, a recent study by Duxbury and Haynie (2021) finds reputation premiums and a non-linear relationship between network embeddedness and prices, in which returning customers tend to pay a higher price until a certain threshold of network composition.

Beyond the reputation system, scholars have also utilized data from cryptomarkets to study prices at the country-level. Cunliffe et al. (2017) document significant differences between Australian and international drug prices, which are argued to be a consequence of importation risks. Risk differentiation has been argued to produce varying quantity discounts between drugs sold on cryptomarkets and social media in Sweden (Moeller, Munksgaard, & Demant, 2021). Červený and van Ours (2019) examine cannabis prices across 18 countries, and find that GDP and electricity prices are positive predictors thereof. Przepiorka et al. (2017) include a measure of international shipping, but find no significant relation, despite the increased risk that follows from it (Décary-Hétu, Paquet-Clouston, & Aldridge, 2016). In addition, purity premiums and differentiation within drug classes have received some attention. Moeller, Munksgaard, and Demant (2021) differentiate between herbal and resin cannabis observing price differences. Przepiorka et al. (2017) observe discounts on "poor quality" cannabis. Červený and van Ours (2019) find no association between price and self-described THC content in cannabis, but find some strains sold at a premium.

While the reputation system has been studied exhaustively, and there is a growing literature on country-level variation, the role of escrow payment and status rankings for price formation is less scrutinized. The absence of courts and contracts is a defining characteristic of illicit markets (Moeller, 2018), yet escrow and dispute resolution introduces de facto analogues thereof. From the perspective of social control theory, the administration holds "settlement" capacities to resolve conflicts (Black, 1990). Notably, this exercise of social control is formalized and standardized (Bakken, Moeller, & Sandberg, 2018; Tzanetakis, 2018b). Holt (2013) finds that some variation in the price of stolen data is explained by the use of escrow, however, to our knowledge, no empirical studies concernings illicit drugs have been published.

As for status, Odabaş et al. (2017) draw attention to the centralized designation and ranking of sellers denoting this as authentication. In contrast to reputation systems, status rankings are administered by a known party (e.g, administrator) and may therefore provide more trustworthy evidence than anonymous ratings (Glückler & Armbrüster, 2003). Marketplaces frequently label and rank vendors as more or less trustworthy, often based on reputation-related metrics, and Tzanetakis (2018b) suggest that such rankings increase trustworthiness. Consequently, rankings should therefore allow sellers to charge a premium.

More generally, we emphasize the influence of internal governance, or social control, by administrators as a potential influence on drug prices through payment systems and status rankings. This is an avenue of study which has received little attention previously, despite escrow payment being one of the defining characteristics of cryptomarkets (Martin, 2014), and administrative governance a key debate in the general literature on illicit online markets (e.g. Lusthaus, 2012).

A framework for price formation in illicit online markets

In the preceding sections we have reviewed the literature on drug prices in offline and online settings. We propose that drug prices in cryptomarkets, and illicit online markets more generally, are shaped by two structures discussed within this body of literature. With respect to crime control and the operation of illicit markets more generally, these two may also be denoted as the internal and external governance of illicit markets (Andreas & Nadelmann, 2006). Externally, drug policy and law enforcement add a "risk tax". The degree to which these factors influence prices is not static. Rather, they develop dynamically in relation to legislation and enforcement which vary across space and time. The same risk tax, for example, is not levied on Colombian cocaine as that sold from Europe (Boivin, 2014). However, a drug like cannabis in its herbal form, which is frequently produced domestically, can be assumed to vary less (Decorte & Potter, 2015). The principal assumption of our model is therefore that external forces shape prices, which will manifest as variation in prices and quantity discounts across and within countries. Following Moeller and Sandberg (2019), we refer to this as the institutional constraint. Internally, we suggest that product and seller certainty is supported by a set of actively trust producing institutional features, specifically, reputation, escrow payment, and status rankings. These can be conceived of as institutions that support trust (Zucker, 1986), or as socio-technical devices that support trust (Muniesa, Millo, & Callon, 2007). The internal component is grounded in analyses that have highlighted the productive function of platform administration, and it builds on empirical findings from studies of reputation in illicit online markets. Empirically, we suggest that the three features, reputation, escrow, and status rankings, allow sellers to charge a premium because of the reduction in uncertainty, but that the primary determinant of prices remains the formal institutional constraint. The first component extends the literature drawing on the scholarship of illicit online markets, while the latter is based on the risks and prices framework.

Research design

We test our model by analyzing how sellers set prices as they receive feedback, utilize escrow or advance payment and attain higher status. Following our model, we seek to capture both the internal and external determinants of price. An adequate statistical approach should therefore account for a) the external variation of drug prices (i.e. between sellers and countries), and b) how sellers respond to changes in their reputation, status, and their use of escrow. We use data from two online drug markets and analyze three different drug classes building replication into the design (Carver, 1993). To estimate the influence of institutional constraint we apply multilevel hierarchical regression. To produce estimates of how sellers respond we exploit repeated measurements of individual products. In the following sections we detail this design.

Data

We use data from two cryptomarkets, Empire Market (from June 2018 to January 2020) and Silk Road 3.1 (from May 2018 to December 2019). These were collected as repeated measurements of products, sellers, and feedback, using webcrawling and -scraping methods as part of the DATACRYPTO project (Décary-Hétu & Aldridge, 2015). Each platform presents a unique and complementary institutional context. While Silk Road 3.1 was relatively small, Empire grew from negligible in size to large over the data collection period. Both platforms offered sellers the possibility to require different payment methods. Silk Road 3.1 introduced an additional option, finalize early (50%), which allows the seller to receive 50% of the payment in advance with the remainder being held in escrow. We analyze three substance classes, herbal cannabis, heroin, and cocaine. These are among the most traded substances (Tzanetakis, 2018a), provide sufficient grounds for statistical analysis, and increase the potential for generalization. Ideally, we would expect, for example, reputation premiums to manifest in all scenarios (three drugs, two markets) to make a strong claim about a generalizable effect (Carver, 1993; Davis & Love, 2019).

An initial machine-learning classifier was applied to classify advertisements into categories (Demant et al., 2018) after which coding of substances, weight and subclasses was qualitative. We aimed to create categories and subclasses within which products were comparable across weight and price. This necessitated the establishment of exclusion criteria and a comprehensive coding scheme. Research on valuation of illicit drugs online provides sparse details on these aspects, and therefore we include a comprehensive discussion of how we constructed the dataset as an appendix[1].

Variables

Our key variables are reputation, escrow and status, and we further control for product potency, quantity and variation in the bitcoin exchange rate. Table 1 shows descriptive statistics for the dataset. To adjust for potency, we separate subclassess of drugs providing an easily graspable comparison to the relative size of estimates for reputation, escrow and status (Bernardi, Chakhaia, & Leopold, 2016). The labeling and justification of drug subclasses is detailed in the appendix. It is based on product differentiation which typically reflects potency, but we also highlight the relative cultural meanings and value of products (see for example Wendel & Curtis, 2000). We briefly discuss these as we present the results. Although sellers set their prices in USD, trade is still facilitated using the volatile Bitcoin cryptocurrency. We therefore control for changes in the value of Bitcoin by also including the log-transformed exchange rate from USD to Bitcoin. We use the daily weighted average from the cryptocurrency exchange BitStamp.

[1] The appendix presents a replicable protocol, which can be modified and extended. We highlight some significant practical challenges that remain unaddressed in the literature, concerning a) defining substances, b) specifying weight, and c) deciding on the appropriate way to measure price. The decisions we make in the establishment of this protocol are informed by the literature on drug markets and drugs as distinct products.

Different measures of reputation are used throughout the literature: lifetime measures (Nurmi, Kaskela, Perälä, & Oksanen, 2017), 0–100 ratings (Červený & van Ours, 2019), and product and seller ratings (Hardy & Norgaard, 2016; Przepiorka et al., 2017). Regardless of the reputation measure, we anticipate that reputation encourages vendors to charge a premium, which should hold under all specifications. We use the sum of negative and positive ratings of a seller over their lifetime which is the most frequent measure. On Empire, reviews are labeled positive or negative, making this measure straightforward. On Silk Road 3.1, however, reviews are on a larger scale with values ranging from -48 to +380. We identify a cut-off point at +1 from which reviews are positive and code accordingly. Both markets offer status rankings. We use vendor trust level and vendor level which are the status rankings offered on the two platforms. For each product observation these attributes are assigned based on the closest observation of the seller (see also Demant et al., 2018). While both marketplaces did offer sellers to require either of the three payment modes, escrow, advance payment and multisignature, the predominant mode on Empire was centralized escrow while on Silk Road 3.1 all three were in use. As advance payment was used infrequently on Empire (0.0%-0.5% of listings), these items were excluded from analysis.

In the case of both reputation and status, we impose a log-transformation for several reasons. It is the standard approach in past studies, improves model fit, and makes coefficients more easily interpretable (Gelman & Hill, 2007, p. 64). Moreover, we expect that these effects are relative rather than additive. An indicator variable designating whether an item or seller had received at least one feedback accounts for sellers who exclusively used the marketplace to advertise goods. Since items were observed multiple times they are measured at varying prices, levels of reputation and status, and escrow status.

Although both markets require cryptocurrency for payment, sellers set prices in USD and the price in cryptocurrency (e.g, Bitcoin) is adjusted thereafter. Platform users can choose which currency to be displayed on the platform. Consequently, no conversion from cryptocurrency to USD was needed on the platform itself. We calculate price-per-gram incorporating the minimal advertised shipping cost, and log-transform both price-per-gram and quantity. The log-transformation accounts for quantity discounts, the tendency to discount larger quantities (Caulkins & Padman, 1993; Moeller & Sandberg, 2015). A similar log-log model for drug prices is applied to both offline and online drug markets (e.g. Ben Lakhdar, 2009; Cunliffe et al., 2017; Moeller, Munksgaard, & Demant, 2021). Additionally, it results in a statistical model that is easily interpretable wherein the intercept corresponds to the log of the estimated price of 1 gram, and the log-transformed predictors correspond approximately to changes in percentage.

We defined exclusion criteria and discarded drug listings with no quantity specified and a small number of outliers (e.g. 1$ for an ounce of cannabis, 1.550$ for 3.5 gram of cannabis). Sellers can in some markets modify a product listing. For example, a seller may use a listing to sell 0.1 gram samples of cocaine, only to later adjust the listing to 1 gram of regular cocaine. We consider these distinct products, and therefore generate unique listings based on the URL, substance, subclass, weight, and origin for every product. Thus, items which were initially advertised at an introduction price, and therefore coded as belonging to the subclass of sample and promotion offers, and later advertised regularly, or which changed quantity, are measured as distinct products. This process results in a dataset consisting of repeated measurements of reputation, escrow payment and status rankings across individual products with fixed qualities (weight, subclass, origin). Table 2 details the dataset before and after exclusion criteria were applied.

Statistical analysis

Central questions in the economic study of illicit markets and drug prices are purity-adjusted prices, price elasticity, and quantity discounts (Bushway & Reuter, 2008). Typically, scholars examine markets

Table 1
Descriptive statistics. Mean, SD, skewness, number of zero-values before log-transformation, and range for continuous variables. Count and percentage for categorical and binary. Log-transformed variables incremented by 1 when containing zero. Note that crack cocaine is not treated as a subclass but as a binary variable. This is to allow differentiation between a cocaine sample and a crack sample.

	Cannabis		Cocaine		Heroin	
	Empire	Silk Road 3.1	Empire	Silk Road 3.1	Empire	Silk Road 3.1
N	43,184	6132	23,295	7051	9069	2921
log(Price per gram)	2.18 (0.51; -0.36; 0) (-0.42 – 3.98)	2.18 (0.52; -0.48; 0) (0.45 – 3.89)	4.19 (0.46; 0.45; 0) (1.11 – 6.31)	4.13 (0.36; 0.30; 0) (2.07 – 5.76)	3.94 (0.86; 0.30; 0) (1.13 – 6.91)	3.52 (0.57; 0.47; 0) (2.08 – 5.48)
log(Weight in grams)	2.76 (1.71; 0.44; 0) (-1.61 – 10.13)	2.73 (1.69; 0.55; 0) (-0.120 – 9.21)	1.46 (1.74; 0.56; 0) (-3.91 – 8.01)	1.60 (1.72; 0.54; 0) (-2.30 – 6.91)	1.26 (1.72; 0.34; 0) (-2.30 – 6.91)	1.94 (1.80; 0.47; 0) (-2.30 – 6.91)
log(USD-BTC exchange rate)	9.08 (0.13; -0.83; 0; 8.24 - 9.25)	8.91 (0.41; -0.87; 0; 8.12 - 9.38)	9.08 (0.13; -0.47; 0; 8.24 - 9.25)	8.95 (0.41; -0.47; 0; 8.12 -9.38)	9.08 (0.13; -0.89; 0; 8.24 - 9.25)	9.01 (0.38; -1.31; 0; 8.12 - 9.38)
Inactive item (%)	18,615 (43.1)	2634 (43.0)	10,861 (46.6)	2667 (37.8)	3735 (41.2)	1292 (44.2)
Subclass (%)					4588 (50.6)	2089 (71.5)
Afghan						
Asian					1237 (13.6)	61 (2.1)
Black Tar (B.T.H.)					626 (6.9)	140 (4.8)
Legal brand	661 (1.5)	27 (0.4)				
Outdoor	1798 (4.2)	182 (3.0)				
Regular	40,009 (92.6)	5905 (96.3)	21,314 (91.5)	6625 (94.0)	2210 (24.4)	577 (19.8)
Sample/intro/promo	716 (1.7)	18 (0.3)	1133 (4.9)	290 (4.1)	408 (4.5)	54 (1.8)
Social			848 (3.6)	136 (1.9)		
Crack (%)			2546 (10.9)	694 (9.8)		
Escrow (%)		1022 (16.7)		2283 (32.4)		945 (32.4)
Finalize early (100%)						
Finalize early (50%)		563 (9.2)		737 (10.5)		218 (7.5)
Centralized escrow	38,335 (88.8)	4547 (74.2)	22,390 (96.1)	4031 (57.2)	8959 (98.8)	1758 (60.2)
Multisignature escrow	4849 (11.2)		905 (3.9)		110 (1.2)	
log(Vendor level)		1.85 (0.73; -1.28; 533) (0.00 – 2.94)		2.06 (0.75; -1.47; 504) (0.00 – 3.00)		2.09 (0.66; -1.65; 140) (0.00 – 3.00)
log(Vendor trust level)	0.88 (0.77; -0.02; 0) (0.00 – 2.30)		0.96 (0.78; -0.16; 0) (0.00 – 2.20)		1.00 (0.75; -0.32; 0) (0.00 – 2.08)	
log(Positive seller ratings)	4.50 (1.98; -0.62; 2355) (0.00 – 9.23)	4.64 (2.04; -1.01; 731) (0.00 – 8.28)	4.73 (2.00; -0.65; 1172) (0.00 – 9.23)	5.24 (2.07; -1.13; 496) (0.00 – 8.28)	4.95 (1.75; -0.71; 195) (0.00 – 8.80)	5.53 (1.84; -1.37; 126) (0.00 – 7.97)
log(Negative seller ratings)	1.54 (1.35; 0.43; 12,955) (0.00 – 6.12)	0.95 (1.03; 0.81; 2714) (0.00 – 4.23)	1.82 (1.40; 0.23; 5199) (0.00 – 5.51)	1.58 (1.28; 0.20; 1933) (0.00 – 4.46)	2.03 (1.35; 0.05; 1385) (0.00 – 5.33)	2.18 (1.37; -0.09; 421) (0.00 – 4.64)

Table 2
Overview of observations before and after exclusion criteria were applied. Observations are the absolute number of product observations within a category. Listings are the number URLs referencing a listing. Vendors and countries are groups used in the analysis (random intercepts). Combinations adjust for the fact that a seller may change the advertised product of a listing (URL). Each is a combination of URL, subclass, weight, and origin country. Outliers are extreme prices that are dropped from the analysis. Missing quantities are products without an associated quantity.

	Cannabis		Cocaine		Heroin	
	Empire	Silk Road 3.1	Empire	Silk Road 3.1	Empire	Silk Road 3.1
Before exclusion						
Observations	46,372	9444	24,567	8589	9734	3545
Listings	12,320	2292	5821	1694	2039	701
Vendors	1031	250	850	277	305	102
Countries	45	24	41	25	22	12
Combinations	12,712	2346	6193	1771	2227	727
Outliers	80	71	51	1	5	1
Missing quantities	892	805	308	143	132	40
After exclusion Observations	43,184	6132	23,295	7051	9069	2921
Vendors	1007	234	822	260	287	91
Origins	45	19	40	24	20	9

within similar institutional constraints. These questions are generally assessed using regular OLS regression or fixed effects regression. Online drug prices differ from traditional data sources on drug prices (see Caulkins, 2007 for an overview and discussion of the former). First, there is only vendors' self-reported data on purity (Červený & van Ours, 2019). Second, prices are set under different institutional constraints (i.e. countries). Third, individual sellers provide prices, rather than being transaction-level observations. Fourth, repeated data collection can provide longitudinal data sets (see for example Martin, Culliffe, Décary-Hétu, & Aldridge, 2019; Tzanetakis, 2018a). These differences introduce two unique problems; seller heterogeneity and product heterogeneity, since sellers may have access to different and dynamic drug sources.

Table 3
Fixed and random effects of hierarchical linear regression models. A model is estimated for each substance and market. 95% confidence interval, *p*-values based on Wald-tests. The listing level is the *combination* described earlier which is a distinct URL, subclass, quantity, and origin. Note that crack cocaine is not treated as a subclass but as a binary variable. This is to allow differentiation between a cocaine sample and a crack sample. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

	Cannabis		Cocaine		Heroin	
	Empire	Silk Road 3.1	Empire	Silk Road 3.1	Empire	Silk Road 3.1
Predictors	β	β	β	β	B	β
Intercept	2.764 ***	2.489 ***	4.819 ***	4.347 ***	4.588 ***	4.249 ***
	(2.684 – 2.845)	(2.371 – 2.607)	(4.664 – 4.974)	(4.234 – 4.459)	(4.234 – 4.942)	(4.003 – 4.496)
log(Weight in grams)	-0.159 ***	-0.171 ***	-0.136 ***	-0.109 ***	-0.156 ***	-0.100 ***
	(-0.172 – -0.147)	(-0.178 – -0.163)	(-0.164 – -0.108)	(-0.129 – -0.090)	(-0.181 – -0.132)	(-0.111 – -0.089)
log(USD-BTC exchange rate)	-0.015 ***	0.003	-0.036 ***	-0.002	-0.036 ***	-0.004
	(-0.022 – -0.009)	(-0.006 – 0.012)	(-0.047 – -0.025)	(-0.006 – 0.003)	(-0.051 – -0.020)	(-0.014 – 0.006)
Inactive item (Reference: Active item)	0.011 ***	0.025 ***	0.011 ***	0.002	0.017 ***	0.009
	(0.008 – 0.013)	(0.017 – 0.033)	(0.007 – 0.015)	(-0.004 – 0.008)	(0.010 – 0.023)	(-0.002 – 0.020)
Subclass (Reference: Regular)						
Legal brand	0.421 ***	0.594 ***				
	(0.385 – 0.458)	(0.415 – 0.772)				
Outdoor	-0.385 ***	-0.369 ***				
	(-0.411 – -0.359)	(-0.432 – -0.305)				
Sample/intro/promo	-0.102 ***	-0.411 ***	-0.096 ***	-0.093 ***	-0.137 ***	-0.224 **
	(-0.133 – -0.070)	(-0.546 – -0.276)	(-0.121 – -0.071)	(-0.137 – -0.048)	(-0.202 – -0.072)	(-0.374 – -0.074)
Social cocaine			-0.508 ***	-0.376 ***		
			(-0.543 – -0.472)	(-0.434 – -0.317)		
Afghan heroin					-0.118 ***	-0.288 ***
					(-0.174 – -0.063)	(-0.388 – -0.188)
Asian heroin					0.315 ***	0.209 *
					(0.240 – 0.390)	(0.037 – 0.381)
Black Tar Heroin (B.T.H.)					-0.127 **	-0.048
					(-0.215 – -0.038)	(-0.226 – 0.130)
Crack (Reference: Cocaine)			0.103 ***	0.069 ***		
			(0.078 – 0.127)	(0.039 – 0.099)		
log(Positive seller ratings)	-0.004	0.006	0.002	0.010 *	0.015 *	-0.005
	(-0.012 – 0.003)	(-0.007 – 0.019)	(-0.004 – 0.009)	(0.000 – 0.020)	(0.002 – 0.029)	(-0.028 – 0.018)
log(Negative seller ratings)	0.010 ***	0.003	0.006 **	-0.007 **	-0.010 **	-0.026 ***
	(0.008 – 0.012)	(-0.005 – 0.010)	(0.002 – 0.010)	(-0.012 – -0.002)	(-0.016 – -0.003)	(-0.035 – -0.017)
log(Trust level)	0.008 ***		0.013 ***		0.011 *	
	(0.004 – 0.012)		(0.007 – 0.020)		(0.000 – 0.021)	
log(Level)		0.011		-0.011 *		-0.004
		(-0.001 – 0.023)		(-0.022 – -0.000)		(-0.023 – 0.015)
Escrow (Reference: Full escrow)						
Multisignature escrow	-0.003		0.025		0.250 *	
	(-0.018 – 0.012)		(-0.029 – 0.079)		(0.059 – 0.441)	
Finalize early (100%)		-0.060 ***		-0.012 **		-0.032 ***
		(-0.081 – -0.039)		(-0.021 – -0.003)		(-0.046 – -0.017)
Finalize early (50%)						
Random Effects		-0.011		-0.009 *		0.014
		(-0.023 – 0.001)		(-0.016 – -0.001)		(-0.001 – 0.029)
Residual Variance	0.002	0.003	0.003	0.002	0.003	0.002
Between-group variance						
Listing	0.039	0.044	0.036	0.025	0.057	0.050
Vendor	0.326	0.189	0.151	0.105	0.300	0.244
Country	0.006	0.006	0.091	0.027	0.455	0.061
Random-slope variance						
Vendor * log(Positive seller ratings)	0.010	0.004	0.004	0.002	0.007	0.005
Country * log(Weight in grams)	0.001		0.005	0.001	0.002	
Slope-intercept correlation						
Vendor	-0.854	-0.779	-0.811	-0.484	-0.776	-0.793
Country	0.492		-0.214	-0.889	-0.905	
ICC	0.988	0.980	0.984	0.987	0.996	0.991
N						
Listings	12,412	2117	6069	1721	2181	711
Vendors	1007	234	822	260	287	91
Countries	45	19	40	24	20	9
Observations	43,184	6132	23,295	7051	9069	2921
Marginal R^2/Conditional R^2	0.306 / 0.992	0.376 / 0.988	0.235 / 0.988	0.212 / 0.990	0.150 / 0.996	0.234 / 0.993

If the aim is to examine effects on one level, for example whether sellers adjust prices based on reputation, a fixed effects approach can make a stronger case for causality while accounting for heterogeneity (Bushway & Reuter, 2008). However, this can limit the analysis of structural components, namely between-country variation. We therefore apply multilevel linear regression. Here, population-level estimates (fixed effects) and group-level coefficients (random effects) can be estimated (Gelman & Hill, 2007). With sufficient data, the random effects allow the estimation of separate intercepts (price of 1 gram), and quantity discounts, for every country. The multilevel specification arguably has downsides. Namely, caution should be taken in interpreting parameters as causal effects (Hill, 2013) and parameter estimates reflect both variation within and between groups (Wang & Maxwell, 2015). An advantage in our setting, however, is that even groups, items in this case, that are observed only once can be used for estimation (Gelman & Hill, 2007, p. 276). Consequently, we neither have to discard data nor reduce it to a higher level (e.g. seller instead of item). We note, however, that parameters estimated using different models did not substantively differ.

Based on the concept of institutional constraint, we assume drugs have varying quantity discounts across sellers, substance, and country. We therefore estimate separate models for each market and substance class. Previous research has estimated within-seller effects (Červený & van Ours, 2019; Espinosa, 2019; Przepiorka et al., 2017), but this assumes product homogeneity and can introduce bias if longitudinal measures are used. For example, a seller may have access to varying supply across the period of measurement and adjust prices accordingly. Consequently, we exploit repeated measurements and nest the level 1 variables (fixed effects) in product observations (level 2). These are in turn nested in countries and sellers (levels 3 and 4), making this a 4-level crossed design wherein sellers can sell from different countries. We allow a separate quantity discount (random slope) for countries when possible to account for varying institutional constraints. In four models the size of the dataset is sufficient to estimate country-level quantity discounts as well.

Findings

We begin the analysis with the random effects and quantity discount estimates showing drug pricing between countries. For the analysis of fixed effects, we emphasize back-transformed and estimated effects rather than focusing on *p*-values and coefficient estimates exclusively, since price-per-gram is an easily graspable and substantive quantity (Bernardi et al., 2016). Models were estimated with restricted maximum likelihood in R using the *lme4* library with tabulation and visual presentation aided by the *sjPlot* and *ggeffects* libraries (Bates, Mächler, Bolker, & Walker, 2015; Lüdecke, 2018, 2020). Variance inflation factors and residual plots showed no indications of multicollinearity (*VIF* < 4.0) or heteroskedasticity, although we note non-normal residuals, which may affect standard errors, though the extent may be mitigated by the large sample sizes.

Quantity discounts and country-level variance in drug prices

In line with the risks and prices framework, we find significant and varying quantity discounts for each substance at the population-level, with cannabis estimated at -0.159 and -0.171, cocaine at -0.136 and -0.109, and heroin at -0.156 and -0.1. As both outcome and quantity are log transformed, the coefficients for quantity discounts can be interpreted so that a 1% increase in quantity yields a reduction of 0.171% in price-per-gram of cannabis at the population-level on the Empire platform. The difference in population estimates and observed group-level slopes is reflective of their demographic composition, in which Silk Road 3.1 skews heavily European. These estimates are broadly consistent with past research on online drug markets which finds quantity discounts for cannabis of -0.17 and -0.18, and -0.10 for cocaine (Červený & van Ours, 2019; Espinosa, 2019; Moeller, Munksgaard, & Demant, 2021), though inconsistent with Przepiorka et al. (2017) which find a discount of -0.20 for all three substances.

All models include a country-level intercept for price-per-gram and a slope for quantity discounts (except for heroin and cannabis on Silk Road 3.1 market). Fig. 1 illustrates the variance observed across countries by plotting the estimated prices. Both markets show the same structural patterns: Variance at the country-level intercept for cannabis is very low (0.006 and 0.006) larger for cocaine (0.091, 0.027), and largest for heroin (0.455, 0.061), as can also be seen from Fig. 1. The lower country-level variance on the Silk Road 3.1 platform, as opposed to Empire Market, is likely attributable to the demographic composition of sellers across countries. The quantity discount on Empire for cannabis shows a pattern of "fanning out" with a correlation between intercept and slope of 0.492. Conversely, for both cocaine (-0.214, -0.889) and heroin (-0.905) we observe negative correlations between intercept and slope, meaning that countries with a higher intercept have a steeper quantity discount.

Product differentiation and bitcoin price variation

For each substance we include a categorical variable to distinguish between the largest and most distinct subclasses. These are within-category classes of products which may be associated with purity/quality premiums and discounts. Fig. 2 shows the estimated price

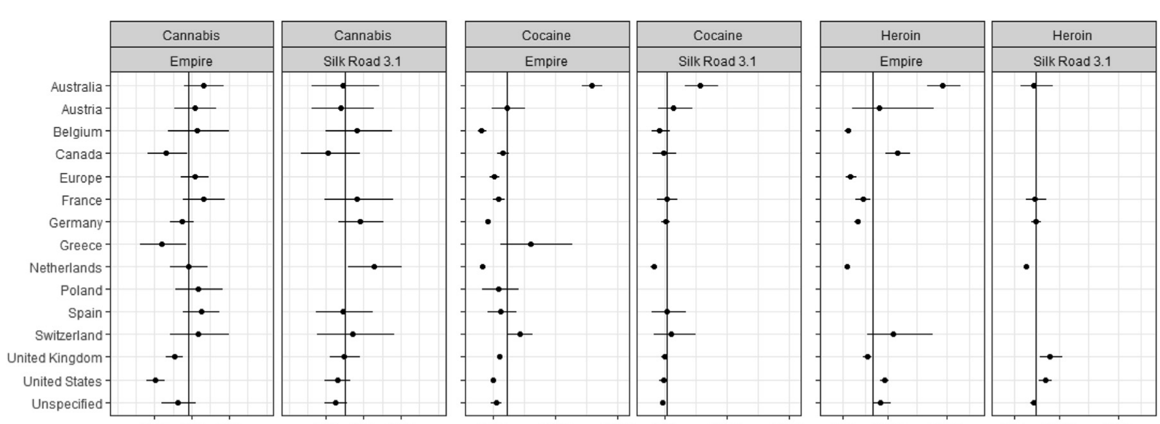

Fig. 1. Estimated price of 1 gram of each substance across the 15 shipping origins with the most observed listings. Dot indicates estimated price of 1 gram adjusted for the country-level intercept and the interval indicates two conditional standard deviations. "Unspecified" refers to products for which the seller did not indicate an origin. Vertical line represents the intercept. Missing points indicate that no products from the country were observed.

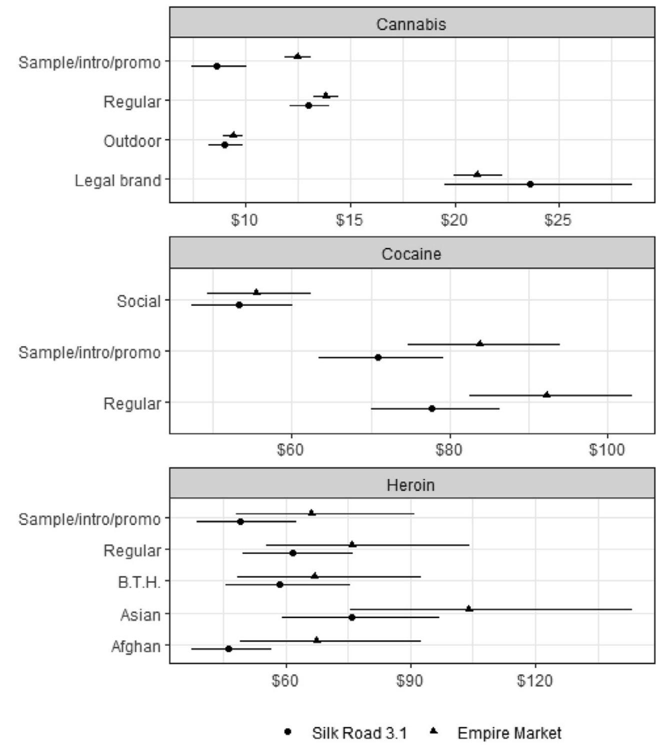

Fig. 2. Estimated price of 1 gram across substances. Internal differentiation is by subclass with reference being "regular" product.

per gram of each drug-subclass combination. Products characterized as introductory, promotions, or samples, are for each drug subclass significantly ($p < 0.01$) reduced in price in the range of -0.093 to -0.411. For herbal cannabis, we find significant discounts of the subclass outdoor at -0.385 and -0.369 in both markets ($p < 0.001$), and large premiums of 0.421 ($p < 0.001$) and 0.594 ($p < 0.001$) on cannabis diverted from legal sources, which are typically Californian brands. For cocaine, the social subclass is significantly discounted ($\beta = -0.508$, $\beta = -0.376$, $p < 0.001$) suggesting price is adjusted by purity (Reuter & Caulkins, 2004) while, interestingly, crack adds a premium ($\beta = 0.103$, $\beta = 0.069$, $p < 0.001$). For heroin, we find products advertised as Asian in origin have a significant premium on both Empire ($p < 0.001$, $\beta = 0.315$) and Silk Road ($p < 0.05$, $\beta = 0.209$), corresponding to its higher purity (Ciccarone, 2009). Conversely, Afghan heroin is sold at a discount ($p < 0.001$, $\beta = -0.118$, -0.288) while Black Tar heroin (B.T.H) is only significantly discounted on Empire ($p < 0.05$, $\beta = -0.127$). These estimates suggest some subclasses carry a large premium while others are discounted.

We also included the weighted exchange rate of bitcoin on the day an item was observed. Five out of six estimates are negative in the range of -0.002 to -0.025, and four of these are significant ($p < 0.001$). We thus observe a relatively consistent trend towards sellers lowering prices when Bitcoin is increasing in price.

Reputation

In line with the literature, we hypothesized that sellers would respond to negative and positive feedback by decreasing and increasing price. Fig. 3 shows the estimated prices per gram for each substance at a scale of the lowest and highest number of positive and negative feedbacks observed for each combination of platform and substance. Positive feedback follows the expected direction in 4/6 cases in the range of 0.002 to 0.015 but is significant in only two cases ($p < 0.05$). Negative feedback follows the expected direction in 3/6 cases, in the range of -0.07 to -0.026 ($p < 0.01$). Our results therefore suggest that sellers neither consistently increase price on receiving positive feedback nor decrease on negative feedback. This is in line with what is observed by both Červený and van Ours (2019) and Espinosa (2019).

We allowed the coefficient of positive feedback to vary across vendors, allowing each to respond differently to an increase in their reputation score. Across all models, we find a negative correlation between a vendor's intercept and the coefficient for reputation ranging from -0.484 to -0.854. This suggests that those who start at a lower price respond to the accumulation of feedback by increasing their prices. Coefficients thus differ on population- and group-levels. This pattern is shown in Fig. 4, which plots the group-level coefficient for positive feedback

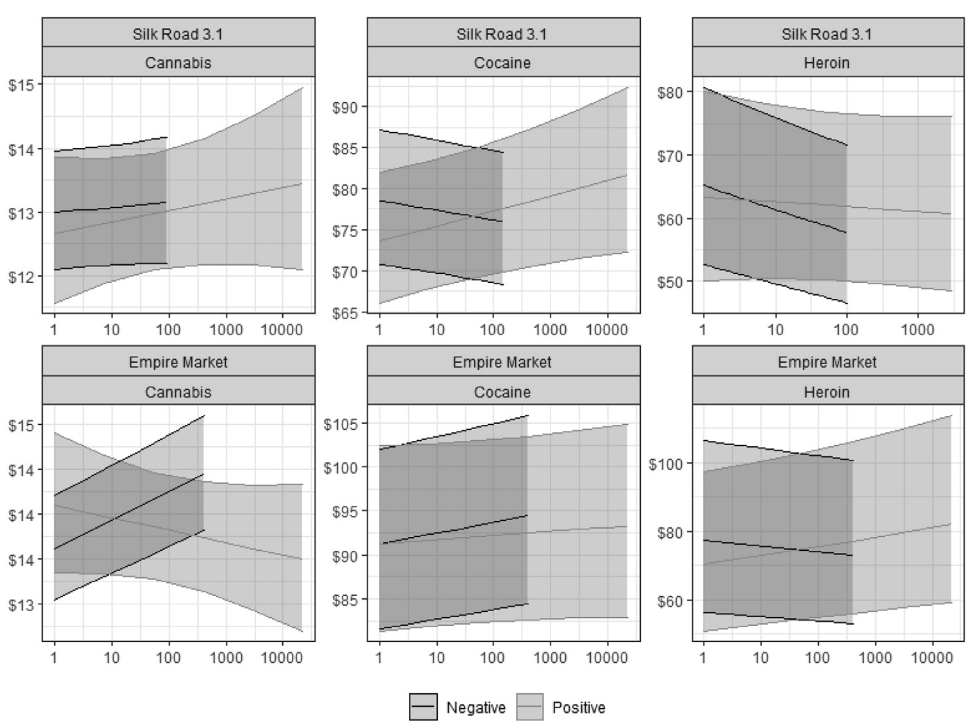

Fig. 3. Estimated differences in price for 1 gram across increasing negative and positive feedback. Note, that the X-axis log-scaled and allowed to reach 10.000 positive feedback.

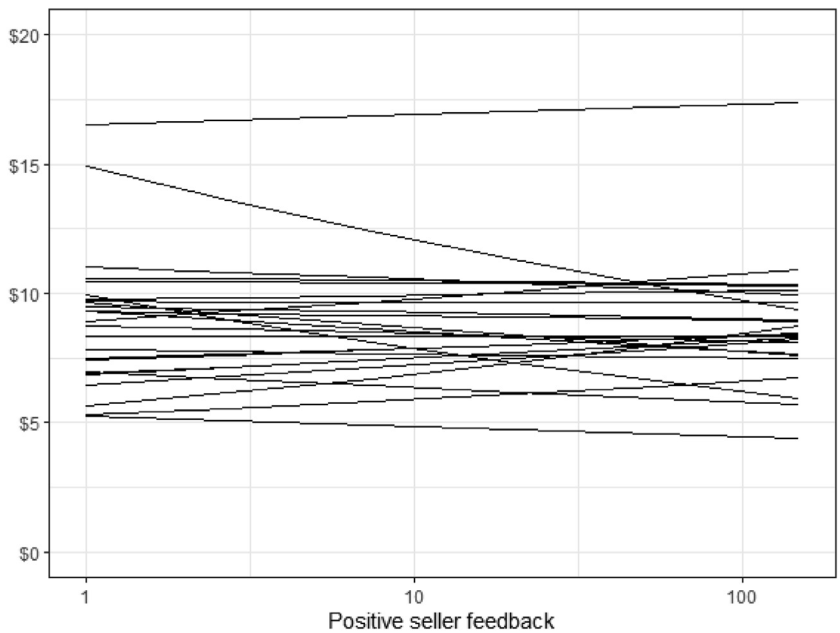

Fig. 4. Estimated group-level coefficient of reputation for 25 random cannabis sellers on Empire.

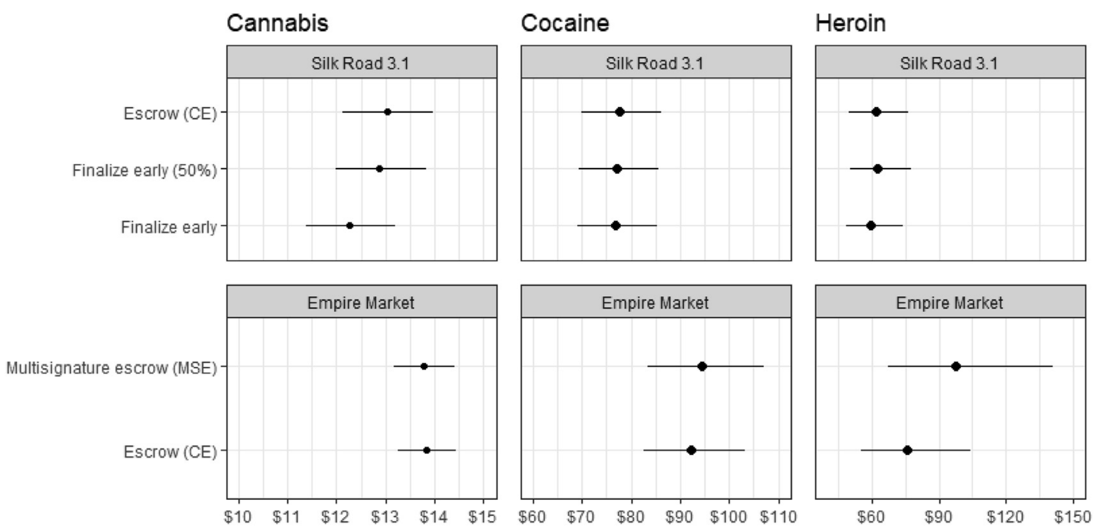

Fig. 5. Estimated price of 1 gram sold using different payment modes.

for 25 randomly sampled cannabis vendors on Empire Market. As illustrated, the coefficient varies and vendors who start at a high mean price-per-gram tend to discount product, while those who begin at low prices add a premium, as their reputation accumulates.

Payment

Fig. 5 shows the estimated prices for one gram of each substance across payment methods. Despite the size of the Empire dataset, centralized escrow is predominant as opposed to Silk Road 3.1 (see Table 1). Coefficient estimates for multisignature are slightly higher, suggesting that vendors charge a premium though estimates are only significant for heroin ($p < 0.05$, $\beta = 0.250$). On Silk Road 3.1, where advance payment (finalize early) is widely available, it is consistently associated with a significant discount reducing the price per gram ($\beta =-0.060$, -0.012–0.032, $p < 0.01$). However, the 50% escrow option is only significant for cocaine ($\beta =-0.009$, $p < 0.05$). We note, however, that estimates are moderate in terms of cents and dollars. At their largest, a seller is estimated to reduce the price of a gram of cannabis from 13 to 12.3 USD.

Status rankings

Fig. 6 shows the estimated prices for 1 gram of each substance at differing intervals of the status devices provided by the platforms, vendor level on Silk Road 3.1 (ranging from 1 to 20) and vendor trust level on Empire (ranging from 1 to 10). On Empire, estimates are consistent and in the expected direction within the range of 0.08 to 0.013 ($p < 0.05$). These estimates suggests that an Empire seller would increase the price of a gram cannabis from 13.7 at the lowest level to 14 USD at the highest level and a gram of cocaine from 91 to 93.8 USD. Conversely, on Silk Road 3.1, we observe inconsistent positive (β = 0.011) and negative estimates (β = -0.011, -0.004) for seller status.

Robustness assessments

Reputation premiums are the most scrutinized in the literature, and argued to replicate those of licit online markets. As noted earlier, results are inconsistent across studies, and within-seller estimates may be biased if they assume homogeneous supply. We therefore replicate past research to examine whether reputation effects are sensi-

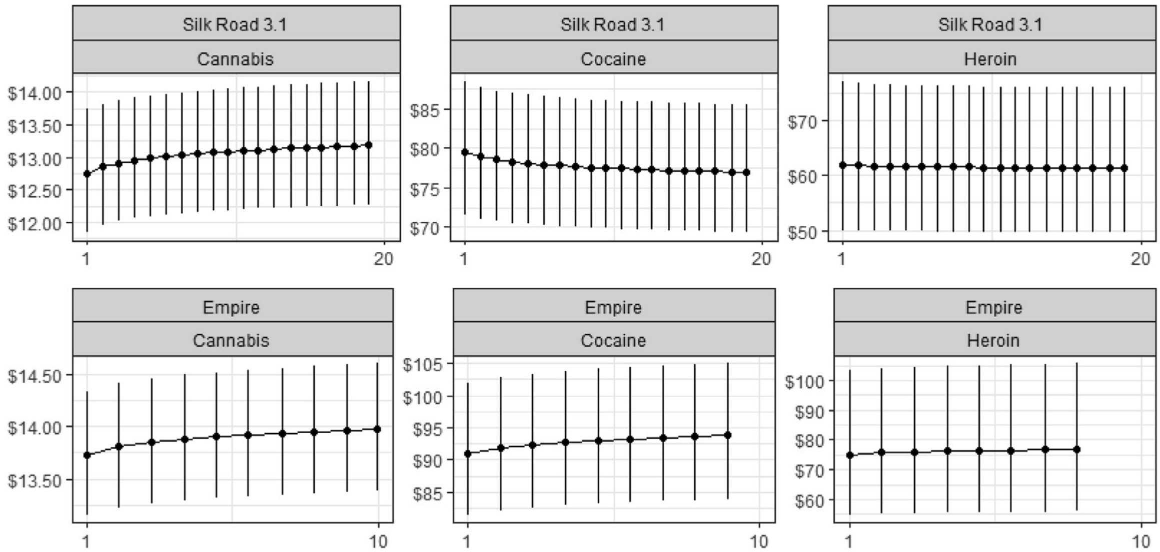

Fig. 6. Estimated differences in price for 1 gram depending on status level.

tive to model specifications and/or sub-setting. In the replications, we mimic the modeling approach of the study in question by either discarding data or using an alternate statistical approach. We replicate Espinosa (2019) using a multilevel model with seller-level random effects based on the largest crawl (Espinosa 1). We exclude status from this model because sub-setting creates multicollinearity. We replicate Przepiorka et al. (2017) using fixed effects regression by a) reducing repeated measurements to their first observation, and b) pooling drugs in the same model using a categorical variable (Przepiorka et al. 1). We then abandon the assumption that all drugs share a population-level quantity discount by estimating the same model for each substance-market combination (Przepiorka et al. 2).

Fig. 7 shows the estimated reputation effects of all models, as well as those derived from our model. We replicate, defined as similar effects, both Espinosa (2019) and Przepiorka et al. (2017). For the cross-sectional replication of Espinosa (2019) coefficients are in the range of 0.06 and 0.13 and replicate the study. We also replicate Przepiorka et al. (2017) using the original specification reaching effects of 0.01 and 0.04 close to the 0.02 observed in the study. However, the second specification, in which a separate model is estimated for each substance, yields coefficients in the range of -0.04 and 0.05 (Przepiorka et al. 2). Thus, on estimating a model for each substance separately, rather than one for all three drugs, there is not a consistent positive effect of reputation. Across different specifications, we therefore find that models which exploit variation at the item-level suggest smaller reputation effects than both a longitudinal within-seller or cross-sectional design (see Fig. 7). Further, we observe that pooling all drugs in one model can suggest reputation effects for all three drugs which does not hold when drugs are analyzed separately.

Discussion

There is increasing awareness of the utility and cost-effectiveness of collecting observational online data with the aim of informing policy (Enghoff & Aldridge, 2019). Online drug markets constitute not only a novel data source for the study of drug markets in general, but also one that may complement law enforcement data (Moeller, Munksgaard, & Demant, 2021). We highlight, specifically, the capacity to examine drug prices internationally and longitudinally. In this paper, we have proposed a framework for the study of price formation in online drug markets wherein sellers are constrained by an external institutional context structured by risks (Moeller & Sandberg, 2019), and internal social processes reducing uncertainty allow sellers to adjust prices (Beckert & Wehinger, 2013; Odabaş et al., 2017). We assessed the model empirically using repeated measurements of prices in two cryptomarkets, and found that prices follow a basic structure outlined in the traditional literature on drug prices: Quantity discounts are significant and vary across substances and countries. Further, we find that sellers relatively consistently set prices in accord with advance payment, but less consistently so for status and reputation. We discuss each of these dimensions in turn, after which we discuss methodological challenges and avenues of future research.

At the random effect level we observe a negative correlation between the intercept and quantity discount for both cocaine and heroin which corresponds to the argument that a higher risk is reflected in a higher price-per-gram and subsequently encourages larger discounts (Moeller & Sandberg, 2015). The varying intercepts for cocaine and heroin likewise conform to the significant mark-ups that follow the costs incurred by import (Boivin, 2014), which indirectly also represents the distance from the originating countries. This is the first component of our model, the assumption that drug prices are principally a function of institutional constraints enforced by states. We also find extensive within-category variation contingent on drug subclasses. Except for crack, all drug subclasses suggest that price is purity-adjusted (Caulkins & Padman, 1993). For example, “social cocaine” distinguishes less pure products. The premium on crack may be caused by its disproportionate policing in line with the risks and prices framework (Davis, 2011). Taken together, our findings concerning country-level variance in prices and quantity discounts, along with the variation across drug types and subclasses, demonstrate that drug policy and enforcement, and the risks and prices framework, remain central to understanding the pricing of illicit drugs online (Bewley-Taylor, 2012).

Whereas country-level variation in prices can be understood as a function of formal institutional constraint, prices also elucidate social organization (Beckert, 2011). We have highlighted the internal dimension of governance - the productive function of informal institutions which can stabilize markets (Beckert & Wehinger, 2013). We find evidence that sellers set prices in accord with reputation, payment mode and status, but these estimates are not uniform across platform and substance. Contrasted to purity-adjustments through subclasses, for example, these should be interpreted cautiously with respect to their magnitude. Put bluntly, the effects of socio-technical devices are less impressive if price can be increased more easily by adding baking powder to cocaine to produce crack (Ouellet, Cagle, & Fisher, 1997). The consistent estimates for samples and promotional offers, however, follow the

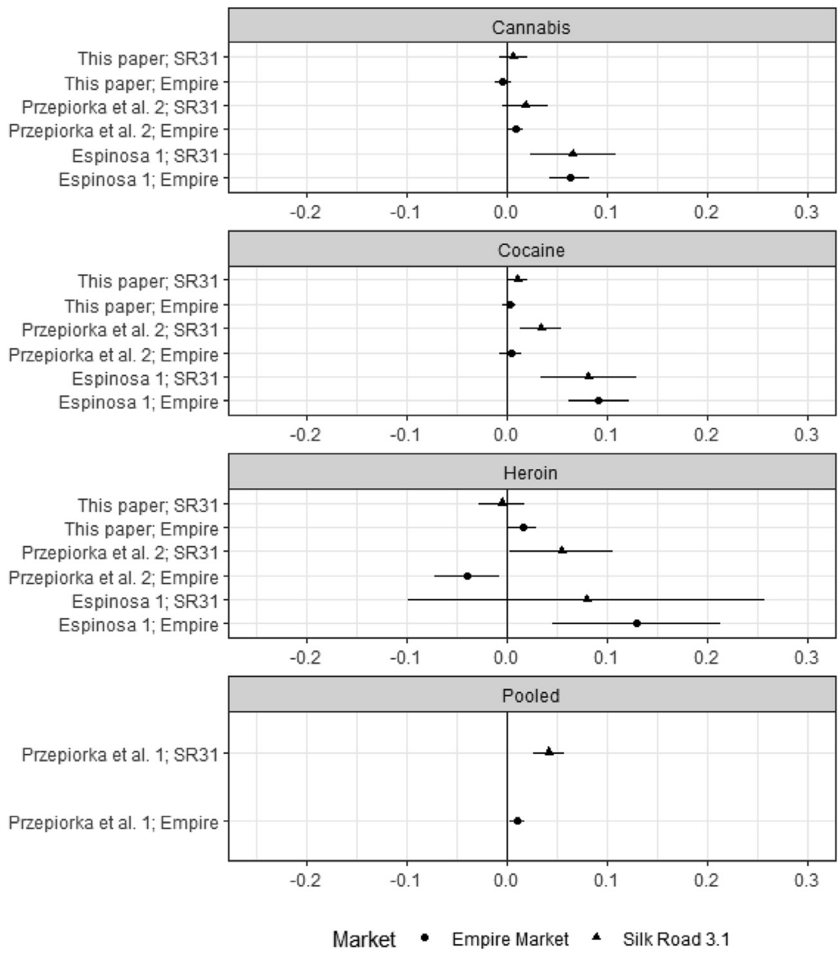

Fig. 7. Estimates for positive reputation contrasted to alternate data- and model specifications. X-axis is the coefficient estimate for positive reputation. Pooled estimates assume similar coefficients for all three substances and only a varying intercept.

reasoning that new or low-reputation sellers use promotional offers to attract customers and build trust as a competitive strategy (Ladegaard, 2018). Although we do not find unanimous evidence that drug prices are set in accord with institutional sources of trust, there is ample evidence of these mechanisms supporting other aspects of exchange (e.g. Duxbury & Haynie, 2018, Norbutas, Ruiter, & Corten, 2020). However, we stress that while reputation effects may be consistent in licit online markets, there is only limited support and inconclusive evidence for illicit ones (Červený & van Ours, 2019; Espinosa, 2019; Hardy & Norgaard, 2016; Przepiorka et al., 2017). One explanation may be inventory costs: Sellers with a high reputation score likely sell more products, which can motivate discounting product to minimize stock and risk (Moeller & Sandberg, 2015). Finally, there may not be much “wiggle room“ in price setting at the “last mile” of drug distribution (Dittus et al., 2018).

We show that reputation effects may be replicated with our data but that this requires violating assumptions about illicit markets. We have argued that homogeneous supply cannot be assumed, and also strongly caution against assuming coefficients are uniform across drugs. Our robustness assessment suggests reputation effects are more complex than what is generally found. Though our design is relatively complex in comparison to past research on online drug prices, we highlight some practical limitations. Principally, we examine the supply side of the market, and some sellers are more active than others (Paquet-Clouston et al., 2018). As such, our results cannot immediately be generalized to the actual prices paid. Furthermore, since risk and product quality can be assumed to vary across countries, we cannot discount that internal governance may have varying effects across these dimensions. With respect to past findings, we analyze a separate dataset, and reputation effects may not remain static over time (Filippas, Horton, & Golden, 2018). We also note that reputation reduced to a numeric or binary scale is not comparable to the value of information supplied by peers who might be trusted (Glückler & Armbrüster, 2003). As such, both reputation and status, conceived of as informal rankings of others within social networks, may still be operational (Duxbury & Haynie, 2021). Indeed, the between-seller variance we observe may reflect this.

Beyond a more holistic approach to studying prices in illicit online markets, the conceptualization of illicit online markets we have suggested, as constrained by external forces and stabilized by internal ones, both opens up new areas of research and frames them as internal and external factors in price formation. By extension, it also highlights the limitations of our study. Externally, we draw attention to more traditional questions about drug prices that may be examined, such as the relation between price and drug enforcement (Reuter & Kleiman, 1986), targeted interventions (Décary-Hétu & Giommoni, 2017), country-level variation and its determinants, and the geographic borders which drugs may need to cross (Boivin, 2014). These are external factors which may explain the high variance in prices between countries, but which are beyond the scope of this study. Moreover, cryptocurrencies introduce a novel risk for sellers and buyers given their extreme volatility, a risk that may influence price setting through external pressure as well (Christin, 2013). We find a relatively consistent negative association between drug prices and the Bitcoin exchange rate, suggesting that sellers respond to increases in the Bitcoin price by lowering their own prices. Internally, we suggest more granular attention may be given to reviews and reputation, which may not be reducible to a score. Similarly, product photographies and tests, as well as potency and quality, are variables that may explain variation in prices (Bakken, 2021). Furthermore, we also note that the influence of competition is yet to be studied in relation to price. An approach to prices in illicit online markets that encompasses both external and internal influences thus opens up a multitude of avenues for future research, whether driven by theoretical questions or policy agendas.

Conclusion

Within this paper we have argued that the formation of drug prices in illicit online markets may be conceived of as produced by two structures: external institutional constraints consisting of law, policy, and enforcement and internal support through escrow, status, and reputation. We applied multilevel hierarchical regression to estimate price-per-gram for three drug types in two online drug markets. We find extensive variation in drug prices and quantity discounts across countries, as well as evidence of purity-adjusted prices. These findings are in accord with the first component of our model and established scholarship on drug prices. We further observe that sellers respond to rankings, ratings, and payment modes by adjusting prices relatively consistently. Generally, advance payment is associated with discounts, whereas results are less conclusive for reputation and status. The synthesis we have proposed can integrate findings from diverging theoretical viewpoints by recognizing both the constraints of formal regulation on illicit markets and their social organization. We suggest that such a holistic approach to illicit markets, taking both external constraint and internal support into account, is theoretically productive and can produce policy relevant research.

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Declarations of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.drugpo.2021.103535.

References

Akerlof, G. A. (1970). The market for "lemons" quality uncertainty and the market mechanism. *The Quarterly Journal of Economics, 84*(3), 488. 10.2307/1879431.

Aldridge, J., & Décary-Hétu, D. (2016). Hidden wholesale: The drug diffusing capacity of online drug cryptomarkets. *International Journal of Drug Policy, 35*, 7–15. 10.1016/j.drugpo.2016.04.020.

Andreas, P., & Nadelmann, E. (2006). *Policing the globe: Criminalization and crime control in international relations* (1st ed.). New York: Oxford University Press.

Bakken, S. A. (2021). Drug dealers gone digital: Using signalling theory to analyse criminal online personas and trust. *Global Crime, 1*(22), 51–73. 10.1080/17440572.2020.1806826.

Bakken, S. A., Moeller, K., & Sandberg, S. (2018). Coordination problems in cryptomarkets: Changes in cooperation, competition and valuation. *European Journal of Criminology, 15*(4), 442–460. 10.1177/1477370817749177.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48. 10.18637/jss.v067.i01.

Beckert, J. (2011). Where do prices come from? Sociological approaches to price formation. *Socio-Economic Review, 9*(4), 757–786. 10.1093/ser/mwr012.

Beckert, J., & Wehinger, F. (2013). In the shadow: Illegal markets and economic sociology. *Socio-Economic Review, 11*(1), 5–30. 10.1093/ser/mws020.

Ben Lakhdar, C. (2009). The determinants of the cannabis pricing: Between credence, brand name and individual characteristics' users. *3rd annual ISSDP Conference*.

Ben Lakhdar, C., Leleu, H., Vaillant, N. G., & Wolff, F. C. (2013). Efficiency of purchasing and selling agents in markets with quality uncertainty: The case of illicit drug transactions. *European Journal of Operational Research, 226*(3), 646–657. 10.1016/j.ejor.2012.12.003.

Bernardi, F., Chakhaia, L., & Leopold, L. (2016). Sing me a song with social significance': The (mis)use of statistical significance testing in European sociological research. *European Sociological Review, 33*(1), jcw047. 10.1093/esr/jcw047.

Bewley-Taylor, D. (2012). *International drug control: consensus fractured*. Cambridge: Cambridge University Press.

Black, D. (1990). The elementary forms of conflict management. In M. J. Lerner (Ed.), *New directions in the study of justice, law and social control* (pp. 43–69). New York: Plenum Press. 10.1007/978-1-4899-3608-03.

Boivin, R. (2014). Risks, prices, and positions: A social network analysis of illegal drug trafficking in the world-economy. *International Journal of Drug Policy, 25*(2), 235–243. 10.1016/j.drugpo.2013.12.004.

Bushway, S. D., & Reuter, P. (2008). Economists' contribution to the study of crime and the criminal justice system. *Crime and Justice, 37*(1), 389–451. 10.1086/524283.

Carver, R. P. (1993). The case against statistical significance testing, revisited. *The Journal of Experimental Education, 61*(4), 287–292. 10.1080/00220973.1993.10806591.

Caulkins, J. P. (1994). What is the average price of an illicit drug? *Addiction, 89*(7), 815–819. 10.1111/j.1360-0443.1994.tb00984.x.

Caulkins, J. P. (2007). Price and purity analysis for illicit drug: Data and conceptual issues. *Drug and Alcohol Dependence, 90*(Suppl. 1), S61–S68. 10.1016/j.drugalcdep.2006.08.014.

Caulkins, J. P., Burnett, H., & Leslie, E. (2009). How illegal drugs enter an island country: insights from interviews with incarcerated smugglers. *Global Crime, 10*(2), 66–93. 10.1080/17440570902782477.

Caulkins, J. P., & Padman, R. (1993). Quantity discounts and quality premia for illicit drugs. *Journal of the American Statistical Association, 88*(423), 748–757.

Červený, J., & van Ours, J. C. (2019). Cannabis prices on the dark web. *European Economic Review, 120*, Article 103306. 10.1016/j.euroecorev.2019.103306.

Christin, N. (2013). Traveling the silk road: A measurement analysis of a large anonymous online marketplace. In *Proceedings of the 22nd international conference on world wide web* (pp. 213–224). Rio de Janeiro, Brazil: ACM. 10.1145/2488388.2488408.

Ciccarone, D. (2009). Heroin in brown, black and white: Structural factors and medical consequences in the US heroin market. *International Journal of Drug Policy, 20*(3), 277–282. 10.1016/j.drugpo.2008.08.003.

Cunliffe, J., Martin, J., Décary-Hétu, D., & Aldridge, J. (2017). An island apart? Risks and prices in the Australian cryptomarket drug trade. *International Journal of Drug Policy, 50*, 64–73. 10.1016/j.drugpo.2017.09.005.

Davis, J. L., & Love, T. P. (2019). Generalizing from social media data: A formal theory approach. *Information, Communication & Society, 22*(5), 637–647. 10.1080/1369118X.2018.1555610.

Davis, L. (2011). Rock, powder, sentencing-making disparate impact evidence relevant in crack cocaine sentencing. *Journal of Gender, Race and Justice, 14*(2), 375.

Décary-Hétu, D., & Aldridge, J. (2015). Sifting through the net: Monitoring of online offenders by researchers. *European Review of Organised Crime, 2*(2), 122–141.

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

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

Decorte, T., & Potter, G. R. (2015). The globalisation of cannabis cultivation: A growing challenge. *International Journal of Drug Policy, 26*(3), 221–225. 10.1016/j.drugpo.2014.12.011.

Demant, J., Bakken, S. A., Oksanen, A., & Gunnlaugsson, H. (2019). Drug dealing on Facebook, Snapchat and Instagram: A qualitative analysis of novel drug markets in the Nordic countries. *Drug and Alcohol Review, 38*(4), 377–385. 10.1111/dar.12932.

Demant, J., Munksgaard, R., Décary-Hétu, D., & Aldridge, J. (2018). Going local on a global platform. *International Criminal Justice Review, 28*(3), 255–274. 10.1177/1057567718769719.

Denton, B., & O'Malley, P. (1999). Gender, trust and business: Women drug dealers in the illicit economy. *British Journal of Criminology, 39*(4), 513–530. 10.1093/bjc/39.4.513.

Dickinson, T., & Wright, R. (2015). Gossip, decision-making and deterrence in drug markets. *British Journal of Criminology, 55*(6), 1263–1281. 10.1093/bjc/azv010.

Diekmann, A., Jann, B., Przepiorka, W., & Wehrli, S. (2014). Reputation formation and the evolution of cooperation in anonymous online markets. *American Sociological Review, 79*(791), 65–85. 10.1177/0003122413512316.

Diekmann, A., & Przepiorka, W. (2019). Trust and reputation in markets. In F. Giardini, & R. Wittek (Eds.), *The oxford handbook of gossip and reputation* (pp. 383–400). Oxford: Oxford University Press.

Dittus, M., Wright, J., & Graham, M. (2018). Platform criminalism. In *Proceedings of the 2018 world wide web conference on world wide web - www '18* (pp. 277–286). New York, New York, USA: ACM Press. 10.1145/3178876.3186094.

Duxbury, S. W., & Haynie, D. L. (2018). Building them up, breaking them down: Topology, vendor selection patterns, and a digital drug market's robustness to disruption. *Social Networks, 52*, 238–250. 10.1016/j.socnet.2017.09.002.

Duxbury, S. W., & Haynie, D. L. (2021). Network embeddedness in illegal online markets: Endogenous sources of prices and profit in anonymous criminal drug trade. *Socio-Economic Review*, 1–26. 10.1093/ser/mwab027.

Dwyer, R., & Moore, D. (2010). Beyond neoclassical economics: Social process, agency and the maintenance of order in an Australian illicit drug marketplace. *International Journal of Drug Policy, 21*, 390–398. 10.1016/j.drugpo.2010.03.001.

Elbahrawy, A., Alessandretti, L., Rusnac, L., Teytelboym, A., & Baronchelli, A. (2020). Collective dynamics of dark web marketplaces. *Scientific Reports*, 1–9. 10.1038/s41598-020-74416-y.

Enghoff, O., & Aldridge, J. (2019). The value of unsolicited online data in drug policy research. *International Journal of Drug Policy, 73*, 210–218. 10.1016/j.drugpo.2019.01.023.

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

Filippas, A., Horton, J. J., & Golden, J. (2018). Reputation inflation. *SSRN Electronic Journal*, 1–59 Retrieved from. 10.2139/ssrn.3136473.

Fligstein, N. (2001). *The architecture of markets: An economic sociology of twenty first century capitalist societies* (1st ed.). Princeton: Princeton University Press.

Gelman, A., & Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models* (17th ed.). Cambridge: Cambridge University Press.

Giommoni, L., & Gundur, R. V. (2018). An analysis of the United Kingdom's cannabis market using crowdsourced data. *Global Crime, 19*(2), 85–106. 10.1080/17440572.2018.1460071.

Glückler, J., & Armbrüster, T. (2003). Bridging uncertainty in management consulting: The mechanisms of trust and networked reputation. *Organization Studies, 24*(2), 269–297.

Gutierrez, D. J. A., & Thomson, F. (2020). Rebels-turned Narcos? The FARC-EP's political involvement in Colombia's cocaine economy. *Studies in Conflict & Terrorism, 0*(0), 1–26. 10.1080/1057610X.2020.1793456.

Hardy, R. A., & Norgaard, J. R. (2016). Reputation in the Internet black market: an empirical and theoretical analysis of the deep web. *Journal of Institutional Economics, 12*(3), 515–539. 10.1017/S1744137415000454.

Hill, J. (2013). Multilevel models and causal inference. The SAGE handbook of multilevel modeling, 201–220. 10.4135/9781446247600.n12.

Holt, T. J. (2013). Examining the forces shaping cybercrime markets online. *Social Science Computer Review, 31*(2), 165–177. 10.1177/0894439312452998.

Hutchings, A., & Holt, T. J. (2015). A crime script analysis of the online stolen data market. *British Journal of Criminology, 55*(3), 596–614. 10.1093/bjc/azu106.

Hutchings, A., & Holt, T. J. (2017). The online stolen data market: Disruption and intervention approaches. *Global Crime, 18*(1), 11–30. 10.1080/17440572.2016.1197123.

Ladegaard, I. (2018). Instantly hooked? Freebies and samples of opioids, cannabis, MDMA, and other drugs in an illicit e-commerce market. *Journal of Drug Issues, 48*(2), 226–245. 10.1177/0022042617746975.

Ladegaard, I. (2020). Open secrecy: How police crackdowns and creative problem-solving brought illegal markets out of the shadows. *Social Forces, 99*(2), 532–559. 10.1093/sf/soz140.

Levitt, S. D., & Venkatesh, S. A. (2000). An economic analysis of a drug-selling gang's finances. *The Quarterly Journal of Economics, 115*(3), 755–789.

Lüdecke, D. (2018). ggeffects: Tidy data frames of marginal effects from regression models. *Journal of Open Source Software, 3*(26), 772. 10.21105/joss.00772.

Lüdecke, D. (2020). *sjPlot: Data visualization for statistics in social science.* 10.5281/zenodo.1308157.

Lusthaus, J. (2012). Trust in the world of cybercrime. *Global Crime, 13*(2), 71–94. 10.1080/17440572.2012.674183.

Mahamad, S., Wadsworth, E., Rynard, V., Goodman, S., & Hammond, D. (2020). Availability, retail price and potency of legal and illegal cannabis in Canada after recreational cannabis legalisation. *Drug and Alcohol Review, 39*(4), 337–346. 10.1111/dar.13069.

Martin, J. (2014). Lost on the silk road: Online drug distribution and the 'cryptomarket. *Criminology and Criminal Justice, 14*(3), 351–367. 10.1177/1748895813505234.

Martin, J., Cunliffe, J., Décary-Hétu, D., & Aldridge, J. (2019). Effect of restricting the legal supply of prescription opioids on buying through online illicit marketplaces: Interrupted time series analysis. *British Medical Journal, 73*, 263–272. 10.1136/bmj.k2270.

Martin, J., Cunliffe, J., & Munksgaard, R. (2019). *Cryptomarkets: A research companion.* Emerald Publishing Limited. 10.1108/9781838670306.

Moeller, K. (2012). Costs and revenues in street-level cannabis dealing. *Trends in Organized Crime, 15*(1), 31–46. 10.1007/s12117-011-9146-9.

Moeller, K. (2018). Drug market criminology. *International Criminal Justice Review, 28*(3), 191–205. 10.1177/1057567717746215.

Moeller, K., Munksgaard, R., & Demant, J. (2017). Flow my FE the vendor said: Exploring violent and fraudulent resource exchanges on cryptomarkets for illicit drugs. *American Behavioral Scientist, 61*(11), 1427–1450. 10.1177/0002764217734269.

Moeller, K., Munksgaard, R., & Demant, J. (2021). Illicit drug prices and quantity discounts: A comparison between a cryptomarket, social media, and police data. *International Journal of Drug Policy, 91*, 102969. 10.1016/j.drugpo.2020.102969.

Moeller, K., & Sandberg, S. (2015). Credit and trust: Management of network ties in illicit drug distribution. *Journal of Research in Crime and Delinquency, 52*(5), 691–716. 10.1177/0022427815583912.

Moeller, K., & Sandberg, S. (2017). Debts and threats: Managing inability to repay credits in illicit drug distribution. *Justice Quarterly, 34*(2), 272–296. 10.1080/07418825.2016.1162321.

Moeller, K., & Sandberg, S. (2019). Putting a price on drugs: An economic sociological study of price formation in illegal drug markets. *Criminology, 57*(2), 289–313. 10.1111/1745-9125.12202.

Morselli, C., Décary-Hétu, D., Paquet-Clouston, M., & Aldridge, J. (2017). Conflict management in illicit drug cryptomarkets. *International Criminal Justice Review, 27*(4), 237–254. 10.1177/1057567717709498.

Muniesa, F., Millo, Y., & Callon, M. (2007). An introduction to market devices. *The Sociological Review, 55*(2 suppl), 1–12. 10.1111/j.1467954X.2007.00727.x.

Naylor, R. T. (2003). Towards a general theory of profit-driven crimes. *British Journal of Criminology, 43*(1), 81–101. 10.1093/bjc/43.1.81.

Norbutas, L., Ruiter, S., & Corten, R. (2020). Believe it when you see it: Dyadic embeddedness and reputation effects on trust in cryptomarkets for illegal drugs. *Social Networks, 63*, 150–161. 10.1016/j.socnet.2020.07.003.

Nurmi, J., Kaskela, T., Perälä, J., & Oksanen, A. (2017). Seller's reputation and capacity on the illicit drug markets: 11-Month study on the Finnish version of the Silk Road. *Drug and Alcohol Dependence, 178*, 201–207. 10.1016/j.drugalcdep.2017.05.018.

Odabaş, M., Holt, T., & Breiger, R. L. (2017). Governance in online stolen data markets. In J. Beckert, & M. Dewey (Eds.), *The architecture of illegal markets: Towards an economic sociology of illegality in the economy* (pp. 87–107). Oxford: Oxford University Press.

Ouellet, L. J., Cagle, H. H., & Fisher, D. G. (1997). Crack" versus "rock" cocaine: The importance of local nomenclature in drug research and education. *Contemporary Drug Problems, 24*(2), 219–237. 10.1177/009145099702400203.

Paquet-Clouston, M., Décary-Hétu, D., & Morselli, C. (2018). Assessing market competition and vendors' size and scope on AlphaBay. *International Journal of Drug Policy, 54*, 87–98. 10.1016/j.drugpo.2018.01.003.

Przepiorka, W., Norbutas, L., & Corten, R. (2017). Order without law: Reputation promotes cooperation in a cryptomarket for illegal drugs. *European Sociological Review, 33*(6), 752–764. 10.1093/esr/jcx072.

Reuter, P. (1984). *Disorganized crime* (2nd ed.). London, England: MIT Press.

Reuter, P., & Caulkins, J. P. (2004). Illegal "lemons": Price dispersion in cocaine and heroin markets. *Bulletin on Narcotics, 56*(1-2), 141–165.

Reuter, P., & Kleiman, M. A. R. (1986). Risks and prices: An economic analysis of drug enforcement. *Crime and Justice, 7*(1986), 289–340. 10.1086/449116.

Ritter, A. (2006). Studying illicit drug markets: Disciplinary contributions. *International Journal of Drug Policy, 17*(6), 453–463. 10.1016/j.drugpo.2006.09.004.

Soska, K., & Christin, N. (2015). Measuring the longitudinal evolution of the online anonymous marketplace ecosystem. In *24th usenix security symposium (usenix security 15)* (pp. 33–48). Washington, D.C.: USENIX Association.

Tzanetakis, M. (2018a). Comparing cryptomarkets for drugs. A characterisation of sellers and buyers over time. *International Journal of Drug Policy, 56*(0), 176–186. 10.1016/j.drugpo.2018.01.022.

Tzanetakis, M. (2018b). Social order of anonymous digital markets: Towards an economic sociology of cryptomarkets. In G. Potter, K. Fountain, & D. Korf (Eds.), *Place, space and time in European drug use, markets and policy* (pp. 61–80). Pabst Science Publishers.

Tzanetakis, M., Kamphausen, G., Werse, B., & von Laufenberg, R. (2016). The transparency paradox. Building trust, resolving disputes and optimising logistics on conventional and online drugs markets. *International Journal of Drug Policy, 35*, 58–68.

Wang, L. P., & Maxwell, S. E. (2015). On disaggregating between-person and within-person effects with longitudinal data using multilevel models. *Psychological Methods, 20*(1), 63–83. 10.1037/met0000030.

Wendel, T., & Curtis, R. (2000). The Heraldry of Heroin: "Dope stamps" and the dynamics of drug markets in New York City. *Journal of Drug Issues, 30*(2), 225–259. 10.1177/002204260003000201.

Zucker, L. G. (1986). Production of trust: Institutional sources of economic structure, 1840–1920. *Research in Organizational Behavior, 8*, 53–111.