

Governing the Agora—Informal Communication in Reputation-Based Online Markets

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Abstract: It has been argued that reputation systems in anonymous online markets supersede informal information exchange in their capacity to promote cooperation among traders. We challenge this view and propose that informal communication plays a crucial role in online market governance. Drawing on a comprehensive theoretical framework of learning and control through social embeddedness, we combine rich data on market transactions, trader reputation scores, and textual data in community forum discussions of two large online markets for illegal goods. Our analyses reveal two key insights. First, despite the availability of standardized scores in reputation systems, both traders and market administrators also rely on informal community discussions when exerting social control in online markets. Second, when reputable sellers are suspected of fraudulent behavior, community discussions involving traders and administrators prove swifter at resolving these issues than reputation systems. Our work shows that informal means of information exchange complement and, at times, supplement reputation systems in supporting the governance of large, anonymous marketplaces.

Keywords: reputation; trust; online markets; text analysis; reputation systems; cryptomarkets

Reproducibility Package: Data and code to reproduce our analyses are available at <https://osf.io/kgpfx/>

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INFORMATION asymmetries where sellers possess private information about products and services, while buyers cannot evaluate them in detail before engaging in transactions, are common in many market exchanges (Akerlof 1970; Beckert 2009; Coleman 1990). Reputational incentives have proven effective in mitigating trust problems resulting from such information asymmetries across various market contexts (Diekmann and Przepiorka 2019). Reputation formation and bottom-up social control through social networks of long-standing trade relations (Geertz 1979; Hillmann 2013; Hillmann and Aven 2011) have been historically used to curb opportunistic market behaviors in contexts where formal institutions had limited reach (Hillmann 2013; Kollock 1994), such as the eleventh-century Mediterranean trade (Greif 1993; Greif 1989) or the 1980s drug markets in the United States (Reuter and Caulkins 2004). However, this enforcement mechanism remains confined to localized, close-knit communities and interpersonal networks (DiMaggio and Louch 1998; Hillmann 2013).

Contemporary anonymous online markets transformed how reputational information is created and disseminated (Diekmann et al. 2014; Resnick et al. 2000; Resnick and Zeckhauser 2002). Unlike in traditional markets (DiMaggio and Louch 1998), traders in online markets engage in numerous one-off transactions with anonymous partners (Duxbury and Haynie 2021; Przepiorka and Aksoy 2021; Przepiorka, Norbutas, and Corten 2017). By collecting, aggregating, and

disseminating quantifiable feedback on traders, reputation systems facilitate the exertion of bottom-up social control on a large scale (Przepiorka 2013), thereby enabling the emergence of large-scale anonymous online markets (Cabral and Hortacsu 2010; Dellarocas 2003; Resnick and Zeckhauser 2002).

Reputation systems have been shown to be effective even in cryptomarkets—online marketplaces for illegal goods located on the Dark Web (Andrei et al. 2024; Przepiorka et al. 2017)—where traders lack both social ties necessary for bottom-up social control and legal assurances that enforce trustworthiness from the top down (Gambetta 2009; Jacques and Wright 2011; Ladegaard 2020; Moeller and Sandberg 2017b; Sandberg 2012). Although quantitative work has focused almost exclusively on the role of reputation systems in cryptomarket governance, qualitative work has highlighted informal information exchange in community forums as important for knowledge sharing and norm enforcement (Bakken, Moeller, and Sandberg 2018; Bancroft 2020; Lorenzo-Dus and Di Cristofaro 2018; Moeller, Munksgaard, and Demant 2017a; Morselli et al. 2017; Norbutas 2020; Tzanetakis 2018; Tzanetakis et al. 2016). Forum posts frequently include evaluations of experiences with sellers (“great stuff for a great price...,” “...vendor shipped late...”) and discussions of recent market developments within the buyer community (“...is [Seller A] finally gone so we can talk about something else???...”) as well as between buyers and market administrators (buyer: “...please investigate [Seller B] guys”; administrator: “fine[,] ... [Seller B] is banned”). Still, it remains unclear whether the role of these forums extends to systematically supporting the creation of reputational information beyond what numerical scores in reputation systems can capture (Faraj et al. 2016).

We address this gap by investigating how traders and market administrators use standardized reputation systems alongside socially contextualized information in community forums to enforce social control in cryptomarkets. We define social control broadly as “the ability to make norms or rules effective” (Reiss 1951:196), that is, in our context, to enforce trustworthy trader behavior in the market. We build on a theoretical framework integrating two sources of reputational information (standardized in reputation systems and contextualized in forums) and two modes of social control (bottom-up by traders and top-down by market administrators). Moreover, focusing on cases of fraud committed by highly reputable sellers, we demonstrate how contextualized information in forums can compensate for the limitations of formal reputation systems. Our empirical analyses combine data from reputation systems and forums of two large cryptomarkets: Silk Road and AlphaBay. We use manual coding and machine learning to determine if sellers are discussed positively or negatively in forum communities. We then use panel and survival models to assess how standardized and contextualized reputational information relate to seller market performance, market survival, and forced exclusion from the market.

Our study is the first to provide systematic quantitative evidence that forums foster trust between buyers and sellers by linking traders’ reputations to their trustworthiness in the market and thereby supporting both bottom-up (by traders) and top-down (by market administrators) social control (DiMaggio and Louch 1998). In addition, we discuss how informal reputational information shared in forums complements, or—in particularly risky cases—even substitutes, the role

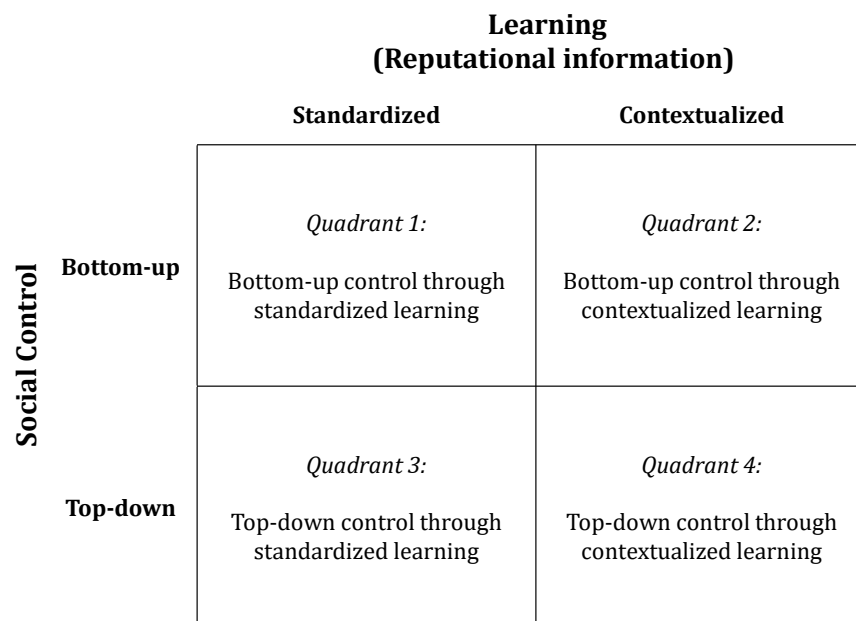


Figure 1: Framework of market governance mechanisms combining bottom-up and top-down social control with standardized and contextualized learning.

of formalized scores in reputation systems. By doing so, our study extends our knowledge of how market participants balance between engaging in self-interested market transactions (Pace 2017; Sandberg 2012) while simultaneously maintaining trust by contributing to the public good of reputational information in both formalized and contextualized ways and enforcing social control (DiMaggio and Louch 1998; Kollock 1999; Matzat 2009).

Governance in Illegal Online Markets

Our framework in Figure 1 combines concepts of learning (information about past experiences with a trader) and control (negative sanctioning of untrustworthy traders) to understand how cryptomarkets are governed (Buskens and Raub 2002).

Social Control

Not delivering goods or services one was paid for constitutes a breach of rules of conduct in (online) markets (for illegal goods). Such breaches can be sanctioned through top-down social control—that is, legitimate sanctioning by centralized entities (Black 2010) such as market administrators (Weesie, Buskens, and Raub 1998)—or bottom-up social control exerted by “the people” (Jacques and Wright 2011)—that is, market participants embedded in social relations (Buskens and Raub 2002; Granovetter 1985).

Conventionally, illicit markets are governed via bottom-up social control (Moeller and Sandberg 2017b) through personal and familial ties (Gambetta 2009; Jacques and

Wright 2011; Ladegaard 2020; Moeller and Sandberg 2015; Moeller and Sandberg 2017b). However, in illicit markets situated in the Dark Web (aka cryptomarkets), users' IP addresses are anonymized (Gehl 2018), which also precludes the enforcement through personal social ties (Beckert and Wehinger 2013; Jacques and Wright 2011).

In cryptomarkets, bottom-up control is, therefore, enforced by market participants who reward trustworthy sellers by buying from them and punish untrustworthy ones by avoiding them (Diekmann et al. 2014; Diekmann and Przepiorka 2019; Matzat 2009; Przepiorka 2013; Przepiorka et al. 2017; Utz, Matzat, and Snijders 2009). In addition, instead of legal entities, cryptomarkets feature a mechanism of top-down control in the form of market administrators who maintain the market infrastructure (Morselli et al. 2017)¹ and can ban untrustworthy traders by removing their account from the market (Holt et al. 2015; Morselli et al. 2017).

Learning

Both top-down and bottom-up control in markets rely on learning—obtaining information about traders' past behavior (Buskens and Raub 2002). In conventional illegal markets, reputational information is mainly distributed through personal ties (Gambetta 2009; Jacques and Wright 2011; Ladegaard 2020; Moeller and Sandberg 2015; Moeller and Sandberg 2017b). In cryptomarkets, information on traders' past behaviors can be obtained from own past experiences (Duxbury and Haynie 2023; Norbutas, Ruiter, and Corten 2020a), as well as through ties with traders one has a shared transaction history with (Duxbury and Haynie 2023; Duxbury and Haynie 2021). As online (crypto)markets expand, however, both these means become insufficient (Duxbury and Haynie 2021), giving way to reputational information shared by third parties via reputation systems (Buskens and Raub 2002; Jiao, Przepiorka, and Buskens 2021; Przepiorka et al. 2017). Reputation systems disseminate reputational information through the whole market by aggregating quantitative evaluations of seller quality into reputation scores—typically a share of positive ratings or a similarly interpretable metric—alongside optional textual feedback. We will refer to scores in such reputation systems as “standardized reputational information.”

Cryptomarket participants also have access to community discussion forums—another source of reputational information. These forums exist alongside cryptomarkets. However, unlike reputation scores that are featured on seller profile pages and item postings, forum discussions are hosted on a platform that users register for separately. Thus, forums allow market participants—but also external users—to discuss seller quality outside the formalized market reputation system (Lorenzo-Dus and Di Cristofaro 2018) and, thus, informally generate contextually rich up-to-date market-related knowledge (Faraj et al. 2016). We will refer to mentions of sellers in forums as “contextualized reputational information.”

Bottom-Up Control through Standardized Learning

Buyers rely on seller reputations in the reputation system to enforce informal social control: they can refuse to transact with sellers with poor reputations, or do so only

if prices are sufficiently low (Jiao et al. 2021; Morselli et al. 2017; Przepiorka 2013; Przepiorka et al. 2017). New sellers must build their reputations by accepting lower prices (Friedman and Resnick 2001; Shapiro 1983), whereas sellers with established reputations can sell more goods at higher prices (Diekmann et al. 2014; Przepiorka et al. 2017; Resnick et al. 2006; Resnick and Zeckhauser 2002). Consistent with existing research on cryptomarkets (Norbutas 2020; Przepiorka et al. 2017), we expect that:

H.1.a The more positive (negative) ratings a seller receives in the reputation system, the more (less) items they sell and the higher (lower) prices they charge;

H.1.b The more positive (negative) ratings a seller receives in the reputation system, the less (more) likely they are to exit the market.

Bottom-Up Control through Contextualized Learning

Even within the formal reputation systems, short texts provided alongside quantitative ratings have been shown to provide additional reputational information in cryptomarkets, particularly for goods carrying higher quality risks (Holtkamp, Duxbury, and Haynie 2025). Because forum discussions do not enter formal reputation scores and have no length restrictions, buyers can provide descriptions of experiences with sellers with even more flexibility and nuance compared to such short texts in the reputation systems. Longer, more detailed textual descriptions of trading experiences in forums can be more informative than numerical scores (Snijders and Matzat 2019) or short texts given that they allow for nuanced argumentation (Mudambi and Schuff 2010), and personal expression (Schindler and Bickart 2012). On the other hand, sifting through lengthy forum texts is cognitively more demanding (Espeland and Stevens 1998) than interpreting numeric reputation scores, and might, thus, not scale as well to comparisons of thousands of sellers operating in the market (Bancroft et al. 2020).

Unlike reputation systems ratings which are restricted to users who completed a transaction with a seller, forum posts can be written by any user, which makes them more susceptible to manipulation. However, despite the built-in protections, reputation systems are vulnerable themselves: sellers routinely engage in “feedback padding”—creating cheap listings, fictively purchasing the product in the listing, and then providing positive feedback to themselves (Chiu, Huang, and Yen 2010; Tadelis 2016). When buyers suspect a seller is engaging in such rating manipulations, forum discussions, in fact, offer a recourse: forum posts can easily be linked to stable usernames with visible posting histories and karma (popularity), which makes them a more reliable source of information compared to an anonymous rating in the reputation system (Kollock 1999).

Finally, forums are often able to respond to changes in seller trustworthiness more quickly than reputation systems. If a reputable seller’s quality suddenly drops, negative ratings erode long-accumulated reputation scores only very slowly, whereas recent forum posts detailing negative experiences can quickly draw the attention of buyers and administrators alike (Jøsang et al. 2007; Bakken et al. 2018).

All above considered, we expect contextualized reputational information in forums to have qualitatively the same effect on buyers' expectations as information in reputation systems, and, thus, facilitate bottom-up social control

H.2.a The more positive (negative) mentions a seller receives in the forum, the more (less) items they sell and the higher (lower) prices they charge;

H.2.b The more positive (negative) mentions a seller receives in the forum, the less (more) likely they are to exit the market.

Top-Down Control through Standardized Learning

Information in reputation systems can help administrators identify sellers that need to be sanctioned (Bakken et al. 2018; Tzanetakis et al. 2016). Administrators can examine standardized feedback for bouts of negative ratings or signs of feedback padding both before and after the seller is suspected of or reported for fraudulent activity in the market, allowing administrators to decide whether the seller should be excluded from the market. We therefore formulate the following hypothesis:

H.3 The more positive (negative) ratings a seller receives in the reputation system, the less (more) likely they are to be excluded from the market by the administrator.

Top-Down Control through Contextualized Learning

Forums provide buyers with an opportunity to discuss signs of intentional fraud and bring any other issues and concerns to administrators' attention (Morselli et al. 2017). Beyond engaging in bottom-up control, market participants might use forums to collect and filter reports on transgressions (Warner 1992) and then delegate sanctioning to top-down bodies of control (Carr 1993; Merry 1984)—in this case, market administrators. With this in mind, we formulate the following hypothesis:

H.4 The more positive (negative) mentions a seller receives in the forum, the less (more) likely they are to be excluded from the market by the administrator.

Standardized and Contextualized Modes of Learning as Complements and Substitutes

The following section uses our theoretical framework to formulate an explanation for an unexpected finding that we encountered while empirically testing the above hypotheses: sellers with different tenures show different patterns of receiving ratings in reputation systems and forums.

To explain this observation, we combine our theoretical considerations above with literature suggesting that informal processes are especially important in dynamic contexts where formalized procedures fail to keep pace with rapid environment changes (Kreutzer et al. 2016; Zenger, Lazzarini, and Poppo 2002). In the cryptomarket context, one particularly relevant risk dynamic is "selective scamming," in which highly reputable and tenured sellers strategically fail to fulfill a

Table 1: Relevant Observations for Both Datasets.

	Silk Road	AlphaBay
Time span	May 2011–July 2012	December 2014–June 2017
Items	24,385	139,853
Sellers	783 ^a	6,344 ^b
Seller ratings	184,751	2,295,594
Forum mentions of sellers	58,745	190,900

^aOur transaction data contain information on 1,017 sellers. We exclude 234 sellers as we either could not identify their full username (only having access to its encrypted version) or could not distinguish their mentions in the forum from other words (e.g., “weed”).

^bOur transaction data contain information on 6,501 sellers. We exclude 157 sellers as we could not distinguish their mentions in the forum from other words.

portion of their orders. Because these sellers possess substantial reputational capital, the negative feedback associated with unshipped orders is diluted by their existing positive ratings, allowing them to preserve a credible reputation despite opportunistic misconduct. In such cases, forums could draw buyers’ and administrators’ attention to the recent misconduct that might not (yet) be reflected in the formal ratings.² In other words, we would expect tenured sellers to become less vulnerable to negative ratings and more vulnerable to negative forum mentions the longer they have been in the market (and, consequentially, the more ratings they have already accumulated). We formulate this reasoning in the following exploratory proposition:

Proposition 1 *The association between market exit or exclusion and negative ratings in the reputation system weakens as seller’s tenure in the market increases, while the opposite holds for the association with negative mentions received in the forum.*

This proposition outlines the expectation that contextualized reputation information in forums might, in certain risky contexts, (partially) substitute rather than merely complement formalized ratings as outlined in H.2 and H.4.

Data and Methods

To test our hypotheses, we use data from two large cryptomarkets: Silk Road (operated between February 2011 and October 2013) and AlphaBay (operated between December 2014 and July 2017). We use Silk Road data collected by Christin (2013) and Branwen (2021) and AlphaBay data collected by Norbutas, Ruiter, and Corten (2020b). Both datasets include information on sellers’ item listings, individual transactions, as well as forum threads, posts, and their authors. Table 1 describes the two datasets in terms of the number of items, sellers, seller ratings, and seller-related forum posts.³

First, we extract information on sellers’ standardized reputations in reputation systems. In Silk Road, quantitative ratings varied on a scale from 1 to 5; in AlphaBay, they could be positive, neutral, or negative. Extracting qualitative evaluations of sellers in posts in informal forum communities is more challenging. We identify

forum posts that (1) mention a seller by their username (e.g., “Having ordered with [Seller A] 3 times now...”) or (2) were written in a thread that references a seller in the title (e.g., a thread called “[Seller A]- Anyone ordered from them?”). We then manually code a sample of 1,000 posts, denoting whether each post was positive, neutral, or negative⁴. In our analyses, we focus on positive or negative tone: positive mentions of sellers engender good reputation, whereas negative ones signal opportunistic behavior that is likely to damage seller reputation (Pavlou and Dimoka 2006).

To expand this coding on the full dataset of posts mentioning sellers, we fine-tune RoBERTa, a transformer language model pretrained on a large amount of textual data (Liu et al. 2019). Transformer language models capture words as vectors in a high-dimensional vector space, positioning words that occur across similar contexts close to each other (Vaswani et al. 2018). Using RoBERTa, we then obtain vector representations of individual forum posts, and fine-tune the model using our manually coded classifications of text tone to allow the RoBERTa to learn how vector representations of forum posts correspond to positive or negative evaluations of sellers (Sun et al. 2019). The model achieves a satisfactory accuracy of 0.82. After fine-tuning the model, we apply these learned patterns on our full dataset. We provide further details on our coding procedure and text analysis in Appendix B in the online supplement.

We compile number of sales and average revenue for each seller in every week they were active in the market. We reconstruct sales and revenues from seller feedback in the reputation system.⁵ To capture standardized reputational information, we accumulate total positive and nonpositive ratings received by the seller up to the given week.⁶ We capture contextualized reputation in forums by accumulating positive and negative seller mentions⁷ in the week preceding the week in question. We choose this operationalization because we assume that (1) buyers will be less concerned with less recent seller evaluations as they might be out of date and (2) accumulating information across a larger time span would be too mentally demanding for most users (Espeland and Stevens 1998).⁸

We include several control variables: the number of forum posts written by the seller in the week preceding the week in question (more active sellers might be more visible to the buyers), the total number of unique items sold up to that week (as sellers with more different items listed can generate more sales), and the number of weeks elapsed since seller’s first feedback or item posting (controlling for seller experience in the market).⁹

When testing H.1.a and H.2.a on the associations between the two types of reputational information and seller performance, we use weekly sales and weekly average revenue as the dependent variables. We fit two-way fixed effects models, introducing seller-level and week-level fixed effects to account for variation due to unobserved seller characteristics and market-level time trends and cluster the standard errors at the seller level. We show the descriptive statistics of these data in Table 2.

To test H.1.b and H.2.b regarding the effects of two types of reputational information on seller market survival, we use a Cox proportional hazards model with time-dependent covariates (as seller reputations vary over time; Fisher and Lin

Table 2: Descriptive Statistics of the Main Variables.

Variable name	Silk Road						AlphaBay					
	N	Mean	SD	Median	5 th Perc	95 th Perc	N	Mean	SD	Median	5 th Perc	95 th Perc
Weekly sales	9,555	17.76	28.97	8.00	1.00	69.30	151,448	14.93	31.11	6.00	1.00	58.00
Avg. weekly revenue	9,555	14.84	27.67	8.78	0.00	44.72	151,448	151.32	416.24	62.15	3.43	540.76
Total pos. ratings	9,555	183.43	357.89	54.00	0.00	821.30	151,448	399.09	1,171.60	106.00	0.00	1,631.00
Total nonpos. ratings	9,555	6.03	14.92	1.00	0.00	31.00	151,448	11.13	37.15	1.00	0.00	48.00
Pos. forum mentions	9,555	0.73	2.17	0.00	0.00	4.00	151,448	0.22	1.34	0.00	0.00	1.00
Neg. forum mentions	9,555	0.28	1.19	0.00	0.00	2.00	151,448	0.26	2.30	0.00	0.00	1.00
Total unique items	9,555	0.97	2.19	0.00	0.00	4.00	151,448	0.77	1.47	0.00	0.00	3.00
Seller's forum posts	9,555	2.12	12.65	0.00	0.00	10.00	151,448	1.09	5.35	0.00	0.00	6.00
Seller's age in weeks	9,555	13.15	11.72	10.00	0.00	37.00	151,448	30.95	26.53	24.00	1.00	84.00
Seller exited ^a	9,555	0.02	0.15	0.00	0.00	0.00	151,448	0.02	0.14	0.00	0.00	0.00
Seller was excluded							151,448	0.00	0.03	0.00	0.00	0.00

^aIn AlphaBay, only voluntary seller exit (i.e., a seller has not been excluded/banned by the administrators but has ceased trading activities in the market).

(1999)) and study the likelihood of seller's market exit. We consider a seller to have exited the market if their last feedback received or item posted for sale was more than 30 days before the last observation collected in our data. As sellers would sometimes take short breaks from trading in the market (and go on a "vacation"), we find this to be a reasonable cut-off.¹⁰ If a seller has exited the market, we denote the week during which they received their last feedback or have posted their last item for sale as the week of their exit.

To test hypotheses H.3 and H.4 on top-down social control, we use the same survival models on data from AlphaBay where we are able to observe forceful exclusion by market administrators. In these models, the event of interest is a seller having been banned from the market (i.e., excluded by the market administrators) more than 30 days before the last observation. In all survival models, we use the number of weeks since seller market entry as our time dimension.¹¹ In both panel and survival models, we log-transform all variables except seller age to account for the fact that their distributions are highly right-skewed.

We explore Proposition 1 by estimating Cox proportional hazard models with step functions, fitting the associations between reputation indicators and market survival separately for sellers with different tenures (see Appendix E in the online supplement for details). This allows us to evaluate how two types of reputational information differentially affect market exit or exclusion depending on tenure length (an indicator of past market success).

We analyze both the Silk Road and AlphaBay datasets to exploit their individual strengths in providing evidence for our mechanisms of interest, rather than to draw systematic comparisons between the two markets. Although both markets maintained a reputation system and an affiliated discussion forum, each dataset lends itself to testing certain hypotheses more naturally. Owing to its reputation system design (see footnote 5), the Silk Road dataset allows for more reliable estimation of sales and revenues, providing us with greater confidence when testing H.1.a and H.2.a. The AlphaBay dataset, in turn, includes reliable indicators of seller exclusion by market administrators, allowing us to test H.3, H.4, and Proposition 1.

Results

Descriptive Results

In Silk Road, 616 of 783 sellers (78.7 percent) were mentioned in the forum at least once,¹² compared to 3,344 of 6,344 sellers (52.7 percent) in AlphaBay. The lower share in AlphaBay most likely reflects the fact that this market featured a large number of sellers who tried entering the market but exited very quickly without generating sufficient sales to attract attention in forums. We find weak-to-moderate correlations between standardized ratings and contextualized mentions of sellers (see Appendix C in the online supplement), confirming that the two indicators are related, but still capture different aspects of information about seller reputations.

Bottom-Up Control through Standardized Learning

Models 1, 2, 4, and 5 in Table 3 show coefficient estimates from our regression models of seller market performance (i.e., sales and revenues) with seller fixed-effects and week fixed-effects. In these models, we report standard errors adjusted for the clustering of week-level observations within a single seller.

Testing H.1.a, we replicate the finding from the literature that an increase in a seller's total positive ratings is associated with an increase in their sales and revenues. For instance, a two-fold increase in the number positive ratings (if a new seller would double their ratings compared to last week) is associated with an increase in sales of 7.7 percent in SilkRoad and 22.6 percent in AlphaBay. In terms of weekly average revenues, the same increase in positive ratings is associated with a revenue increase by 4.5 and 11.2 percent in Silk Road and AlphaBay, respectively. When it comes to nonpositive ratings, there is no association with sales and revenues in Silk Road. In AlphaBay, a comparable increase in the number of nonpositive ratings is associated with decreases in sales and average revenues in the current week by 2.7 and 8.9 percent, respectively. These results support H.1.a in AlphaBay, and support H.1.a with regard to positive ratings in Silk Road.

Models 3 and 6 report the results of Cox proportional hazard models of seller market survival and allow us to evaluate H.1.b. In these survival models (Model 3 for Silk Road and Model 6 for AlphaBay), positive coefficients indicate that an increase in the value of the independent variable is associated with an increase in the hazard of market exit (and vice versa). These models show that changes in formal ratings are associated with the likelihood of market exit in AlphaBay. A two-fold increase in the number of positive (negative) ratings, holding all other covariates constant, is associated with an 18.5 percent decrease (19.5 percent increase) in the hazard of voluntary market exit in AlphaBay. There is no association of positive (negative) ratings with the hazard of market exit in Silk Road. These results provide support for H.1.b in AlphaBay, but not in Silk Road.

Bottom-Up Control through Contextualized Learning

We proceed to evaluate H.2 regarding the extent to which contextualized reputational information complements the standardized scores in reputation systems when supporting bottom-up control. First, in line with H.2.a, Models 1, 2, 4, and 5 in Table 3 show that an increase in the number of positive mentions in the preceding week, holding the positive and negative ratings in the reputation market constant, is associated with an increase in sales and average revenues of a seller in the following week in both markets. However, negative mentions are only associated with lower sales in AlphaBay. For instance, a two-fold increase in the number of last week's positive and negative mentions of a seller in AlphaBay forums is associated with, respectively, a 9.3 percent increase and a 5.2 percent decrease in their sales in the following week.

Testing H.2.b, survival Models 4 and 6 in Table 3 show that an increase in positive mentions in the forum community is associated with a lower hazard of market exit in AlphaBay but not in Silk Road.¹³ A 2-fold increase in the number of positive seller mentions is associated with a 20.2 percent decrease in the hazard

Table 3: Regression Models of Weekly Sales (1, 4) and Average Weekly Revenue (2, 5) with Time and Seller FE (1 and 2) and Cox Proportional Hazards Survival Models of Seller Hazard of Market Exit (3, 6) and Market Exclusion (7) for Two Markets.

	(1) Silk Road Sales	(2) Silk Road Revenues	(3) Silk Road Exit Hazard	(4) AlphaBay Sales	(5) AlphaBay Revenues	(6) AlphaBay Exit Hazard ^c	(7) AlphaBay Excl. Hazard
Avg. weekly revenue ^a	0.248 ^{***} (0.021)		0.148 [*] (0.065)	0.108 ^{***} (0.004)		0.121 ^{***} (0.012)	0.529 ^{***} (0.065)
Total positive ratings ^{a,b}	0.108 ^{***} (0.030)	0.063 ^{**} (0.020)	0.029 (0.078)	0.294 ^{***} (0.011)	0.153 ^{***} (0.011)	-0.295 ^{***} (0.020)	-0.498 ^{***} (0.071)
Total nonpositive ratings ^{a,b}	-0.011 (0.029)	-0.023 (0.024)	0.125 (0.083)	-0.040 ^{***} (0.010)	-0.135 ^{***} (0.009)	0.259 ^{***} (0.023)	1.714 ^{***} (0.092)
Positive forum mentions ^{a,b}	0.154 ^{***} (0.024)	0.063 ^{***} (0.017)	-0.055 (0.140)	0.128 ^{***} (0.012)	0.032 ^{**} (0.011)	-0.325 ^{**} (0.073)	-0.510 [*] (0.184)
Negative forum mentions ^{a,b}	-0.017 (0.028)	-0.013 (0.022)	0.389 [*] (0.179)	-0.077 ^{***} (0.011)	-0.006 (0.010)	0.638 ^{***} (0.047)	0.748 ^{***} (0.110)
Total unique items sold ^{a,b}	0.293 ^{***} (0.051)	0.219 ^{***} (0.036)	-0.272 [*] (0.120)	-0.054 ^{***} (0.018)	0.371 ^{***} (0.018)	-0.002 (0.032)	-0.039 (0.132)
Seller's forum posts ^{a,b}	0.098 ^{***} (0.019)	0.090 ^{***} (0.016)	-0.116 (0.090)	0.123 ^{***} (0.007)	0.094 ^{***} (0.009)	-0.119 ^{**} (0.029)	-0.356 [*] (0.131)
Seller's age in weeks	-0.022 ^{***} (0.003)	-0.023 ^{***} (0.002)		-0.011 ^{***} (0.003)	0.004 (0.004)		
Seller FE	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	N/A	Y	Y	N/A	N/A
N	9,555	9,555	9,555	151,448	151,448	151,448	151,448

^aThe variable has been log-transformed.^bThe variable has been lagged by one week.^cExcluding the cases where sellers were forcefully excluded.Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

of market exit for sellers in AlphaBay. In both markets, however, a comparable increase in last week's negative mentions is associated with a significant increase in the hazard of market exit in the current week: an increase of 31 percent in Silk Road and 55.6 percent in AlphaBay. These results provide partial support for H.2.b: while negative seller mentions in community forums are associated with an increase in the likelihood of sellers' market exit in both marketplaces, positive mentions are associated with a decreased hazard of exiting the market in AlphaBay only.

Top-Down Control through Standardized Learning

Our results provide support for H.3 on the effect of ratings in the reputation system on the likelihood of administrator-enforced market exclusion. Model 7 in Table 3 shows that a two-fold increase in sellers' total positive ratings is associated with a 29.2 percent decrease in the hazard of top-down market exclusion. A comparable increase in total negative ratings is associated with a staggering 228.1 percent increase in the hazard of being banned by the administrators.

Top-Down Control through Contextualized Learning

Finally, we evaluate H.4 on the effect of contextualized reputational information in forums on the hazard of market exclusion. Model 7 shows an association between both positive and negative forum mentions and forceful market exclusion: a two-fold increase in the number of positive mentions, holding other covariates constant, is associated with a 29.8 percent decrease in the hazard of being banned from the market. A comparable increase in the number of negative forum mentions is associated with a 67.9 percent increase in the hazard of market exclusion. These results support H.4, pointing to a protective effect of being positively discussed and a damaging effect of being negatively discussed in the forum with regard to the likelihood of top-down control being exerted.

Standardized and Contextualized Modes of Learning as Complements and Substitutes

We now turn to the proposition on the substitution of formal ratings by forum mentions for sellers with long tenure. Tables E1, E2, and E3 in Appendix E of the online supplement show the results of our Cox proportional hazard models with step functions, allowing us to analyze the association of nonpositive ratings and negative mentions with market exit and exclusion for sellers of different tenures.¹⁴

In SilkRoad (Table E2 in the online supplement), we find no evidence for statistically significant associations between ratings or mentions and sellers' likelihood of market exit at any length of tenure. In AlphaBay (Table E3 in the online supplement), the association of market exit and nonpositive ratings weakens with seller tenure and stops being significant for sellers with tenures longer than 40 weeks. Although the association with negative mentions similarly decreases with tenure, it remains larger compared to nonpositive ratings and is statistically significant at all lengths of seller tenure.

The association between the risk of market exclusion by administrators and nonpositive ratings in AlphaBay (Table E4 in the online supplement) is weaker for seller with longer tenure as well. However, the opposite holds for the association between negative mentions and market exit—negative mentions become increasingly damaging as seller tenure increases. A two-fold increase in negative mentions is associated with a 44 percent increase in the hazard of being excluded from the market for sellers with tenures up to 20 weeks, whereas for sellers with tenures longer than 40 weeks the same increase in negative mentions results in a much higher 150 percent increase in market exclusion hazard.

These results suggest that, as tenure increases, sellers become increasingly “immune” to the pressure of nonpositive ratings—but this is less the case when it comes to negative forum mentions. In fact, experienced sellers become increasingly “sensitive” to negative mentions when it comes to the risk of being banned by the market administration.

Robustness Checks

In Appendix C in the online supplement, we show and discuss models with alternative independent variable specifications. Notably, many associations between mentions and market exit cease to be statistically significant if we consider total, rather than last week’s mentions, suggesting that, in line with the idea that sifting through many mentions is cognitively demanding and difficult to scale, more recent forum mentions mattered more for seller survival compared to their aggregate number. In Appendix D, we show the results of robustness checks with regard to the market exit cut-off in survival models; overall, our results remain qualitatively robust to different specifications. Apart from informing our results, models in Appendix E in the online supplement also serve to check the robustness of conclusions we draw from Cox models regarding H.1–H.4 given that the proportional hazards assumptions are violated for some covariates. Our main conclusions do not qualitatively change.

Conclusions and Discussion

Prior research has shown how the emergence and growth of large-scale online marketplaces—including those for illegal goods—was enabled by traders overcoming trust problems with the help of quantitative information about seller quality available in reputation systems (Diekmann et al. 2014; Jiao et al. 2021; Munksgaard and Tzanetakis 2022; Przepiorka et al. 2017; Resnick and Zeckhauser 2002). This focus on bottom-up social control based on standardized reputation systems, however, has led much of the quantitative work in the field to overlook both the shortcomings of reputation systems (Tadelis 2016) and the complexity of marketplace governance.

To address this gap, we develop a comprehensive theoretical framework of market governance positing that two sources of reputational information (standardized scores in reputation systems and contextualized discussion in forums) support bottom-up and top-down social control in online marketplaces. Applying this framework to online markets for illegal goods (cryptomarkets) allows us to

systematically evaluate suggestions from qualitative literature that traders and market administrators rely not only on reputation systems but also on rich informal forum discussions to overcome information asymmetries (Bakken et al. 2018; Bancroft 2020; Holtkamp et al. 2025; Lorenzo-Dus and Di Cristofaro 2018; Moeller et al. 2017a; Morselli et al. 2017; Munksgaard 2024; Norbutas 2020; Tzanetakis 2018; Tzanetakis et al. 2016).

Using data from two large cryptomarkets—Silk Road and AlphaBay—we integrate information on market transactions, sellers' formal ratings, and textual discussions in affiliated marketplace forums. We construct measures of contextualized seller reputation in community forums with the help of manual coding combined with transformer language models, and, alongside with standardized reputation scores, evaluate how they support bottom-up and top-down social control in cryptomarkets.

First, we evaluate whether community discussions support buyers' trading decisions and affect sellers' pricing and market exit behaviors. We find that, controlling for formal reputation, unobserved seller heterogeneity, and time trends, sellers' sales and average revenues are positively associated with increases in the number of positive forum posts they are mentioned in. In AlphaBay, negative discussions about sellers are also associated with lower sales, providing evidence for our hypothesis that buyers draw on positive and negative reputation in forums when choosing sellers, thereby enforcing informal social control. We find further evidence of informal control relying on forum mentions, as a higher number of negative forum mentions is associated with higher odds of market exit in both markets; a higher number of positive mentions is also associated with lower risk of exiting the market in AlphaBay. Our evidence on the importance of informal communication is qualitatively consistent across different outcomes of interest in both markets, though the statistical significance of effects is more volatile in Silk Road. As the main features of reputation systems and online forums in both markets were comparable, this volatility is likely attributable to reduced power stemming from the substantially smaller size of the Silk Road dataset.

Second, we evaluate the role of standardized and contextualized reputational information in supporting top-down social control in AlphaBay, the market in which we knew which sellers were forcefully excluded from the market. We find a significant association between both positive and nonpositive ratings in reputation systems and the likelihood of market exclusion. Sellers with more negative forum mentions had a higher, and those with more positive mentions a lower hazard of being forcefully excluded from the market. These results suggest that, similar to bodies of governmental control, cryptomarket administrators rely on "citizen" cooperation when it comes to detection and sanctioning of deviant behaviors (Bergemann 2017; Bergemann 2024; Black 1970; Carr 1993; Headworth 2019). Additionally, testing our exploratory proposition reveals that tenure moderates the relative importance of the two modes of reputational learning: experienced sellers with longer market tenures become more "immune" to negative feedback in reputation systems over time, but much less so to negative information shared in the forums. This relation shows in bottom-up social control and is even more pronounced for top-down control. In short, even though good reputation can buffer veteran sellers against negative

ratings, forum discussions remain an effective channel for flagging their fraudulent behaviors to buyers and market administrators alike. These findings suggest a substitution dynamic worthy of further theoretical development and confirmatory testing.

Whereas past research would suggest that informal communication is entirely supplanted by quantitative ratings in mature, large-scale online marketplaces (Diekmann and Przepiorka 2019; Duxbury and Haynie 2021; Tadelis 2016), we find, on the contrary, that informal communication in forums not only persists in cryptomarkets, but, in fact, plays two important roles. First, forum discussions of seller quality reinforce bottom-up and top-down governance by providing additional reputational information alongside that supplied by reputation systems. Second, they play a crucial role in overcoming the structural limitations that make reputation scores susceptible to lucrative fraud schemes by tenured sellers (Moeller et al. 2017a). Precisely because it cannot be quantified into a single average score, up-to-date reputational information in marketplace forums draws the attention of experienced buyers and market administrators to recent fraudulent behavior not yet reflected in reputation scores.

Our work, thus, adds to still rather scarce research on mechanisms beyond reputation scores that support trust in online marketplaces (for illegal goods), including action by market administrators (Dupont et al. 2016; Moeller et al. 2017a), payment protection systems (Andrei et al. 2024; Tzanetakakis et al. 2016), and traders' own experiences and shared purchase histories (Duxbury and Haynie 2023; Duxbury and Haynie 2021; Norbutas et al. 2020a). As such, our work also highlights how online market participants and administrators jointly govern the "virtual commons" (Kollock and Smith 1996), combining different technological solutions to support both bottom-up and top-down social control (Andrei et al. 2024; Duxbury and Haynie 2021; Macanovic and Przepiorka 2024; Morselli et al. 2017; Norbutas et al. 2020a; Norbutas et al. 2020b; Przepiorka et al. 2017). More broadly, our findings illustrate a general relationship between technologically mediated formal and informal modes of reputational learning: not only do the two complement each other, but informal learning proves crucial for establishing trust precisely when technologically sophisticated reputation systems fail.

Because our main goal was establishing whether informal information exchange supports market governance, we emphasized the similarities in the design of core market features across the two markets rather than some of the more nuanced differences between them. Although Silk Road's and AlphaBay's reputation systems and forums operated in comparable ways, they were not identical. For instance, unlike Silk Road, AlphaBay displayed, on some pages, seller feedback both overall and broken down by the last 1, 6, and 12 months, and provided additional measures such as "vendor levels" which combined reputation scores and sales volumes and "trust levels" which measured market participants vouching for or against a seller. The two markets also followed somewhat different trajectories. Silk Road began with a tight-knit forum community (Maddox et al. 2016) and pioneered foundational features of cryptomarket design; as it grew, professionalized, and adjusted its reputation systems, the importance of reputation scores relative to forum communication may have changed (Duxbury and Haynie 2021). AlphaBay followed in Silk

Road's footsteps but grew far larger, became more professionalized, and featured additional trustworthiness measures. Either the market design differences or the size and culture differences—or both—could explain part of the gap in the size and statistical significance of the effects we find across the two marketplaces. By tracing how the demand for informal reputational information varies with reputation system design and market evolution, further research could shed light on the broader processes of governance in community-based online markets. Methodologically, future research could further rely on recent advances in text analysis to offer an even more nuanced overview of reputational information generated in rich forum discussions compared to just quantifying the tone of a forum post as a whole.

Notes

- 1 As cryptomarket administrators facilitate activities that are often illegal as defined by national and international laws, they present a different body of control compared to conventional governmental control bodies enforcing legal sanctions. However, within these markets, administrators indeed function as a legitimate governing body authorized to sanction market rule violations (Matzat 2009).
- 2 Another common form of fraud in cryptomarkets is the “exit scam,” in which reputable sellers collect advance payments and then disappear from the market without fulfilling orders (Moeller et al. 2017a). Exit scams resemble selective scams in that they are most often carried out by tenured sellers who exploit high reputations to request upfront payment, bypassing the marketplace escrow system that releases funds to the seller only after the buyer confirms delivery. In principle, forums could help warn buyers and administrators of impending exit scams before reputation systems reflect seller's recent behavior. In practice, however, unlike selective scams that exploit reputation systems' weaknesses over longer periods, exit scams occur abruptly and conclude within days and are, thus, largely undetectable before the seller leaves the market on their own. For this reason, we do not discuss them further here. Still, it is worth noting that forums appeared informative about exit scams, particularly in advising buyers how to avoid them—for instance, by always using escrow and steering clear of product offers with features common to past exit scams (also see Moeller et al. (2017a)).
- 3 In Appendix A in the online supplement, we discuss data coverage in detail.
- 4 In Appendix B in the online supplement, we discuss our sampling strategy. Each post was independently coded by three coders. Our coders achieve satisfactory level of intercoder agreement—with a Krippendorff's alpha of 0.75 (Krippendorff 2004).
- 5 In Silk Road, feedback was mandatory for transaction completion. Even if the buyer did not actively leave feedback, the marketplace would automatically assign a 5-star rating after a certain time has elapsed, and the seller has confirmed having sent the item. This is why our estimations of sales and average prices charged are likely very accurate (Christin 2013). In AlphaBay, feedback was not mandatory and our estimations rely only on sales which buyers voluntarily provided feedback on. In Appendix A in the online supplement, we provide some information about our estimates of feedback rates in AlphaBay. In our analyses, we assume that there were no systematic patterns in feedback giving in this market. This assumption can potentially be problematic in panel analyses that evaluate sales and revenues; however, we can compare our results qualitatively to those from Silk Road, where we have reliable sales and revenue information.

- 6 Because neutral quantitative ratings resemble negative ones more closely than positive ones (Przepiorka et al. 2017), we split seller ratings into “positive” and “nonpositive.” In Silk Road, we consider ratings of 5 as positive, and all others (4–1) as nonpositive. In AlphaBay, we consider “positive” ratings as positive, and “neutral” and “negative” ones as nonpositive.
- 7 We exclude posts mentioning multiple sellers. As our approach captures a post’s overall tone, it cannot isolate the tone with which individual sellers were discussed within a single post. We also exclude posts written by the sellers themselves.
- 8 In Table C2 in the Appendix C of the online supplement, we relax this assumption and discuss models with total mentions of a seller up to the preceding week.
- 9 In Table C3 in the Appendix C of the online supplement, we also control for seller’s total mentions, excluding last week’s ones (which are included in the model as main covariates of interest). Sellers mentioned more frequently over their lifetimes could be more salient for buyers who are active on the forum and might therefore be more popular. Our main results remain robust to the inclusion of this additional control variable.
- 10 We show the results with other exit cutoffs in the Appendix D in the online supplement.
- 11 We consider that a seller has entered the market when they have posted their first item or, if this information is unavailable (for instance, because the item was later deleted) received their first feedback.
- 12 We have transaction data of 1,017 sellers; we exclude data of 234 sellers. Of those, for 201 we could not link their usernames to their encrypted counterparts in the transaction data—and thus, to their formalized reputations. If we recalculate the share of mentioned sellers including these 201 sellers, we arrive at 59.3 percent.
- 13 Since we can distinguish voluntary market exit from market exclusion in AlphaBay, in Model 6 we only analyze sellers who were not forcibly banned by the administrators.
- 14 There are several tenure points at which we see sellers exit the market in large numbers in our data. We use these as cutoffs in the survival models, estimating separate coefficients at different tenure stages. For Silk Road (AlphaBay), these cutoffs are up until week 15 (20), between weeks 15 and 19 (20–29), and after week 20 (40) of sellers’ trading in the market.

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