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Article

Better Bang for the Buck? Generalizing Trust in Online Drug Markets

Rasmus Munksgaard, Jason A. Ferris, Adam Winstock, Larissa J. Maier and Monica J. Barratt*,

*Rasmus Munksgaard, Department of Sociology and Social Work, Aalborg University, Fibigerstræde 13, 9220 Aalborg Ø, Denmark; email: ramuan@socsci.aau.dk; Jason A. Ferris, Centre for Health Services Research, Faculty of Medicine, University of Queensland, Woolloongabba, Queensland, Australia; Adam Winstock, Institute of Epidemiology and Health Care, University College London, London, UK; Global Drug Survey, London, UK; Larissa J. Maier, Department of Clinical Pharmacy, University of California, San Francisco, USA; Monica J. Barratt, Social and Global Studies Centre and Digital Ethnography Research Centre, RMIT University, Melbourne, Victoria, Australia; National Drug and Alcohol Research Centre, UNSW Sydney, NSW, Australia

Past research into illicit online markets suggests that trust is produced by governance, reputation systems and the formation of social ties. In this paper, we draw on accounts of abstract and institutional trust, examining whether using a market is associated with general positive beliefs about product quality. Using data from the 2018 Global Drug Survey (n = 25,471) we utilize propensity score matching and multilevel linear regression to examine the association between having purchased drugs online and general expectations about product quality in value, weight, purity and price. We find strong evidence of a positive association between general beliefs and individual experience. This suggests that trust in illicit online markets can extend beyond interpersonal relations and towards an abstract market.

KEY WORDS: trust, drug markets, cryptomarkets, illicit markets, darknet, drug supply

INTRODUCTION

Problems of trust, especially concerning product quality, are central to illicit markets (Beckert and Wehinger 2013). Trust problems can constitute a barrier to attracting buyers and they increase transactional frictions (Moeller 2018). The problems of traditional face-to-face illicit exchanges are reproduced in online drug markets; information asymmetry, quality uncertainty and opportunism. These are compounded by physical distance and anonymity (Wehinger 2011; Moeller et al. 2017), but cannot be resolved by their traditional means; the social embeddedness of the illicit trade, informal social control and social norms (Moeller 2018; Bouchard et al. 2021). In this paper, we extend the literature on trust in online drug markets and examine whether interaction with the market institution is conducive to abstract institutional trust. We thus examine trust not as a quality of interpersonal relations, as is it typically conceived of in criminological scholarship (e.g. von Lampe and Johansen 2004), but as an attitude towards an abstract market order. We focus on the issue of product, rather than cooperative, uncertainty, a problem we argue is more pressing for buyers. We therefore address a dual research gap, the problem of product uncertainty and the existence of institutional trust in online drug markets. With an eye towards drug policy, we contribute to a discussion that has persisted since the first studies of online drug markets—their performance relative to offline markets (Aldridge et al. 2018).

Trust

Sztompka (1999) defines trust as a *'bet on the future contingent actions of others'* (p. 25). This definition captures distinct elements; an orientation towards the future, risk and potential harm, belief and expectation, rationality and emotionality and action. This is a broad sociological definition of trust as an attitude towards the future, but it is reflective of general sentiments within the social sciences (e.g. Lewis and Weigert 1985; Blomqvist 1997; Rousseau et al. 1998). The psychological function of trust is to allow action oriented towards a future goal, while suspending concerns about potential harms—acting as if risk and doubt were nonexistent (Möllering 2017). The social function of trust is complexity reduction, allowing individuals to act as if others will abide by expectations (Luhmann 1979). This does not mean that trust is uniformly good since naiveté is exploitable (Hardin 1993). However, an expectation that others are honest can be socially productive because it supports cooperation and social cohesion (Misztal 1996). At the individual level, trust is a cognitive process that takes factors like reputation and experience into account (Lewis and Weigert 1985); a Bayesian process in which the accumulation of information informs an estimate about the honesty of others (Granovetter 1985; Hardin 1993).

Sztompka (1999) suggests the notion of concentric circles of trust that extend from near and concrete ties of family and friendship towards abstract objects like social roles or institutions (p. 41–43). Misztal (1996) makes a similar distinction, separating interpersonal and abstract trust. Importantly, these beliefs in abstract institutions support individual cooperative behavior (McEvily et al. 2012). How individuals come to build trust in larger social systems is a long-standing area of inquiry (Luhmann 1979; Nannestad 2008). One explanation is *experiential*, suggesting that *'people's perceptions of the generalized other (their social trust) are thought to be formed by their experiences with representatives'* of institutions (Sønderskov and Dinesen 2016: 181). That is, the individual Bayesian process not only concerns an estimate of a specific other, but is also generalized to abstract institutions (Carlsson et al. 2018).

Trust in illicit markets

In the context of economic exchange and drug markets, problems of trust can be separated across two axes: cooperation and product (Dimoka et al. 2012). Uncertainty about the *performance* of the seller and *quality* of their product are distinct (Schilke et al. 2016). A seller may choose to act dishonestly, robbing a buyer, for example, or they may sell a drug 'cut' with another substance or diluted (Naylor 2003). This uncertainty grows in complexity, because chemical purity and perceived quality are not necessarily correlated (Bancroft and Reid 2017).

In this paper, we concern ourselves with the problem of product uncertainty. Though the two may seem to overlap, sellers often have imperfect information about their product, since cutting and dilution are often at the layers above them (Broséus et al. 2016). Thus, even sellers rarely have perfect product information (Reuter and Caulkins 2004). At a structural level, a state of information asymmetry therefore exists between sellers and buyers (Akerlof 1970). The roots of product and seller uncertainty in illicit markets are the absence of the state, which in licit markets support stability (Fligstein 2001). An example of the productive capacity of the state in supporting trust is drug sellers using drug checking services to verify the purity and content of their product (Betsos et al., 2021). Absent courts, contracts and regulation the bases of trust and cooperation in illicit markets often resemble those of pre-modern society (Beckert and Wehinger 2013); community, informal social control, repeated exchanges, norms, reputation, face-to-face exchange, kinship and friendship (Moeller 2018; Varese et al. 2019).

Trust in illicit online markets

The fundamental trust problems of illicit markets are reproduced online: There is information asymmetry, opportunism is unrestrained by legal institutions, product is unstandardized and cannot be sampled or inspected before purchase (Tzanetakis et al. 2016). Herley and Florêncio (2010), for example, document the endemic fraud and product uncertainty in a market for stolen credit cards. Although the trust problems of illicit markets persist online, the traditional means to resolve them are unavailable: Opportunism is no longer restrained by informal social control, and exchange is socially disembedded (Bakken et al. 2018). Concerns about product quality are justified by the accumulating evidence that adulteration and false advertising persist in online drug markets (Quintana et al. 2017), although seller uncertainty is also well-justified by the high rates of predation (Espinosa 2019).

A larger body of research has concerned itself with the ways in which trust problems are resolved in illicit online markets. The ways in which these are resolved may be seen as *functional replacements* (Luhmann 1979) to the social networks and informal control of traditional illicit markets (Moeller 2018), and some general trends can be observed within the literature. A significant proportion of scholarship has followed Gambetta (2009) and concerned itself with signs and signals. Scholars have found that sellers who emit signals of trustworthiness tend to be more successful (Décary-Hétu and Leppänen 2013; Holt et al. 2016). Other scholars have documented tendencies to repeat purchases (Décary-Hétu and Quessy-Doré 2017; Duxbury and Haynie 2018; Norbutas et al. 2020). Przepiorka et al. (2017) and Hardy and Norgaard (2016) stress the centrality of the reputation system in which people who purchase products review those who sell them (see also Tzanetakis et al. 2016; Bakken et al. 2018). Some criminologists have drawn attention to the centrality of administrators and institutional arrangements like escrow systems and formalized rules in the production of trust (Lusthaus 2012; Odabaş et al. 2017). Finally, sellers providing chemical analysis results of advertised drugs as a signal of quality to increase trust have also been observed (Caudevilla et al. 2016).

A primer on cryptomarkets

Cryptomarkets, also known as darknet markets or anonymous online markets, first appeared in 2011 (Martin et al. 2019). They have grown from a niche phenomenon into a stable, institutional form of illicit drug commerce (Tzanetakis 2018b). Cryptomarkets function as other e-commerce platforms like eBay or Amazon. In exchange for commissions, they provide people who sell and buy illicit drugs with a platform for the sale and purchase of products. Despite several website closures, either from administrators absconding with funds or seizure by law enforcement (Décary-Hétu and Giommoni 2017; Moeller et al. 2017), the economy has grown continually (Tzanetakis 2018a). With few exceptions, cryptomarkets have followed the same script as the first cryptomarket, Silk Road, launched in 2011. They offer escrow services in which the marketplace releases funds upon reception of product, use Tor to anonymize internet traffic, facilitate transactions using cryptocurrencies, and drugs are delivered by mail or as 'dead drops' (Christin 2013; Barratt and Aldridge, 2020). More generally, cryptomarkets are one manifestation of illicit online commerce, which also takes place in secretive or open forums and on social media (Odabaş et al. 2017; Demant et al. 2019).

People who purchase drugs on cryptomarkets often have wider experience of drug use than the general population (Barratt et al. 2016b). They tend to be male, white, young and relatively well-educated (Van Hout and Bingham 2013; Barratt et al. 2014). Digital literacy and knowledge of technologies for anonymization and encryption are prerequisites to access these markets (Bancroft and Reid 2017). Compared to traditional modes of sourcing drugs offline, people report lower probabilities of encountering violence and predation related to drug purchase (Barratt et al. 2016a). Qualitative and survey research suggests this may be an additional incentive in combination with higher drug quality (Van Hout and Bingham 2013; Barratt et al. 2016b; Werse and Kamphausen 2019).

However, drug purchases, even in cryptomarkets, remain fraught with uncertainties for people who buy drugs (Moeller et al. 2017). People who purchase drugs online therefore face questions of who they can trust to supply products in a secure manner as advertised and to not be law enforcement. Whereas there exist several mechanisms that reduce cooperative uncertainty (e.g. escrow systems, administrative control), the problem of product uncertainty is more difficult to resolve.

THIS STUDY

In the preceding sections we introduced the problem of product uncertainty and the notion of trust in abstract others. We then reviewed the literature on trust in illicit online markets, and introduced cryptomarkets, the object of this study. Generally, research on trust in illicit online markets revolves around cooperation between individuals as either the manifestation of trust or a key producer thereof. However, the concept of trust need not be restricted to this seller–buyer dyad. On the contrary, sociological scholarship on what Sztompka (1999) terms 'abstract trust' emphasizes the production of general attitudes and expectations towards institutions on the basis of individual experience (Zucker 1986; Nannestad 2008). Thus, similar to how one can trust social institutions, courts, the political system or the police, we suggest one can trust an illegal institution as well.

Past research suggests that buyers in illicit online markets build trust in sellers through repeated exchanges (Décary-Hétu and Quessy-Doré 2017; Duxbury and Haynie 2018; Norbutas et al. 2020), and we draw on experiential or institutional accounts of trust to suggest this process may be generalized onto the institution itself (Dahlberg and Linde 2018; Nannestad et al. 2014). That is, we posit that a simple Bayesian process is operational: Buyers purchase drugs and accumulate experience, and in turn they update their beliefs about the performance of the individual sellers and the cryptomarket institution. In contrast to past research on online drug markets, we therefore suggest that exchange fosters not only interpersonal, but also abstract institutional trust. Consequently, we posit that:

1. People who purchase drugs via cryptomarkets (buyers) will hold more firm general beliefs about product quality than those who do not use cryptomarkets (non-cryptomarket-buyers).

The literature on repeated exchanges in illicit online markets finds that buyers are likely to return to sellers, suggesting that interpersonal trust evolves from recurrent exchange. If so, we suggest that general beliefs about the institution will follow the same direction, and we posit that:

2. The general beliefs of people who purchase drugs via cryptomarkets will be more positive than those who do not use cryptomarkets.

We test these propositions using data from the 2018 Global Drug Survey (GDS), which has been tracking cryptomarket utilization for drug purchases since 2012. The 2018 GDS included a specialist section exploring motivations, experiences and beliefs around cryptomarket transactions (using the colloquial term 'darknet market'), probing the respondent's belief in product quality (value, weight, purity and price). In these questions, respondents rated their agreement to four 6-item Likert-scale statements concerning perceived product quality on cryptomarkets. The statements are as such:

1. For the same drug type, weight and purity, darknet market drug deals are usually better value for money than street or dealer sourced drugs.
2. A '1 gram' purchase from darknet markets is more likely to weigh the full 1 gram than a '1 gram' purchase from dealers or street.
3. Darknet market drugs are usually of higher purity than street or dealer sourced drugs.
4. Darknet market prices are usually higher than street or dealer prices.

These questions constitute attitudinal, not behavioral, measures of trust that specifically pertains to product certainty (McEvily et al. 2012). Moreover, they are specific and directed, which is recommended for the study of institutional trust (Carlsson et al. 2018). Since the survey contains both buyers and non-buyers, we can compare responses across the two groups in which one has experience and one has not.

METHODS AND DATA

Global Drug Survey (GDS) runs the world's largest drug survey. GDS conducts annual cross-sectional surveys using an encrypted online survey platform. Participation is voluntary and the GDS therefore obtains a non-probability sample. Under the assumption that *conditional on covariates, treatment assignment is essentially random*, propensity score matching approximates randomization and allows us to posit a stronger case for causality (Apel and Sweeten 2010). We apply propensity score matching as pre-processing and analyze the matched data using multilevel linear regression to provide estimates of how beliefs differ between people who purchase drugs via cryptomarkets and those who use other sources (Ho et al. 2007). Because the GDS is a non-probability sample, the dataset is not representative of the general population (Barratt et al. 2017). Our aim is to estimate the difference in beliefs between people who purchase drugs via cryptomarkets and those who use other sources, which does not necessitate a representative sample of the population of people who use drugs. A comparable sample of people who purchase drugs elsewhere serves as control. Although we apply propensity score matching, we caution against strict causal interpretation of the findings for two reasons: First, the data is cross-sectional. Second, we are unable to control whether a respondent has any peers who have used a cryptomarket.

Practically, matching entails the creation of a control group that is balanced across covariates. The propensity score is therefore a 'balancing score' (Apel and Sweeten 2010). It is typically estimated using logistic regression with the treatment condition being the outcome (in this case having purchased drugs via cryptomarkets). When matching, traditional concerns such as multicollinearity, model fit, significance and parsimony are not primary concerns. Rather, the aim is to approximate randomization through covariate balancing (Stuart 2010). Ideally, such a model can be derived from theory and a body of literature. A final concern is unmeasured confounding variables. However, if these confounding variables are correlated with the balanced covariates, these are argued to be indirectly included (Apel and Sweeten 2010). For example, matching that includes an urban/regional/urban distinction, as ours do, is likely to implicitly include access to street markets in urban areas.

Data

76,984 respondents from 182 countries completed screening questions for the darknet market module in the 2018 Global Drug Survey (GDS2018). We restrict our sample to people who have used cryptomarkets within the preceding 12 months by either purchasing drugs themselves or through someone else. This limits our sample to recently treated which is preferable for matching. The control group is matched from 21,984 respondents who have heard about cryptomarkets but never used them. The GDS survey is unbalanced across countries, and we include only 33 countries which had 50 respondents or more. This restriction aids convergence when estimating multilevel regression models, specifically for the robustness tests, and restricts the analysis of group-level variation to countries where informative estimates can be produced. The final dataset used for matching consists of 25,471 respondents from 33 countries of which 2,146 (8.43 per cent) have used a cryptomarket themselves and 1,341 (5.26 per cent) had an intermediary purchase for them. These respondents (buyers) have on average made 11 purchases (SD = 18,3) with a median of 5 purchases throughout their entire career. We refer to the control group as non-buyers to specify they have not purchased drugs through a cryptomarket.

Matching

GDS respondents are nested within countries which will correlate with usage of cryptomarkets (Barratt et al. 2014). This bias may be reduced by incorporating grouping structure into matching (Arpino and Cannas 2016). We therefore use preferential within-country matching implemented in the *CMatching* library in R (Cannas 2019). To avoid inadvertently conditioning on the treatment variable (i.e. having purchased drugs via cryptomarkets), matching based on variables that may change after using a cryptomarket, we limit our matching to a select number of variables (Stuart 2010). Each respondent who used cryptomarkets was matched with a respondent who never used cryptomarkets on the basis of their country, and age (linear and curvi-linear), gender, nightlife/clubbing frequency and recent technology usage, factors that are associated with cryptomarket usage (Barratt et al. 2014). We exclude the use of drug-related forums and reddit, as well as the technologies Tor, Bitcoin and PGP as each might involve conditioning on the treatment (Bancroft and Scott Reid 2016). Similarly, because drug use may change after using a cryptomarket, we do not include frequency of use for the same reason. For transparency, we show estimates for a model that includes drug use, referring to the two models as 'strict' (no drug use) and 'loose' (including drug use), as well as an model estimated using the unadjusted sample.

We use a caliper—the upper bound of a match—of 0.2 standard deviations of a covariate (Benedetto et al. 2018). Using preferential within-country matching for both the strict and loose model, 2 and 16 respondents from the treated group were left unmatched, with 2.5 per cent and 3.2 per cent being matched outside their country. Whether covariate balance has been achieved may be assessed based on the standardized mean difference (SMD). This entails dividing the difference in means and with the standard deviation for each variable in the two groups (Zhang et al. 2019). Shown in Table 1 and Figure 1, all variables are within an acceptable threshold of 0.25 after matching (Stuart 2010).

Statistical analysis

Table 2 shows the 4 Likert-scale items, descriptive statistics for the responses on the original scale and two reduced scales. How to treat Likert-scale responses is a longstanding debate within the social sciences (e.g. Carifio and Perla 2008). Some argue that Likert-scale responses can be treated as discrete interval variables, and thus analyzed within an OLS framework, while others argue that the scale is inherently ordinal, maybe even nominal, and should be analyzed using categorical methods (Norman 2010). Analyzing nested data further complicates this. We make two crucial choices in our analysis which we discuss in turn: Recoding an ordinal response and treating *don't know* responses as neutral.

Table 1. Balance scores for strict model: standardized mean difference for unadjusted and adjusted samples

Variable	Type	Unadjusted	Adjusted
Gender			
Male	Binary	0.09413	0.01683
Female	Binary	−0.10033	−0.01113
Other gender identity	Binary	0.00620	−0.00571
Age	Contin.	−0.27627	−0.09423
Age^2	Contin.	−0.30147	−0.09521
Non-White	Binary	0.00357	0.00257
Education			
Primary school or no formal schooling	Binary	0.00990	−0.00428
Lower secondary, school/intermediate certificate	Binary	−0.03298	0.01683
Technical or trade certificate	Binary	−0.00793	−0.00143
Higher secondary school	Binary	0.04371	0.00456
College certificate/diploma	Binary	−0.00646	0.00114
Undergraduate degree	Binary	−0.00578	0.00257
Postgraduate degree	Binary	−0.00045	−0.01940
Lives in			
City/urban area	Binary	0.01454	−0.02539
Regional area	Binary	−0.01104	0.02482
Remote area	Binary	−0.00350	0.00057
Clubbing			
Never	Binary	0.04232	−0.04822
Less than once every 3 months	Binary	−0.02464	−0.01512
Once every 3 months	Binary	0.00321	0.00713
Once a month	Binary	−0.00182	0.02767
Once every fortnight	Binary	−0.00966	0.02311
Once a week or more	Binary	−0.00941	0.00542
Apps used within last week			
Facebook	Binary	−0.02700	0.01997
Snapchat	Binary	0.06895	−0.00856
Twitter	Binary	0.04952	−0.03509
Instagram	Binary	−0.01794	−0.01341
Skype	Binary	−0.00020	0.00285
WhatsApp	Binary	−0.01875	−0.01056
Pinterest	Binary	−0.03817	−0.00399
Signal	Binary	0.04788	0.00485
Telegram	Binary	0.06150	0.00285

Table 1. Continued

Variable	Type	Unadjusted	Adjusted
Tinder	Binary	0.03060	0.00171
Grindr	Binary	0.00409	0.00171
Venmo	Binary	0.01278	−0.00770
Wickr	Binary	0.04919	0.00342

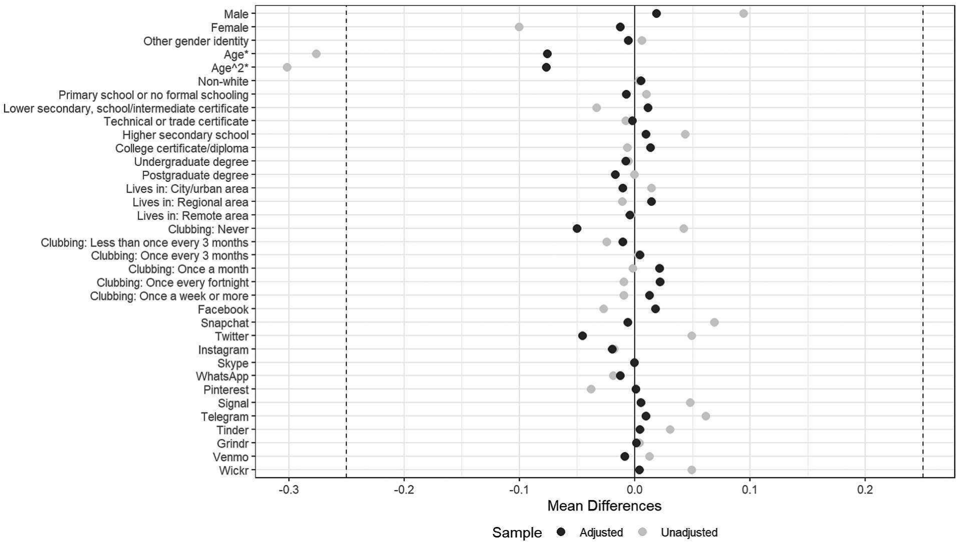

Fig. 1 Standardized mean differences in matched (adjusted) and unmatched (unadjusted) samples. Continuous predictors marked with asterisk

A test of means or a non-parametric group comparison, even after matching, is not ideal because respondents are grouped in countries and it is reasonable to expect some country-level variation. Statistical analysis should therefore balance informativeness and analytic interest in the group structure of the data. Our compromise is to apply and present multilevel linear regressions which allow a more comprehensive overview of country-level variation (Gelman and Hill 2007). As the response options are symmetrical and ordered we believe this approach is justifiable (Carifio and Rocco 2007). We create a discrete outcome in which −2 is strongly disagreeing, 0 is neutral and don't know/unsure, and 2 is strongly agreeing with the proposition. This makes an easily interpretable scale in which 1 point corresponds to e.g. a change from 'Agree' to 'Strongly agree'. In the original survey the last question concerning price was phrased negatively, but since the scale is symmetrical we invert it.

In line with our theoretical framework, we consider product certainty as a continuum from negative to positive beliefs. Responses to the statements may be seen as attitudes towards products on cryptomarkets. Table 2 shows that people who have never used cryptomarkets predominantly answer *don't know/unsure*, though some people who purchased drugs via cryptomarkets share the same opinion, and some people expressed negative and positive beliefs without ever having used such markets. This suggests that the answer is not random, but follows from a lack of experience with cryptomarkets (De Leeuw et al. 2003). A lack of personal experience does not imply one cannot hold beliefs, as the responses show. However, it appears more likely that

Table 2. Distribution of Likert-scale responses. Price beliefs are inverted in the dichotomized and continuous transformations

	Has not used a cryptomarket	**Has used cryptomarket within last 12 months to purchase drugs.**
N	21,950	3,521
Value		
Original scale (%)		
Strongly disagree	263 (1.2)	73 (2.1)
Disagree	586 (2.7)	102 (2.9)
Neutral	2,105 (9.6)	342 (9.7)
Agree	3,953 (18.0)	1,037 (29.5)
Strongly agree	1,911 (8.7)	1,690 (48.0)
Don't know/unsure	13,132 (59.8)	277 (7.9)
Continuous scale (mean (SD))	0.30 (0.71)	1.18 (0.96)
Agree/strongly agree (%)	5,864 (26.7)	2,727 (77.4)
Purity		
Original scale (%)		
Strongly disagree	241 (1.1)	58 (1.6)
Disagree	788 (3.6)	109 (3.1)
Neutral	1,978 (9.0)	309 (8.8)
Agree	4,479 (20.4)	1,108 (31.5)
Strongly agree	1,922 (8.8)	1,654 (47.0)
Don't know/unsure	12,542 (57.1)	283 (8.0)
Continuous scale (mean (SD))	0.32 (0.73)	1.19 (0.93)
Agree/strongly agree (%)	6,401 (29.2)	2,762 (78.4)
Price		
Original scale (%)		
Strongly disagree	1,326 (6.0)	1,269 (36.0)
Disagree	3,487 (15.9)	1,092 (31.0)
Neutral	1,767 (8.1)	335 (9.5)
Agree	1,410 (6.4)	324 (9.2)
Strongly agree	460 (2.1)	214 (6.1)
Don't know/unsure	13,500 (61.5)	287 (8.2)
Continuous scale (mean (SD))	0.17 (0.72)	0.82 (1.19)
Agree/strongly agree (%)	4,813 (21.9)	2,361 (67.1)
Weight		
Original scale (%)		
Strongly disagree	292 (1.3)	59 (1.7)
Disagree	817 (3.7)	129 (3.7)
Neutral	2,027 (9.2)	424 (12.0)

Table 2. Continued

	Has not used a cryptomarket	Has used cryptomarket within last 12 months to purchase drugs.
Agree	4,318 (19.7)	1,090 (31.0)
Strongly agree	1,700 (7.7)	1,453 (41.3)
Don't know/unsure	12,796 (58.3)	366 (10.4)
Continuous scale (mean (SD))	0.29 (0.72)	1.06 (0.96)
Agree/strongly agree (%)	6,018 (27.4)	2,543 (72.2)

one will state *don't know/unsure* if one has no reason to hold a strong belief (Luskin and Bullock 2011). We therefore consider this response as similar to a neutral response; no firm belief in either direction.

The above choices necessitate some caution in interpreting the results. To assess the robustness of our findings, we reanalyzed data under different specifications. We estimated multilevel logistic and ordinal regressions both using the matched data including and excluding *don't know/unsure* responses pre-matching. In the former, beliefs were dichotomized in the hypothesized direction (e.g. agreeing or strongly agreeing that cryptomarkets are superior). For transparency we also present models in which *don't know/unsure* responses were excluded before matching and include these in the Appendix.

FINDINGS

After matching we apply multilevel linear regression to estimate the association between using a cryptomarket and beliefs. Using matching as pre-processing for regression is preferred over comparing means post-matching. This is also known as a 'doubly robust' approach correcting for residual variance and prognostic covariates (Ho et al. 2007; Apel and Sweeten 2010). Given the hypothesized relation between using a cryptomarket and trusting it, the prognostic covariates we use are similar to those that predict cryptomarket use discussed in the section *Matching* (see also Barrat et al. 2014). Statistical analysis was conducted in R taking advantage of the *lme4* and *ggeffects* packages (Bates et al. 2015; Lüdecke 2018). We begin by presenting our model, after which we summarize the fixed effects. Hereafter we discuss the difference in beliefs between the group of people who purchased drugs via cryptomarkets and those who never accessed them. Table 3 shows descriptive statistics for the matched sample across the covariates used in the regression models.

We estimate a model for each Likert-item wherein the outcome is the scaled belief shown in Table 2. Analyzing grouped data using regular OLS violates the assumption of uncorrelated error terms. We therefore use multilevel linear regression and allow a random intercept for each country to account for country-level variance. We further allow the effect of being a buyer to vary as well, under the advice to utilize the maximal random effect structure when possible (Harrison et al. 2018). Except in the case of beliefs about weight, the sample composition allowed us to fit this structure.

We fit models similar to our matching process with minor modifications. For parsimony we include an index of the apps used, rather than a binary indicator for each As before, we include clubbing, education, where the respondent lives, age, gender and ethnicity. Table 4 shows the results of the four models. Since beliefs are scaled from −2 to 2, coefficient estimates for both fixed and random effects can be interpreted straightforwardly: An estimate of 0.5 suggests an increase in beliefs from the intercept that corresponds to half a point where 1 is an increase from e.g. agree to strongly agree.

Table 3. Descriptive statistics for unadjusted and adjusted samples. For continuous predictors mean and SD are shown. For categorical predictors percentage is shown. Only predictors included in matching or regression are shown

	Unmatched data	Matched data
N	25,471	7,010
Has used cryptomarket within last 12 months (%)	3,521 (13.8)	3,505 (50.0)
Age	25.6 (8.82)	24.2 (7.26)
Gender (%)		
Male	18,992 (74.6)	5,725 (81.7)
Female	6,181 (24.3)	1,145 (16.3)
Other gender identity	298 (1.2)	140 (2.0)
Non-White (%)	2,099 (8.2)	580 (8.3)
Education (%)		
Primary school or no formal schooling	933 (3.7)	340 (4.9)
Lower secondary, school/intermediate certificate	3,444 (13.5)	711 (10.1)
Technical or trade certificate	2,272 (8.9)	584 (8.3)
Higher secondary school	5,450 (21.4)	1,724 (24.6)
College certificate/diploma	6,023 (23.6)	1,574 (22.5)
Undergraduate degree	5,849 (23.0)	1,606 (22.9)
Postgraduate degree	1,500 (5.9)	471 (6.7)
Lives in (%)		
City/urban area	17,954 (70.5)	5,066 (72.3)
Regional area	6,384 (25.1)	1,639 (23.4)
Remote area	1,133 (4.4)	305 (4.4)
Clubbing (%)		
Never	4,012 (15.8)	1,520 (21.7)
Less than once every 3 months	4,780 (18.8)	1,205 (17.2)
Once every 3 months	3,496 (13.7)	968 (13.8)
Once a month	5,176 (20.3)	1,341 (19.1)
Once every fortnight	4,726 (18.6)	1,171 (16.7)
Once a week or more	3,281 (12.9)	805 (11.5)
N social media apps used last week	3.27 (1.44)	3.48 (1.52)
Apps used within last week		
Facebook (%)	21,745 (85.4)	
WhatsApp (%)	15,480 (60.8)	
Instagram (%)	14,435 (56.7)	
Snapchat (%)	10,958 (43.0)	
Twitter (%)	5,713 (22.4)	
Skype (%)	3,947 (15.5)	
Telegram (%)	3,410 (13.4)	

Table 3. Continued

	Unmatched data	Matched data
Tinder (%)	3,184 (12.5)	
Pinterest (%)	2,234 (8.8)	
Signal (%)	989 (3.9)	
Wickr (%)	490 (1.9)	
Venmo (%)	414 (1.6)	
Grindr (%)	395 (1.6)	

Across all four models we observe that social media use, gender, and age follow consistent patterns. We find that women, compared to men, express significantly less positive beliefs in value, purity and weight ($\beta = -0.185, -0.227, -0.235, p < 0.001$). A similar trend, though insignificant, is observed for price ($\beta = -0.058, p > 0.05$). Respondents identifying neither as male nor female exhibit the same tendency ($\beta = -0.165, -0.253, -0.118, -0.206$), though estimates are only significant for value ($p < 0.05$) purity ($p < 0.001$) and weight ($p < 0.01$). We also find that younger respondents consistently tend to harbor more positive sentiments ($p < 0.001$), with 1-year increase in age being associated with a decrease in beliefs ranging from −0.007 to −0.014. We observe positive but insignificant estimates for social media.

Differences in beliefs

After matching and adjusting for covariates we observe large and significant differences between people who purchased drugs via cryptomarkets and the control group: Non-buyers have a perception of cryptomarkets that is slightly above neutral, while buyers express more positive sentiments in the range of *Agree* on average. As discussed previously, we re-coded *don't know/unsure* responses as neutral (0) and these are predominantly the response chosen among people who never purchased drugs via cryptomarkets. This confirms our first hypothesis, that people who use cryptomarkets express more certain and firm beliefs. The difference in beliefs is significant in all cases ($p < 0.001$), ranging from 0.559 to 0.786. This pattern is evident from simple means and remains in regressions. Raw comparisons of responses and estimated effects are shown in Figure 2 which includes both the main model and alternate specifications including drug use ('loose') and excluding don't know/unsure responses ('w/o don't know'). These findings support our second hypothesis: Respondents who have purchased drugs on cryptomarkets express more positive beliefs.

The difference in beliefs is smaller for price compared to purity, value and weight and confidence intervals are larger. We also find markedly less explanatory power at the fixed effect level for price (marginal $R^2 = 0.086$). While there are no comparative studies concerning weight, purity or value on cryptomarkets, country-level variation in prices is reproduced on cryptomarkets (Cunliffe et al. 2017). If prices vary extensively, this is likely reflected in the smaller estimate and larger variation.

For all four models we allow the intercept of beliefs to vary across countries. Figure 3 shows the country-level intercepts, and some systematic tendencies may be observed. For example, all four beliefs are on average lower in the Netherlands and Italy. Country-level variance is similar across countries (0.03). For value, purity and price we allow the effect of the treatment to vary as well. We observe a positive correlation for value and price (0.12, 0.49), and a negative correlation for purity (−0.11). A positive correlation suggests that the difference in beliefs is larger in countries wherein trust among the control group is higher. For example, respondents residing

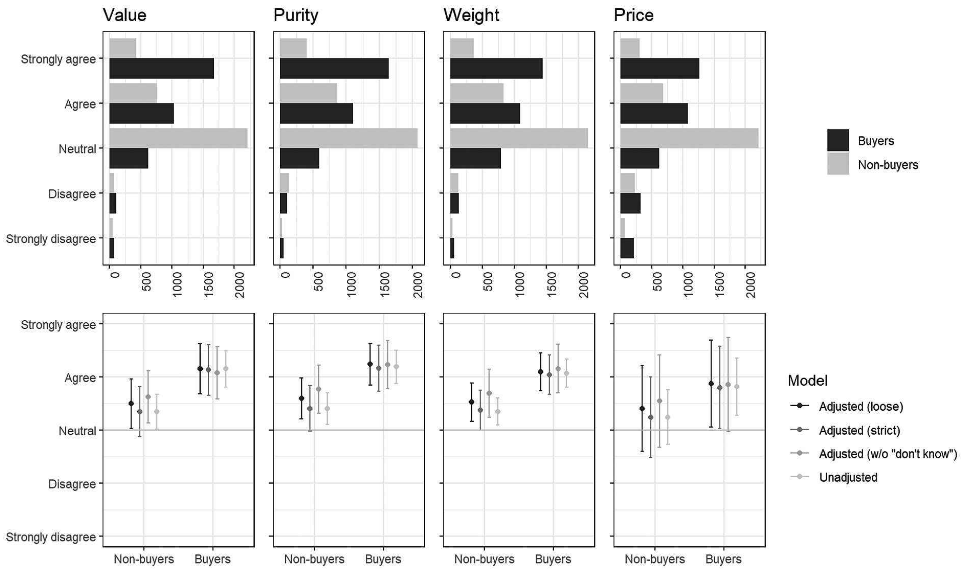

Fig. 2 Top: distribution of responses in matched treatment and control group. Bottom: estimated increase in beliefs holding all covariates at their mean or reference category. The estimated effects include random effect variance

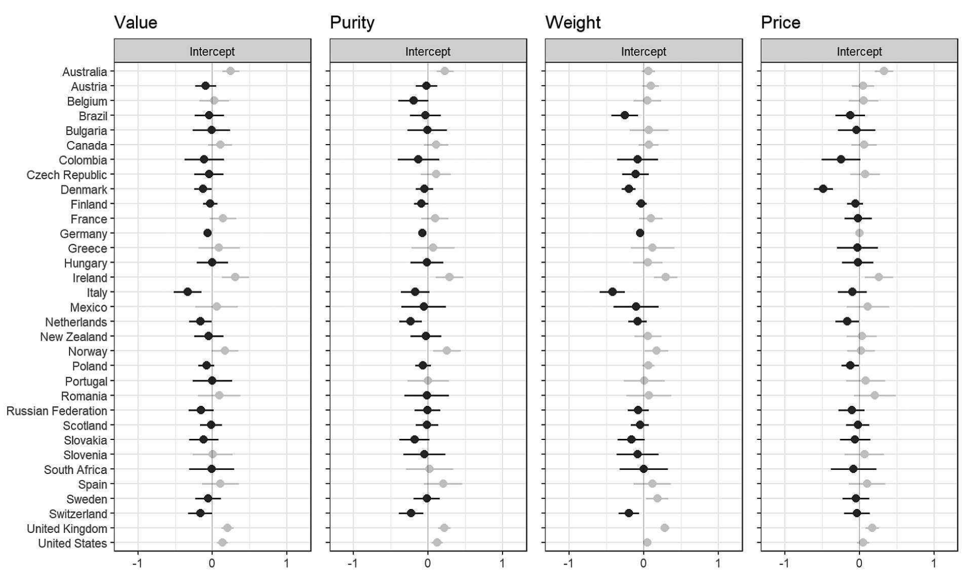

Fig. 3 Group-level intercepts (random effects) of multilevel linear regression across countries

in Italy are estimated to hold a belief in value that is 0.33 points lower, and the estimated effect of using a cryptomarket is −0.40 points weaker. Conversely, respondents residing in France are 0.14 points above the mean and using a cryptomarket is estimated to increase beliefs by an additional 0.11 points.

Table 4. Results from multilevel linear regressions. 95% confidence intervals based on SE. Outcome is scaled belief in value, purity, price, or weight (strongly disagree = 2, neutral or don't know/unsure = 0, strongly agree = 2). $*p < 0.05$, $** p < 0.01$, $***p < 0.001$

Predictors	**Value**	**Purity**	**Price**	**Weight**
	Beta	***Beta***	***Beta***	***Beta***
Intercept	0.538*** (0.388 – 0.688)	0.605*** (0.456 – 0.754)	0.583*** (0.417 – 0.749)	0.521*** (0.369 – 0.672)
Has used cryptomarket within last 12 months	0.786*** (0.691 – 0.882)	0.758*** (0.667 – 0.849)	0.559*** (0.403 – 0.714)	0.667*** (0.627 – 0.707)
Gender				
Female	−0.185*** (−0.239 – −0.130)	−0.227*** (−0.280 – −0.173)	−0.058 (−0.119 – 0.003)	−0.235*** (−0.289 – −0.180)
Other gender identity	−0.165* (−0.308 – −0.021)	−0.253*** (−0.393 – −0.112)	−0.118 (−0.278 – 0.042)	−0.206** (−0.350 – −0.062)
Age	−0.009*** (−0.012 – −0.006)	−0.010*** (−0.013 – −0.006)	−0.014*** (−0.017 – −0.010)	−0.007*** (−0.010 – −0.004)
Education				
Lower secondary, school/intermediate certificate	0.008 (−0.107 – 0.123)	0.044 (−0.069 – 0.157)	−0.075 (−0.203 – 0.054)	0.003 (−0.113 – 0.118)
Technical or trade certificate	0.049 (−0.070 – 0.168)	0.042 (−0.075 – 0.159)	0.003 (−0.130 – 0.136)	−0.010 (−0.129 – 0.110)
Higher secondary school	0.067 (−0.036 – 0.169)	0.056 (−0.044 – 0.157)	−0.017 (−0.132 – 0.097)	0.054 (−0.049 – 0.157)
College certificate/ diploma	0.149** (0.041 – 0.257)	0.113* (0.008 – 0.219)	0.070 (−0.050 – 0.191)	0.101 (−0.008 – 0.209)
Undergraduate degree	0.139* (0.031 – 0.247)	0.116* (0.010 – 0.222)	0.025 (−0.096 – 0.145)	0.097 (−0.012 – 0.205)
Postgraduate degree	0.085 (−0.043 – 0.213)	0.105 (−0.021 – 0.231)	−0.054 (−0.197 – 0.089)	0.116 (−0.012 – 0.245)
Lives in				
Regional area	−0.014 (−0.063 – 0.035)	−0.018 (−0.066 – 0.030)	−0.000 (−0.055 – 0.054)	−0.010 (−0.059 – 0.040)
Remote area	−0.048 (−0.149 – 0.052)	−0.105* (−0.203 – −0.006)	−0.016 (−0.128 – 0.097)	−0.104* (−0.205 – −0.003)
Clubbing				
Less than once every 3 months	−0.009 (−0.078 – 0.060)	−0.008 (−0.075 – 0.060)	−0.064 (−0.141 – 0.013)	−0.047 (−0.116 – 0.022)
Once every 3 months	−0.028 (−0.102 – 0.046)	−0.065 (−0.138 – 0.007)	0.058 (−0.024 – 0.141)	−0.039 (−0.114 – 0.035)
Once a month	0.008 (−0.061 – 0.077)	−0.024 (−0.092 – 0.044)	0.071 (−0.006 – 0.148)	0.017 (−0.053 – 0.086)
Once every fortnight	−0.001 (−0.075 – 0.072)	−0.015 (−0.087 – 0.057)	0.010 (−0.072 – 0.092)	0.007 (−0.067 – 0.081)
Once a week or more	−0.044 (−0.124 – 0.037)	−0.054 (−0.134 – 0.025)	0.089 (−0.001 – 0.179)	−0.092* (−0.174 – −0.011)

Table 4. Continued

Predictors	Value *Beta*	Purity *Beta*	Price *Beta*	Weight *Beta*
N social media apps used (7 days)	0.011 (−0.003 – 0.025)	0.011 (−0.002 – 0.025)	−0.003 (−0.018 – 0.013)	0.008 (−0.006 – 0.022)
Random effects				
Residual variance	0.71	0.69	0.89	0.72
Between-country variance	0.03	0.03	0.03	0.03
Country-level slope variance	0.04	0.04	0.16	
Intercept–slope correlation	0.12	−0.11	0.49	
N (countries)	33	33	33	33
Observations	7,010	7,010	7,010	7,010
Marginal R^2/ Conditional R^2	0.180/0.237	0.179/0.229	0.086/0.214	0.144/0.180

To assess the robustness of our models, we estimated models using logistic and ordinal regressions. In the former, we estimated the probability of expressing positive beliefs, and in the latter the probability of expressing more positive beliefs. In both cases, we find the same direction and sign of the predictors. We also assessed models in which we excluded *don't know/unsure* responses to the Likert questions and matched on a smaller sample (see Appendix). Across all specifications we observed the same patterns as above for age, gender, and social media use. Similarly, an increase in general positive expectations among people who purchased drugs via cryptomarkets remained significant and proportional. Finally, we found that removing *don't know/unsure* responses from the linear model yielded a higher intercept, between 0.706 and 0.909, and a weaker effect of using a cryptomarket between 0.311 and 0.464 ($p < 0.001$). Our conclusions are therefore robust to both removing *don't know/unsure* responses as well as alternate model specifications through logistic or ordinal regressions.

DISCUSSION

The higher quality of substances has been posited as one of the reasons for the growth of online drug markets, but quantitative studies of chemical composition have not produced conclusive evidence (Caudevilla et al. 2016; Rhumorbarbe et al. 2016). Whereas the conclusions of scholars are limited by representativeness and data, we find that people who purchase drugs via cryptomarkets are willing to generalize to a broad population of sellers based on experience with only a few. These findings have implications for scholarship on trust in illicit online markets as well as policy. We discuss each in turn, and draw attention to questions posed by our findings and methods. Matching seeks to approximate randomization, but we limit our claims of causality to suggestive, rather than definite, to err on the side of caution.

Our findings suggest that trust in illicit online markets is not restricted to the dyad, the relationship between people who buy and sell drugs that emerges through repeated exchanges (Décary-Hétu and Quessy-Doré 2017; Duxbury and Haynie 2018), the reputation system (Hardy and Norgaard 2016; Przepiorka et al. 2017), or the governance of markets (Odabaş et al. 2017).

Rather, our findings suggest a story that encompasses all three: The regulation of dishonest behavior by peers and administrators through reputation systems and governance, increases the probability that buyers make positive experiences. In turn, these experiences produce interpersonal trust which is generalized towards the institution itself. This thesis draws on experiential perspectives on the production of institutional trust through individual experience (e.g. Zucker 1986; Sztompka 1999). More broadly, we would suggest that buyers may just as well develop abstract trust towards in other illicit markets. In the context of illicit online markets such a process has implications for drug enforcement policy, which tends to focus on platforms and sellers (Décary-Hétu and Giommoni 2017). Platforms may be seized, and sellers arrested, but institutional trust can persist.

Our findings suggest that institutional trust in cryptomarkets is not equally distributed across countries, and that there are gender and age differences as well. We suggest two tentative hypotheses for these patterns, network/reputation effects and variation in institutional performance. First, trust is transitive and transferable, and the word of a trusted friend carries more weight than that of a stranger (Glückler and Armbrüster 2003). If a country has a high rate of adoption, the probability of knowing someone who has had a positive interaction with a cryptomarket increases—a reputation or network effect (Sztompka 1999: 71). A similar pattern may explain gender and age variation. However, it should not be discounted that the interpretation of Likert-scales can vary across cultures and nations (Lee et al. 2002). Second, if institutional trust develops on the basis of institutional performance, then country level-variation may reflect local variation in the performance of cryptomarkets. Buyers tend to purchase from local sellers (Demant et al. 2018), and there may be variation in their performance, namely on parameters such as purity and price (Cunliffe et al. 2017). Consequently, country-level variation may be caused by buyers encountering different localized markets. Concerning gender differences specifically, we draw attention to two limitations. We do not know whether respondents have friends of either gender who recommend cryptomarkets. Moreover, preliminary analyses suggested women were more inclined to purchase through proxies, a finding which was beyond the scope of our analysis. A combination of network/reputation effects and less direct experience may explain the gender difference (Fleetwood et al. 2020).

Our findings support the sentiment that cryptomarkets are a preferable alternative to other drug markets in terms of product quality (Werse and Kamphausen 2019). These findings contribute to the harm reduction discussion that revolves around cryptomarket use relative to offline drug markets (Aldridge et al. 2018; Martin et al. 2019). Higher quality substances that are less likely to be diluted or of higher potency have concrete implications. Whether these reduce or increase harms, is debatable and dependent on whether the product content matches the advertisements. The risk of overdose may increase if potency is unexpectedly higher than announced, and people inexperienced with the use of high doses may be overwhelmed by the effects (Martin et al. 2019). However, if the information matches the content of the product it helps people to make more informed decisions about how to use the drugs and reduces the risk of overdose and adverse effects (Lefrancois et al. 2020). In either case, consumption and harm reduction practices are crucial, and cryptomarkets have been argued to promote safer drug use (Bancroft 2017). Higher quality substances may also promote higher consumption (Barratt et al. 2016a; 2016b). This study cannot answer whether cryptomarkets increase or reduce harms related to drug use, but we provide evidence that people who purchase drugs via cryptomarkets believe they access higher quality substances. These findings can inform both the harm reduction discussion, as well as enforcement aspects of drug policy (Martin 2018).

CONCLUSION

Within this paper we have examined the association between the expression of general positive expectations and cryptomarket usage. We hypothesized that people who purchase drugs via cryptomarkets would express positive sentiments when compared with people who use drugs purchased offline. Using data from the 2018 Global Drug Survey we applied propensity score matching to build a control group balanced across covariates after which we applied multilevel linear regression. Following matching we find consistent and large differences in beliefs between people who purchase drugs via cryptomarkets and those who use other avenues, and variation between countries. These findings suggest that actors in illicit online markets are capable of building general attitudes of trust, despite uncertain circumstances, based on relatively little evidence. By extension, these findings also provide evidence that cryptomarkets perform better than offline alternatives as the group of people who purchase drugs via cryptomarkets, relative to a control group, generally agrees with statements concerning better, or more correct, value, purity, price and weight. Our findings make two important and intertwined contributions to the literature on online drug markets. Principally, we extend the discussion of trust in illicit online markets by highlighting the presence and production of abstract institutional trust and providing evidence that relative to a control group, people who purchase drugs via cryptomarkets express general and positive beliefs in the performance of these markets to supply better products in terms of weight, value, purity and price. By extension, these findings provide evidence that illicit online markets perform better than offline drug markets in terms of product quality, which has implications for users who are likely to experience more desirable and predictable drug effects.

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APPENDIX

Descriptive statistics for matched samples excluding 'don't know/unsure' responses. For continuous predictors mean and SD are shown. For categorical predictors percentage is shown.

N	**Value**	**Purity**	**Weight**	**Price**
	6,482	**64,70**	**6,306**	**6,464**
Has used cryptomarket within last 12 months (%)	3,241 (50.0)	3,235 (50.0)	3,153 (50.0)	3,232 (50.0)
Age	24.14 (7.27)	24.21 (7.26)	23.97 (7.15)	24.07 (7.27)
Gender (%)				
Male	5,339 (82.4)	5,369 (83.0)	5,250 (83.3)	5,372 (83.1)
Female	1,030 (15.9)	983 (15.2)	956 (15.2)	988 (15.3)
Other gender identity	113 (1.7)	118 (1.8)	100 (1.6)	104 (1.6)

N	Value	Purity	Weight	Price
	6,482	**64,70**	**6,306**	**6,464**
Non-White	510 (7.9)	495 (7.7)	520 (8.2)	526 (8.1)
Education (%)				
Primary school or no formal schooling	329 (5.1)	339 (5.2)	335 (5.3)	343 (5.3)
Lower secondary, school/ intermediate certificate	626 (9.7)	606 (9.4)	643 (10.2)	635 (9.8)
Technical or trade certificate	554 (8.5)	560 (8.7)	502 (8.0)	547 (8.5)
Higher secondary school	1,646 (25.4)	1,582 (24.5)	1,593 (25.3)	1,646 (25.5)
College certificate/diploma	1,492 (23.0)	1,465 (22.6)	1,422 (22.5)	1,537 (23.8)
Undergraduate degree	1,438 (22.2)	1,488 (23.0)	1,421 (22.5)	1,393 (21.6)
Postgraduate degree	397 (6.1)	430 (6.6)	390 (6.2)	363 (5.6)
Lives in (%)				
City/urban area	4,676 (72.1)	4,701 (72.7)	4,532 (71.9)	4,664 (72.2)
Regional area	1,544 (23.8)	1,517 (23.4)	1,503 (23.8)	1,529 (23.7)
Remote area	262 (4.0)	252 (3.9)	271 (4.3)	271 (4.2)
Clubbing (%)				
Never	1,397 (21.6)	1,354 (20.9)	1,354 (21.5)	1,387 (21.5)
Less than once every 3 months	1,113 (17.2)	1,119 (17.3)	1,050 (16.7)	1,064 (16.5)
Once every 3 months	919 (14.2)	936 (14.5)	904 (14.3)	941 (14.6)
Once a month	1,248 (19.3)	1,207 (18.7)	1,191 (18.9)	1,263 (19.5)
Once every fortnight	1,069 (16.5)	1,107 (17.1)	1,070 (17.0)	1,049 (16.2)
Once a week or more	736 (11.4)	747 (11.5)	737 (11.7)	760 (11.8)
N social media apps used last week	3.48 (1.53)	3.47 (1.52)	3.47 (1.52)	3.47 (1.52)

Results from multilevel linear regressions based on matched data excluding 'don't know/unsure' responses. 95% confidence intervals based on SE. Outcome is scaled belief in value, purity, price or weight (strongly disagree = 2, neutral or don't know/unsure = 0, strongly agree = 2). $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Predictors	Value	Purity	Price	Weight
	Beta	***Beta***	***Beta***	***Beta***
Intercept	0.863*** (0.690 – 1.037)	0.883*** (0.713 – 1.054)	0.883*** (0.676 – 1.089)	0.750*** (0.578 – 0.922)
Has used cryptomarket within last 12 months	0.476*** (0.431 – 0.520)	0.482*** (0.408 – 0.555)	0.304*** (0.180 – 0.427)	0.448*** (0.392 – 0.504)
Gender				
Female	−0.132*** (−0.194 – −0.071)	−0.223*** (−0.284 – −0.162)	0.004 (−0.069 – 0.077)	−0.144*** (−0.209 – −0.080)
Other gender identity	0.019 (−0.153 – 0.190)	−0.190* (−0.352 – −0.028)	0.019 (−0.190 – 0.227)	−0.086 (−0.270 – 0.098)
Age	−0.010*** (−0.014 – −0.007)	−0.006*** (−0.010 – −0.003)	−0.016*** (−0.020 – −0.011)	−0.004 (−0.007 – 0.000)

Predictors	**Value**	**Purity**	**Price**	**Weight**
	Beta	***Beta***	***Beta***	***Beta***
Education				
Lower secondary, school/intermediate certificate	0.112 (−0.016 – 0.241)	−0.001 (−0.125 – 0.122)	−0.138 (−0.285 – 0.009)	−0.116 (−0.245 – 0.013)
Technical or trade certificate	0.072 (−0.060 – 0.204)	0.012 (−0.113 – 0.138)	0.009 (−0.143 – 0.162)	−0.088 (−0.222 – 0.046)
Higher secondary school	0.168** (0.054 – 0.282)	0.097 (−0.011 – 0.205)	0.013 (−0.117 – 0.143)	0.021 (−0.093 – 0.135)
College certificate/ diploma	0.189** (0.069 – 0.309)	0.126* (0.012 – 0.240)	0.048 (−0.089 – 0.185)	0.101 (−0.020 – 0.221)
Undergraduate degree	0.197** (0.076 – 0.318)	0.115* (0.001 – 0.230)	0.017 (−0.121 – 0.155)	0.093 (−0.029 – 0.214)
Postgraduate degree	0.232** (0.086 – 0.378)	0.101 (−0.036 – 0.238)	−0.018 (−0.190 – 0.154)	0.123 (−0.025 – 0.270)
Lives in				
Regional area	−0.029 (−0.084 – 0.026)	0.003 (−0.050 – 0.056)	−0.017 (−0.081 – 0.048)	0.018 (−0.038 – 0.074)
Remote area	−0.181** (−0.298 – −0.065)	−0.135* (−0.249 – −0.020)	−0.049 (−0.184 – 0.085)	−0.077 (−0.193 – 0.039)
Clubbing				
Less than once every 3 months	0.030 (−0.047 – 0.107)	0.023 (−0.051 – 0.097)	−0.137** (−0.227 – −0.046)	−0.027 (−0.106 – 0.052)
Once every 3 months	−0.039 (−0.121 – 0.044)	−0.046 (−0.125 – 0.032)	0.042 (−0.053 – 0.137)	−0.063 (−0.147 – 0.021)
Once a month	−0.041 (−0.119 – 0.037)	−0.013 (−0.089 – 0.063)	0.057 (−0.034 – 0.147)	−0.021 (−0.101 – 0.060)
Once every fortnight	−0.009 (−0.092 – 0.075)	−0.024 (−0.104 – 0.055)	0.068 (−0.029 – 0.166)	−0.012 (−0.096 – 0.072)
Once a week or more	0.007 (−0.084 – 0.099)	−0.051 (−0.138 – 0.036)	0.085 (−0.020 – 0.190)	−0.142** (−0.235 – −0.050)
N social media apps used (7 days)	0.022** (0.006 – 0.037)	0.011 (−0.004 – 0.026)	0.008 (−0.010 – 0.026)	0.024** (0.008 – 0.039)
Random effects				
Residual variance	0.83	0.77	1.13	0.85
Between-country variance	0.06	0.06	0.10	0.05
Country-level slope variance		0.01	0.08	0.00
Intercept–slope correlation		−0.43	0.70	0.07
N (countries)	33	33	33	33
Observations	6,482	6,470	6,464	6,306
Marginal R^2/ Conditional R^2	0.074/0.133	0.079/0.136	0.035/0.178	0.064/0.116

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