TRUST ON THE DARK WEB

AN ANALYSIS OF ILLEGAL ONLINE DRUG MARKETS

LUKAS NORBUTAS

TRUST ON THE DARK WEB

An analysis of illegal online drug markets

Lukas Norbutas

Manuscript committee:

Prof.dr. P.G.M. van der Heijden	Utrecht University
Prof.dr. A. Flache	University of Groningen
Prof.dr. C.C.P. Snijders	Eindhoven University
Prof.dr. W. Bernasco	Netherlands Institute for the Study of Crime and Law Enforcement NSCR / Vrije Universiteit Amsterdam
Dr. D. Décary-Héту	Université de Montréal

This dissertation was supported by the Netherlands Organization for Scientific Research (NWO) Talent Grant [grant number: 406-15-106].

ISBN: 978-94-6375-750-8
Cover & Layout: Marilou Maes, persoonlijkproefschrift.nl
Printing: Ridderprint BV | www.ridderprint.nl

© 2020 Lukas Norbutas

All rights reserved. No part of this publication may be reproduced or transmitted in any form or by any means, electronic or mechanical, including photocopy, recording, or any information storage or retrieval system, without permission in writing from the author. The copyright of the articles that have been accepted for publication or that already have been published, has been transferred to the respective journals.

TRUST ON THE DARK WEB

An analysis of illegal online drug markets

VERTROUWEN OP HET DARK WEB

Een analyse van illegale drugsmarkten

(met een samenvatting in het Nederlands)

Proefschrift

ter verkrijging van de graad van doctor aan de
Universiteit Utrecht op gezag van de rector magnificus,
prof.dr. H.R.B.M. Kummeling, ingevolge het besluit van het
college voor promoties in het openbaar te verdedigen op
vrijdag 6 maart 2020 des middags te 2.30 uur

door

Lukas Norbutas

geboren op 19 oktober 1990
te Kaunas, Litouwen

Promotor: Prof. dr. S. Ruiter

Copromotor: Dr. R. Corten

CONTENTS

Chapter 1	Synthesis	9
	Introduction	10
	Theoretical framework	14
	Chapter overview and summary of findings	20
	Conclusions	26
	Limitations and future research	30
	Practical implications	32
Chapter 2	Order without law: Reputation promotes cooperation in a cryptomarket for illegal drugs	35
	Introduction	37
	Reputation in markets and the problem of embeddedness	39
	Data and Methods	43
	Results	47
	Conclusions and discussion	51
Chapter 3	Believe it when you see it: dyadic embeddedness and reputation effects on trust in cryptomarkets for illegal drugs	55
	Introduction	57
	Theory	60
	Data and methods	66
	Results	72
	Conclusions and discussion	79
Chapter 4	Reputation transferability across contexts: Maintaining cooperation among anonymous cryptomarket actors when moving between markets	83
	Introduction	85
	Theory	88
	Data and methods	94
	Results	101
	Conclusions and discussion	109
Chapter 5	“Cheap talk” signaling in full anonymity: An empirical study of seller behavior and success in a drug cryptomarket	113
	Introduction	115
	Theory	118
	Data and methods	124
	Results	130
	Conclusions and discussion	137
Chapter 6	Offline constraints in online drug marketplaces: An exploratory analysis of a cryptomarket trade network	143
	Introduction	145
	Structure of offline and online retail drug trade networks	147
	Data and methods	150
	Exponential random graph models	152
	Descriptive results	153
	ERGM results for geographic clustering patterns	161
	Conclusions and discussion	165

APPENDIX 1. Supplementary material for Chapter 2	170
APPENDIX 2. Supplementary material for Chapter 4	174
APPENDIX 3. Additional analysis for Chapter 4	177
NEDERLANDSE SAMENVATTING (Summary in Dutch)	179
REFERENCES	191
ACKNOWLEDGEMENTS	207
CURRICULUM VITAE	211
ICS DISSERTATION SERIES	215

List of figures

Figure 1.1. A screenshot of the Abraxas cryptomarket Home screen.	11
Figure 1.2. Trust game.	15
Figure 2.1. The changes in item price and selling speed due to changes in the number of 5-star and non-5-star ratings of a seller.	50
Figure 3.1. Structure of the dataset used in the analyses.	68
Figure 3.2. Cumulative distribution of buyers' repeated exchanges in the marketplace.	72
Figure 3.3. Estimated odds ratios by different operationalizations of negative ratings.	76
Figure 3.4. Estimated interaction effects by different operationalizations of negative ratings.	77
Figure 3.5. Cox proportional hazards model of buyer leaving the marketplace based on having negative experience with at least 1 seller.	78
Figure 4.1. Seller migration patterns between cryptomarkets. Cryptomarket lifetimes and seller account statistics.	102
Figure 4.2. The number of daily new seller accounts and number of feedback messages in AlphaBay.	103
Figure 4.3. The main results of logistic regression models of seller properties on odds of migrating to a new market with the same identity.	105
Figure 4.4. The main results of multi-level negative binomial regression models on weekly number of sales.	106
Figure 4.5. The main results of multi-level random-intercept multinomial logistic regression models of buyer migration history on migration-based seller selection.	108
Figure 5.1. Sellers' forum posting activity by forum section before and after market entrance	130
Figure 5.2. Term frequency of thread names that sellers participated in, by forum section.	131
Figure 5.3. Distribution of total volume of sales (in USD) by drug category. Number of items in parentheses.	132
Figure 6.1. An example of buyer-seller 2-star structures used in the ERG models.	153
Figure 6.2. Number of buyers, sellers and drug items over time. Cumulative distribution of unweighted degree (number of individual contacts) by market user type.	153
Figure 6.3. Distribution of number and volume of purchases among drug buyers in Abraxas.	159
Figure 6.4. Network of market trades between drug buyers and sellers. The same network of drug buyers and sellers.	159

List of tables

Table 2.1.	Descriptive statistics of the main variables used in our analyses	46
Table 2.2.	Regression models of item price and sales per day with seller fixed effects	49
Table 3.1.	Variables used in the regression models	70
Table 3.2.	Conditional fixed-effects logistic regression models. Buyers' choices of sellers.	74
Table 4.1.	Descriptive statistics of variables used in the analyses	98
Table 5.1.	Descriptive statistics of variables used in the analysis	129
Table 5.2.	Hybrid (Between-Within) effects negative binomial regression model for item's number of sales	133
Table 5.3.	Fixed-effects linear regression model for item's price	134
Table 5.4.	Hybrid (Between-Within) negative binomial regression models for market section and discussion section forum post counts	135
Table 5.5.	Cox proportional hazard model on weeks until the last week of seller's activity	136
Table 6.1.	Market item and transaction statistics by drug category in Abraxas.	156
Table 6.2.	Recoding scheme of Abraxas' sellers' locations.	160
Table 6.3.	Descriptive statistics of variables used in the ERG model.	161
Table 6.4.	ERG model estimates – likelihood of geographically homogenous (diagonal) and heterogenous buyers 2-stars	162

1

Synthesis

INTRODUCTION

Bob was nervously scrolling up and down the webpage, hesitating to hit the “Send” button. It was the first time he was buying ecstasy pills online and not from his acquaintance. His friends had told him about a website on the Dark Web, where hundreds of sellers were selling all sorts of drugs, most of which he had never even heard of. Getting to the website was not the difficult part – he googled “TOR”, downloaded the browser and used the link his friends had given him. He registered an account, bought some bitcoins online with his credit card and sent them to his marketplace account. Allegedly, that was all he needed to become anonymous on the Dark Web and be safe when buying something illegal.

The difficult part was clicking the button. The website seemed legitimate and professional, identical to those Bob had used all the time for ordering food or buying clothes. *Party_Alice*, the seller who offered ecstasy for a good price had several positive reviews from previous buyers. But it still seemed like a huge risk – who knows who *Party_Alice* really is? The website stated she lived a thousand kilometers away, but that might as well have been a lie. What if she decides to disappear with the money? What if the pills are fake, or too strong, or different from those he knew? What if she decides to blackmail Bob? She would have Bob’s address. What if the police find the pills in the postal package and track them down to his home? Maybe this was not a great idea after all.

After a significant time of browsing through users’ messages in the website’s discussion forum and reading through *Party_Alice*’s posts, Bob decided to take a leap of faith and finalize the order. Four days later an opened business envelope and a small vacuum sealed bag with pills laid on his bed.

Bob is one of thousands of users who go through the same or similar considerations while buying drugs on the Dark Web. Illegal online marketplaces, or cryptomarkets, are websites hosted on the “hidden” part of the Internet. They cannot be found by regular search engines like Google, Bing or Yandex, and can only be accessed using a specialized Internet browser called TOR (Barratt and Aldridge, 2016). This browser is specifically made to fully anonymize its users, concealing their offline location by routing signals through a chain of intermediary computer nodes all around the world. Websites hosted on this network also benefit from the same degree of anonymity – physical servers where these websites are hosted are equally difficult to find. Originally created by the United States Naval Research Laboratory for protecting intelligence communications, today the network is used for various purposes, including secure communication with whistleblowers, hosting radical political discussions and, most commonly, for trading illegal goods (Owen and Savage, 2016).

Cryptomarkets are market platforms hosted on the TOR network, designed primarily as spaces for individual buyers and sellers to exchange illegal substances (Martin, 2014; Barratt and Aldridge, 2016). The full anonymity provided by the network allows users to exchange goods and services relatively safely without getting exposed to law enforcement. Cryptomarket websites usually look very similar to typical online stores, such as eBay or Amazon (see Figure 1.1). Sellers list the items they are willing to sell with pictures and additional information, such as the weight and price. Buyers select the item they would like to purchase and contact the seller. The financial part of the exchange is done in cryptocurrency, such as Bitcoin or Monero, which also conceal the identity of the sender and the receiver (Christin 2013, Nakamoto, 2008). The final stage of the exchange is the physical delivery of the ordered drug to the buyer, which is usually carried out using some form of concealed package (e.g., vacuum-sealed envelopes) sent via regular mail delivery systems or courier services.

Figure 1.1. A screenshot of the Abraxas cryptomarket Home screen.

While full anonymity is the main reason why cryptomarkets have been able to operate without getting completely shut down by national authorities, it also creates uncertainty and various risks that cryptomarket users must face, just like Bob did in the introductory story. Buyers cannot be certain that the drug they ordered will be of the same quality as advertised by the seller. Product quality uncertainty is especially relevant given the potential harm of some of the substances, including the risk of overdosing¹. In some cases, buyers also cannot be sure that the seller will ship the goods after receiving the money in the first place. After all, anonymous sellers have

1 For example, multiple deaths due to overdose have been reported after a batch of pills containing a toxic compound have been sold as MDMA (e.g.: <https://www.theguardian.com/society/2015/jan/02/fourth-death-linked-superman-ecstasy>)

a monetary incentive to trick a customer, especially since contracts are not secured by the law. On the other hand, sellers might get abused by opportunistic customers who claim to have never received a good. Both buyers and sellers might attempt to blackmail, threatening to deanonymize the other party or spread false information about a good (Moeller *et al.*, 2017).

Despite the high uncertainty and various risks, the popularity of cryptomarkets has grown tremendously during the last 8 years. The first cryptomarket, Silk Road, was founded in early 2011. By 2013, the marketplace had grown to account for an estimated \$300,000 in volume of drugs exchanged per day (Soska and Christin, 2015). During most of its time, Silk Road was the only large cryptomarket website on the Dark Web. After Silk Road's shutdown and the arrest of its founder in late 2013, multiple new cryptomarkets took its place. Although large-scale comparative data on different platforms over time are scarce, Soska and Christin (2015) found that already in 2014 there were at least 5 platforms that had the same volume of exchanges per day or larger, while more than 60 cryptomarkets were opened between 2013 and 2015 (Branwen, 2019). The number of unique seller identities has grown from around 600 during the time of Silk Road, to almost 10,000 by the end of 2014. While there are no good estimates of the number of cryptomarket buyers, the Global Drug Survey 2017 reports that around 9% of drug users that participated in the global survey in 2016 reported ever buying drugs on the Dark Web, while 7% reported making a purchase during the previous year (Winstock *et al.*, 2017).

Cryptomarkets pose an important puzzle that motivates this study – how can we explain the rapid growth and popularity of cryptomarkets, given all the uncertainty and risks that are embedded in this environment? How do users in these marketplaces overcome trust issues and what can we learn from it? The general goal of this dissertation is therefore to understand how cryptomarket buyers and sellers come to trust each other in an environment where every user is anonymous, has an incentive to abuse other users and there is no legal safety net to rely upon when contracts are breached. More specifically, the research question of this dissertation is *what are the mechanisms that increase cooperation and trust between buyers and sellers in cryptomarkets?*

The specific aim of this dissertation is two-fold. First, we will use cryptomarkets as a testbed for social scientific theories that propose conditions under which anonymous actors are more likely to trust each other, and mechanisms that increase cooperation under uncertainty. These theories will be shortly reviewed in the remainder of this chapter.

Cryptomarkets provide a unique opportunity to test social scientific theories on interpersonal cooperation, since it is a highly risky environment with no central coordination, residing outside the legal system. Researchers of cryptomarkets get a rare chance to obtain a large amount of unobtrusive behavioral data of individuals naturally exchanging in high uncertainty. We are able to observe what social mechanisms and institutions emerge to sustain cooperation and substitute centralized legal enforcement of contracts. We might even argue that this environment is as close to studying the emergence of social order without central governance at a large scale as we can get, which is a unique chance to test the external validity of theories previously tested in laboratory settings or observational settings embedded in legal systems that provide reassurance and reduce uncertainty (e.g. legal online marketplaces).

Our second aim is to understand cryptomarkets as a phenomenon in itself. While testing theories is the core part of scientific inquiry, some chapters in this dissertation also tackle problems that are specific to trust between users in cryptomarkets and do not necessarily generalize to settings outside of the Dark Web. The number of studies focusing on various aspects of cryptomarkets have grown tremendously over the last 5 years. An interdisciplinary community of scholars have analyzed technical developments and operational security (e.g., Horton-Eddison and Di Cristofaro, 2017; Ladegaard, 2017b; van Hardeveld *et al.*, 2017; Afilipoaie and Shortis, 2018), monitored new drugs (Van Hout and Hearne, 2017; Wadsworth and Drummond, 2018), analyzed libertarian aspirations among cryptomarket users (Munksgaard and Demant, 2016; Maddox *et al.*, 2016; Sotirakopoulos, 2018; Tzanetakis, 2019), and other social dynamics, such as methods of conflict resolution (Morselli and Décary-Héту, 2017; Moeller and Munksgaard, 2017) and cooperation (Tzanetakis *et al.*, 2016; Bakken *et al.*, 2018). The current knowledge about how trust emerges in this environment is lacking a stronger theoretical backbone, which would allow to pose new questions more systematically.

This dissertation adds to this branch of interdisciplinary research a theory-driven explanation of the main factors that promote cooperation and trust in this specific context. We pose new questions based on existing social scientific theories to explain how trust emerges and develops at different levels – for example, in dyadic relations between buyers and sellers, or when anonymous actors migrate between marketplaces.

We realize the aims of this research by analyzing digital footprints of cryptomarket buyers and sellers (Décary-Héту and Aldridge, 2015), aggregated in large collections of cryptomarket website copies by other researchers (Christin, 2013; Branwen, 2019) and also specifically collected for this study. Cryptomarket websites contain traces of users' activity, such as item information, time-stamped buyer feedback messages left

for sellers, conversations in discussion forums and other information. These data allow to reconstruct users' actions over time on a large scale and operationalize concepts necessary for this study, such as who bought from whom and when, what was the reputation of each seller at any given point in time, or how likely Bob is to return to *Party_Alice* after his trust is abused. While this approach of data collection is relatively novel and provides great opportunities to obtain large amounts of behavioral data to study social problems, it also comes with specific challenges, which will be discussed in each chapter of this dissertation.

THEORETICAL FRAMEWORK

The trust problem

Trust between individuals has been studied in different strands of social scientific research, which has resulted in a wide variety of definitions. The concept has been defined with a focus on psychological elements (e.g., Robinson, 1996), such as individual's subjective expectations or beliefs about another individual's favorable actions on the one hand, and rational cost-benefit calculations on the other (Arrow, 1974; Dasgupta, 1988; Coleman, 1990). A unifying aspect in this diverse spectrum of definitions is the notion that an actor is dependent on the future decision of another individual and, therefore, faces a risk.

Coleman (1990) defined the core elements of a trust situation that can be applied to market exchanges. Trust implies that a person (the *trustor*) puts some amount of resources at the disposal of another person (the *trustee*), who can then abuse or honor that trust. This first element implies that the trustee can only make a decision if the trustor places trust. The trustor would only prefer to place trust if the trustee returns the favor but would not do so if it was known that the trustee will abuse it. Finally, there is no formal commitment of the trustee to honor the trustor's trust, and their decisions are sequential (i.e. the trustee makes a decision after the trustor's decision is made).

What follows from this definition of a trust situation is that trust is an actor's decision to put some of his resources at risk to the benefit of another actor, in expectation that trust will be returned, and the focal actor will be better off. Coleman argued that this decision will be based on the trustor's assessment of the trustee's trustworthiness, which can be described as the subjective probability that trust will be honored, the amount of loss in case trust is abused, and benefit in case trust is honored.

Coleman's concept of trust-placing fits neatly with buyer-seller exchanges in cryptomarkets. In terms of the situation discussed in the introduction of this chapter,

we can conceptualize Bob's trust as his decision to send money to the seller *Party_Alice* knowing that she can either honor the trust by sending the product of the promised quality, or abuse Bob's trust by either sending a product of inferior quality or not sending it at all. *Party_Alice* can only make this decision if she receives the money. If Bob's trust is honored, he gets higher utility than in the case of not placing the order at all. In case of *Party_Alice*'s opportunistic behavior, the loss of money would incur Bob higher cost than in the case of not having placed an order in the first place.

A similar rational-choice based concept of trust has been used throughout game-theoretic formalizations of the trust dilemma, which shed light on the problem at the core of cryptomarket exchanges. The Trust Game (Dasgupta, 1988; Kreps, 1990) formalizes a situation in which the trustor makes a choice between trusting and not trusting, followed by trustee's decision to either honor or abuse this trust. If the trustor chooses to trust and the trustee abuses trust, the trustee gets the highest possible number of points (T_2), while the trustor gets the lowest possible number of points (S_1). If the trustor chooses to trust and the trustee honors that trust, the trustee gets the reward R_2 , which is lower than T_2 , while the trustor gets R_1 , which is higher than S_1 . If the trustor chooses not to trust, the trustee can make no decision, and gets the reward P_2 , which is lower than both R_2 and T_2 , while the trustor gets P_1 , which is lower than the reward R_1 in the case of honored trust, but higher than S_1 , in the case of abused trust. The structure of this game is visualized in Figure 1.2.

$$S_1 < P_1 < R_1; \quad P_2 < R_2 < T_2$$

Figure 1.2. Trust game.

What follows from this formalization is that the outcome with the highest return for Bob is to place trust and have it honored by *Party_Alice*. Not trusting *Party_Alice* at all would be a better solution to trusting and having the trust abused, which is consistent with Coleman's definition. The seller, on the other hand, if only trusted by Bob, is always better off by abusing trust. The core of the problem lies in the equilibrium of the game – if we assume that Bob has information about the *Party_Alice*'s payoffs, and he is rational and self-interested, he will never make the decision of placing trust, since that would inevitably lead to the worst outcome. In other words, if there are no additional mechanisms that either increase *Party_Alice*'s benefits from honoring trust, or increase the cost of her abusing trust, Bob will never choose to trust in the first place.

This dilemma is evident in cryptomarket exchanges. Sellers typically have an incentive to cheat on buyers – they can either save on product costs by sending goods of low quality or by not sending the goods at all. Knowing that and having no information about sellers' intrinsic motives, buyers will be unlikely to buy from such sellers, and the marketplace will not be sustainable without additional mechanisms that keep sellers cooperative.

Reputation and embeddedness

The trust dilemma discussed in the previous part of this chapter has several simplifications. First and foremost, exchanges in the real world, including those in cryptomarkets, are typically not isolated encounters. In cryptomarkets, exchanges might take place repeatedly among a group of registered buyers and sellers. Buyers and sellers are embedded at the network level – they can exchange information about trustworthiness of each actor. Additionally, each actor might also be embedded dyadically – Bob and *Party_Alice* might exchange repeatedly over time, especially given that drugs are consumable goods.

The former type of embeddedness and specifically the ability of market actors to exchange information enables reputation effects. In many real-life situations our social ties or institutions can provide us with information that we might use to assess the trustworthiness of a potential exchange partner. For example, we might be less willing to lend a book to an acquaintance, who has a notorious reputation for spilling coffee on them, as reported by our friends. At a larger scale, a professional investor might be less tempted to invest in a company that has a low credit score reported by Moody's.

In large online marketplaces, including cryptomarkets, social ties and centralized reputation scoring institutions have been replaced by rating systems (Diekmann et al., 2014), where individual buyers can publicly share information about their past exchanges with specific sellers. Each seller over time accumulates a reputation,

which can be a proxy of his or her trustworthiness for potential buyers. Reputation systems incentivize sellers to honor buyers' trust by both increasing the benefits of cooperation and the costs of defection (e.g., Standifird, 2001; Resnick and Zeckhauser, 2002; Przepiorka, 2013). A good reputation attracts new buyers and allows sellers to charge a higher price for their goods, since buyers are willing to pay more for a lower risk. A bad reputation might deter buyers from trusting the seller and make him or her lower the price to compensate for it.

A substantial body of research shows that reputation also works at the dyadic level (for a review, see Buskens and Raub, 2013). Since the same buyers and sellers might exchange repeatedly, buyers have an ability to learn from seller's past actions and control his future actions by retaliating after seller's defection and choosing another seller or reciprocating and returning to the same seller in the future. While sellers might have an incentive to abuse buyer's trust in a one-shot exchange, dyadic embeddedness introduces the shadow of the future – given that a seller expects repeated interactions to take place again, he or she might be more willing to cooperate.

The effects of actors' ability to exchange reputation information and those of dyadic and network embeddedness on cooperation have been tested in laboratory settings (e.g., Buskens and Raub, 2002; Bolton, Katok and Ockenfels, 2004; Barrera and Buskens, 2009) and large-scale natural settings, such as legal online marketplaces and sharing platforms (e.g. Kollock, 1999; Snijders and Weesie, 2009; Przepiorka, 2013; ter Huurne et al., 2018). It is not self-evident, however, that these findings readily generalize to cryptomarkets. In Chapter 2 of this dissertation, we will argue that previous research has tested reputation effects under favorable conditions, namely, in online marketplace settings that are embedded in legal and financial systems that attract and back up exchanges among individuals with mostly good intentions.

While dyadic- and network-level reputation effects have been tested in laboratory settings, there has been little research in observational settings where both of these effects work simultaneously and actors have to take into account their individual history with a seller and his general reputation simultaneously. In Chapter 3, we will focus on buyers' decision-making in more detail, and analyze how trust decisions are related to the two levels of information.

In Chapter 4, we will focus on a reputation problem that is specific to cryptomarkets, namely, whether reputation effects can be transferable between cryptomarkets. Due to frequent closures of cryptomarket platforms, buyers and sellers are made to migrate between different contexts. A context-specific problem in the case of cryptomarkets is to what extent the effects tested in Chapters 2 and 3 extend beyond a single cryptomarket boundaries.

Information asymmetry and signaling

Information asymmetry between buyers and sellers is one of the central aspects of the trust problem in cryptomarkets. Buyers cannot be certain about the true quality of goods they are considering, nor the intentions of their sellers. In this case, trustworthy sellers might aim to convince buyers by producing some kind of signals that prove their trustworthiness to the buyers. On the other hand, opportunistic sellers might aim to mimic such signals, to deceive sellers into trusting them and subsequently abuse their trust.

Signaling theory uses game theoretic models to formalize such situations (Gambetta, 2009; Przepiorka and Berger, 2017). The theory argues that in order to be credible or convincing, a signal must be cheap to produce for the trustworthy actors, and costly to fake for the untrustworthy ones. Reputation, discussed earlier, might be a reliable signal of trustworthiness, since building up a good reputation takes time, effort and capital required to purchase inventory. Verbal communication with buyers, on the other hand, can be considered a “cheap” signal, since it is easy to produce for both trustworthy and untrustworthy sellers. On the other hand, empirical studies of the effect of face-to-face or written communication among actors in social dilemma situations, show that it might have a positive effect on trust and cooperation.

In Chapter 5, we argue that sellers’ communication with buyers in cryptomarket discussion forums might act as a signal of other-regarding preferences, which in turn increases buyers’ trust. We also test whether such signals are used by sellers as a substitute for lacking or damaged reputation – cases when “cheap talk” might be trustworthy sellers’ only recourse. It is worth noting that Chapter 5 is the only chapter where we assume actors’ other-regarding preferences. In all other chapters we derive our hypotheses based on an assumption of purely self-interested actors. We relax this assumption in order to explore the online community aspects of cryptomarkets and analyze non-market related conditions, under which sellers are more likely to engage in discussions with other community members.

Uncertainty and macro-level exchange network structure

The network structure of offline (i.e., street) retail drug trade networks is heavily shaped by trust considerations. Due to risks related to violence and threat of the law enforcement, drug sellers offline often screen potential customers and incentivize loyal ones (Chalmers & Bradford, 2013; Jacques et al., 2014). The geographic area of retail drug sellers offline is often limited to minimize additional exposure to the law enforcement and avoid violence by competitors (Reuter, 1983). The information about trustworthiness of sellers and quality of their goods is scarce, which makes it costly for buyers to look for market alternatives (Galenianos *et al.*, 2012). As a result, the

structure of these networks can be described as “closed” or “overembedded” (May & Hough, 2004; Uzzi, 1997).

Online drug markets, on the other hand, minimize many of the uncertainties faced by offline retail market actors. The risk of violence is minimized by the absence of face-to-face contact between marketplace users. To encourage trust and cooperation between buyers and sellers, marketplaces aim to minimize the level of uncertainty for these actors by introducing various mechanisms, such as reputation systems, that help users assess potential costs and benefits of potential exchanges (Beckert and Wehinger, 2012). Online buyers do not suffer from large search costs for alternatives in the market, since all options are publicly displayed in cryptomarket websites.

These aspects of cryptomarkets might lead us to expect the buyer-seller exchange network structure of cryptomarkets to be less “closed” than those offline and connect buyers and sellers of drugs globally (Décary-Héту et al., 2016). On the other hand, there are also cryptomarket-specific risks that might shape choices of buyers and sellers and, in turn, the macro-level network structure of the markets. The shipping stage of cryptomarket transactions, when packages are sent to buyers via the postal system, has been identified by users as the riskiest part of the process in terms of the likelihood of getting exposed to the law enforcement (Aldridge and Askew, 2017). This is especially applicable to international orders, where most interceptions have been found to take place (Décary-Héту et al., 2016). These orders also lead to a longer shipping time and make buyers more likely to choose domestic sellers.

As a result, the network structure of online drug trade might be shaped by multiple sources of risk and uncertainty that actors face. Although cryptomarkets reduce uncertainty and provide buyers with access to drug supply globally, actors need to balance potential market benefits with possible threats. In Chapter 6, we study the structure of a complete cryptomarket buyer-seller network and analyze whether cryptomarkets’ capability to globalize retail drug trade might be limited by various risks and limitations imposed by the illegal nature of exchanges and offline constraints, such as long shipping time.

CHAPTER OVERVIEW AND SUMMARY OF FINDINGS

In the remaining part of Chapter 1, we will present a short overview of the empirical chapters of this dissertation and a summary of their findings.²

Chapter 2. Order without Law: Reputation Promotes Cooperation in a Crypto-market for Illegal Drugs

Reputation, or ability of individuals to share information about others' trustworthiness, has been identified as one of the main mechanisms that enables trust and cooperation in anonymous, highly uncertain environments. Multiple studies suggest that reputation systems in large online marketplaces successfully substitute for the lack of users' embeddedness in social networks' and creates sufficient incentives for cooperative behavior (Diekmann *et al.*, 2014). Buyers tend to select well-reputed sellers and agree to pay higher prices, which compensate sellers for good conduct and create incentives to remain cooperative in the future.

We argue that previous findings related to reputation effects have been established under favorable conditions. Most observational studies have been conducted in legal online marketplaces, which are embedded in legal systems. The threat of law enforcement creates additional costs of sellers' opportunistic behavior and might deter the most untrustworthy sellers from entering the market. Online markets can be made accountable for sellers' misconducts and typically cooperate with law enforcement agencies in monitoring and sanctioning users. Finally, embeddedness in the banking system creates various insurances for buyers, such as in the case of using credit cards. As a result, buyers might have a strong *a priori* inclination to trust and sellers who choose to enter the market might be a self-selected sample of mostly law-abiding individuals. Therefore, reputation may merely function as a coordination system that helps buyers sort sellers by quality.

In this chapter, we study reputation effects on trust in Silk Road, an illegal online drug market on the Dark Web, not embedded in any legal or banking systems. We use longitudinal data on 3,153 drug items sold by 445 sellers and study how sellers' reputation, as reported by previous buyers, affects subsequent sales and price of their goods.

We find that reputation affects the behavior of both buyers and sellers. Sellers adjust their prices in accordance with their reputation – sellers increase the prices of their

2 The chapters of this dissertation have been written as individual manuscripts, which have either been published or submitted to scientific journals. This might result in some overlap (e.g., introducing crypto-markets and the trust problem) and/or stylistic inconsistencies (e.g. table/figure notes and formatting) that could not be avoided.

goods as their reputation increases, which compensates for the costs of building a good reputation. Sellers with worse reputation decrease their prices, which compensates buyers for the risk they incur when buying from an ill-reputed seller. Sellers with good reputation also sell more goods during the same amount of time, which shows that buyers tend to choose based on seller's reputation, which might gradually push untrustworthy sellers out of the market. Finally, we find that negative ratings have a larger absolute effect than positive ratings on sellers' market outcomes, which is in line with the negative asymmetry effect found in previous studies.

We conclude that reputation systems create real economic incentives for actors to cooperate, even in the absence of any centralized authority or social embeddedness. Reputation systems are therefore an important organizational assurance that protect online traders from opportunistic behavior by their peers.

Chapter 3. Believe it when you see it: dyadic embeddedness and reputation effects on trust in cryptomarkets for illegal drugs

In the second chapter, we found indirect evidence at the aggregate level that reputation affects buyers' decisions - they are more likely to buy from sellers with higher reputation. However, goods sold on cryptomarkets are mostly consumable drugs and exchanges between the same buyer and seller can be repeated.

This has two important implications for the reputation effect. First, any buyer can leave multiple feedback messages to the same seller, which might lead to an overestimation of reputation effects in terms of attracting new buyers. Second, the ability to exchange repeatedly creates a dyadic history of transactions, or dyadic embeddedness. On top of seller's reputation reported by other buyers, a focal buyer now has information from their own history of transactions, which they can use to evaluate seller's trustworthiness in the future.

Information from these two sources about a seller might complement or contradict each other. Previous studies from laboratory experiments show that both reputation information from other users and dyadic history of transactions affect buyers' decisions whom to trust in the future. When both effects are studied simultaneously, however, the results are not consistent. Studies outside laboratory settings typically focus on sellers' sales (see also Chapter 2), and not buyers' decisions, making it difficult to disentangle these two effects.

In this chapter, we analyze how buyers choose whom to trust, taking into account individual dyadic histories of exchanges with each seller, and each seller's overall reputation in the market. Theoretically, we aim to understand how dyadic and network

learning effects influence buyers' decisions, when analyzed simultaneously at the buyer level.

We reconstruct seller alternatives (i.e. choice sets) that each buyer had at the time of making each purchase and analyze whether and to what extent individual history of exchanges and overall reputation of each seller-alternative affect the likelihood that the buyer chooses the seller from all the alternatives. We analyze 10,234 choice sets (i.e. exchanges) between 282 sellers and 3,192 buyers of illegal drugs in a cryptomarket Abraxas, and we use a seller choice model to test the hypotheses.

We find that dyadic embeddedness effects on trust are much stronger than those of reputation information from other buyers. Buyers tend to repeatedly select sellers they already exchanged with, despite having cheaper or better reputed alternatives in the market. In turn, this creates strong dyadic embeddedness in the market, where buyers mostly exchange with a single or few sellers.

Sellers' general reputation significantly affects buyers' decisions, especially during the first exchange after buyer's market entry, when they do not yet have an individual history of exchanges with any seller. After the first exchange, however, reputation effects at the network level become weaker, and dyadic embeddedness becomes the primary driver of future decisions.

We do not find the expected retaliation effects within dyads after abused trust. Instead, we find that buyers tend to choose the exit option and leave the market, instead of choosing another seller.

Finally, although buyers do not retaliate themselves, their reported negative experiences have a detrimental effect on other buyers' trust in that seller. We find that buyers who already have a history of trust with a seller are less likely to choose that seller again, the more negative rating the seller has.

We conclude that reputation in cryptomarkets works primarily at the dyadic level, although sellers' overall reputation affects buyers' decisions as well. Strong dyadic embeddedness between buyers and sellers is an important mechanism that helps in sustaining trust and might overshadow the effect of network embeddedness

Chapter 4. Reputation transferability across contexts: Maintaining cooperation among anonymous cryptomarket actors when moving between markets

Reputation effects in previous chapters have been analyzed under "stable" conditions. Namely, we analyzed buyers' and sellers' decisions within a single cryptomarket environment. At any given point in time during the previous 5 years, however, there have been dozens of cryptomarkets operating at the same time. Cryptomarkets

are known to get frequently shut down due to law enforcement operations, hacks, or exit scams by the marketplace administrators, who occasionally disappear with users' funds. The cryptomarket ecosystem is nevertheless resilient – multiple new cryptomarkets typically open in the place of an old one that gets shut down, making anonymous market actors constantly migrate between contexts.

In this chapter, we analyze whether and how buyers and sellers, constantly migrating between market contexts, maintain their trust in a fully anonymous environment, where online identities are often impossible to be verified, and information about sellers' histories of reputation in previous markets might be scarce and incomplete. More specifically, we analyze transferability of reputation effects across marketplaces after users' migration and whether reputation affects buyers' decisions to migrate in the first place.

We use data from several cryptomarkets and link seller accounts using their self-provided PGP encryption keys, that are used to verify identities on the Dark Web. We use these accounts to analyze under what conditions sellers choose to migrate using the same online identity, and whether reputation information from previous markets affect their market outcomes in new marketplaces.

The results of this chapter show that sellers with high reputation and number of sales are more likely to migrate between cryptomarkets using the same online identity than sellers with a lower or no reputation and sales. History of sales and good reputation in previous contexts leads to better market outcomes for migrant sellers who maintain their online identity compared to those that enter the market with a new identity and no history. We also find that the effect of transferred reputation on seller's market sales in new contexts is of similar size to the effect of reputation that sellers accumulate in the new market. Finally, we find that migrating buyers are more likely to select migrating sellers in new contexts, which shows that dyadic embeddedness (see Chapter 3) might extend beyond a single marketplace.

We conclude that reputation transferability effects embed actors beyond the boundaries of a single cryptomarket. This effect might also extend the “shadow of the future”, further increasing the incentives of good conduct and costs of opportunism for sellers. The results also suggest that reputation transferability might contribute to a quick recovery of online drug trade after shutdowns, potentially limiting the effectiveness of law enforcement operations aimed at specific marketplaces.

Chapter 5. “Cheap talk” signaling and full anonymity: an empirical study of seller behavior and success in a drug cryptomarket

Previous chapters analyzed reputation effects in trust creation between cryptomarket buyers and sellers. Reputation is considered to be a strong signal of seller’s trustworthiness, since a high reputation score is very costly to fake by opportunistic sellers. Other signals of trustworthiness, such as sellers’ verbal communication with buyers, are easy to fake, since both truthful and opportunistic sellers can easily try to convince buyers that their intentions are good. Buyers, on the other hand, have no way to reliably check the truthfulness of sellers’ communication. Theoretically, such signals should therefore not be effective in increasing buyers’ trust and ensuring cooperation.

These conclusions stand in contrast to laboratory experiments and empirical findings from observational studies, which demonstrate that “cheap talk” does increase cooperation among actors in social dilemma situations. Previous studies on cryptomarkets also show that discussion forums are nearly universally present in cryptomarket websites, where buyers and sellers actively engage in direct communication.

In this chapter, we analyze under what conditions sellers engage in direct communication with buyers in cryptomarket discussion forums, and to what extent sellers’ discussion forum activity increases their market outcomes, net of market reputation. We expect, based on theory and previous findings, that sellers will engage in two types of communication. We expect that sellers will use market related communication with buyers (e.g., advertising) strategically, mostly upon market entry, to compensate for damaged reputation, and less frequently as their market reputation increases. In contrast, we expect some sellers to be actively engaged in non-market related discussions (e.g., harm reduction strategies of drug use) as online community members, motivated by other-regarding preferences or group identity. We argue that the latter kind of communication will not be strategically timed by sellers, as it is not driven by market profit maximization incentives.

The results of this chapter show that both forms of discussion forum activity increase sellers’ sales, controlling for their market reputation. Interestingly, sellers’ engagement in non-market related discussions is positively associated with their market sales. We argue that community discussions might create social bonds beyond thin market relations and provide market benefits for sellers active in the community.

We find some evidence of sellers’ differential use of communication - market-related messages are timed strategically, more frequently at the time of market entry and with decreasing frequency as their reputation increases, while general discussion messages are posted more uniformly over time. We do not find that sellers use communication

signals to repair damaged reputation. Resonating with our findings from Chapter 3, we find that after receiving negative ratings sellers are also more likely to exit the market instead of adjusting their behavior within the market.

Based on these findings, we suggest that communication and social embeddedness are important building blocks in creating trust between users in a market environment marked by anonymity and high uncertainty.

Chapter 6. Offline constraints in online drug marketplaces: an exploratory analysis of a cryptomarket trade network

In the final chapter we take a step back to the macro level and analyze the structure of a complete buyer-seller exchange network in a cryptomarket. Cryptomarkets have generally been discussed as global platforms for drug sales, that might revolutionize offline retail drug networks, which are highly localized and clustered. Drug sellers in cryptomarkets can offer international shipments of goods, but information on where the goods are shipped from is typically not provided. Based on sellers' listed shipping destinations, multiple studies have concluded that a significant portion of drug listings are sold internationally. These conclusions might be incorrect if goods that have an option for international shipping are only ordered by domestic buyers.

We aim to overcome the scarcity of buyer-level geographical data by analyzing the structure of a cryptomarket buyer-seller exchange network, that might indirectly reveal geographical patterns without knowing the location of buyers.

Our findings show yet another form of strong embeddedness between market actors in cryptomarkets - a very strong clustering of buyers and sellers in terms of geographical locations, namely, continental and country-level clusters. We find that buyers are more likely to buy from multiple sellers within a single country, and avoid buying from sellers in different countries, which signal a strong preference for domestic orders.

We conclude that uncertainty and risk with regards to law enforcement tracking of international shipments and shipping times fragment cryptomarkets into tight geographical clusters. As a result, uncertainty related to the illegal nature of goods might limit cryptomarkets' ability to internationalize retail drug trade much more than thought before.

CONCLUSIONS

The main research question of this dissertation was: *what are the mechanisms that increase cooperation and trust between buyers and sellers in cryptomarkets?* We aimed at testing social scientific theories explaining the conditions under which trust is more likely to emerge among anonymous actors under uncertainty. Additionally, our goal was to shed some more light on cryptomarkets as a phenomenon in itself, focusing on trust-related aspects of these venues that might be context-specific.

The first underlying theme throughout most of the findings of this dissertation is the ability of reputation systems to create incentives for cryptomarket users to cooperate. In the first four chapters, we either focused on sellers' reputation specifically or included it as a control variable to test other effects. In all four chapters we found that sellers with a good reputation are rewarded by an increase in the sales of their goods, while those with damaged reputation get punished by lower sales and often have to compensate buyers for the increased risk by lowering the prices.

The finding itself is not novel – many studies of legal online marketplaces showed that buyer ratings are important in ensuring trust and cooperation (Kollock, 1999; Dellarocas, 2003; Przepiorka, 2013; Diekmann *et al.*, 2014). What is new, however, is the finding that reputation systems are also efficient in environments outside the legal system³. The lack of legal enforcement in cryptomarkets reduces the cost of sellers' opportunistic behavior and might attract more actors with doubtful intentions. This dissertation provides robust evidence from multiple cryptomarkets, that reputation effects are an important driver of trust and cooperation between a large number of fully anonymous users, net of legal and moral assurances.

Perhaps not surprisingly, during the course of writing this dissertation, we have not come across a cryptomarket, or even a single-vendor shop that has no buyer rating system. Unfortunately, this also means that a more precise research design, such as a natural experiment where the level of cooperation is compared between a cryptomarket with and without a reputation system, is not possible at this point.

The second recurring finding throughout several chapters of the dissertation is that trust and cooperation between cryptomarket users are created and maintained via strong dyadic embeddedness. To come back to the situation of Bob and *Party_Alice* introduced in the beginning of this chapter, the findings in Chapter 3 show that *Party_Alice's* overall reputation is primarily important for Bob when he makes the

3 Although it could be argued that cryptomarket administrators act as local substitutes of centralized authority, these actors themselves are not subject to any threat of legal sanctions and cannot be held responsible for collusion with fraudulent sellers (Bancroft, 2017) or theft of buyer funds (Moeller, Munksgaard and Demant, 2017).

first purchase after entering the market. Subsequently, buyers show a strong tendency towards repeated interactions with the same seller, given that the seller reciprocates their trust. So if *Party_Alice* ships the promised goods, Bob will most probably stick with her even if cheaper vendors enter the market. When a trust relation is established within a dyad, negative feedback from other buyers about the seller only slightly decrease the buyer's likelihood to trust the seller again in the future.

Dyadic embeddedness is important with regard to trust in several ways. First, repeated exchanges enable dyadic learning and control mechanisms (Buskens and Raub, 2002). Sellers have an incentive to honor buyer's trust, knowing that otherwise the buyer might retaliate and choose another seller in the market. Buyers, repeatedly choosing the same seller, do not incur search costs related to finding a new seller. Although reputation information publicly available on all sellers in the market arguably diminishes these costs, it might still contain noise and create uncertainty for the buyer considering alternative sellers, making repeated exchanges with a trusted seller a more beneficial strategy.

In this sense, cryptomarkets resemble offline retail drug networks, which have been found to have a "closed", "overembedded" structure consisting of long-lasting dyads of repeated interactions between drug sellers and buyers (May and Hough, 2004; Beckert and Wehinger, 2013; Chalmers and Bradford, 2013; Jacques *et al.*, 2014). High search costs, the risk of violence and exposure to the police and product quality uncertainty have been argued to drive this effect in the street market. Although many of these uncertainties should arguably be alleviated by the reputation systems and lack of face-to-face contact in cryptomarkets, our results show that the online exchange structure does not resemble an open market, where buyers constantly seek the cheapest or the most well-reputed seller.

The constant risk of being exposed to the law enforcement creates an important tension between seller's willingness to preserve reputation and remain anonymous on the other. Volatility of the cryptomarket ecosystem in terms of frequent market closures creates an environment where fully anonymous actors are made to constantly migrate between contexts. Reputation cannot be transferred from market to market, unless sellers verify their online identity using encryption techniques (see Chapter 4; Broseus *et al.*, 2016; Bancroft and Reid, 2016). On the other hand, a constant online identity increases the risk of leaking small bits of sensitive information over time, potentially compromising seller's anonymity. The dilemma resembles the "efficiency/security trade-off" in criminal organizations (Morselli, Giguère and Petit, 2007), where covert actors have to balance the communicative efficiency of an organized network structure, and simultaneously ensure that the network is not vulnerable. A dense and

stable communication network is more efficient, but also easier to monitor by third parties and hence riskier. Similarly, trustworthy cryptomarket sellers would highly benefit from a stable long-term online identity that buyers associate with their past actions. However, the risk of getting exposed might outweigh these benefits and make sellers more likely to shift their identities.

Our findings show that sellers with an accumulated history of sales and good reputation are more likely to maintain their identity when moving to new markets. Migrating buyers tend to prefer these sellers to newcomers. These findings have two important implications. First, users' ability to verify their online identity enables reputation transferability between contexts. Reputation is no longer bound to a specific context, which extends the "shadow of the future" and further incentivizes sellers to cooperate, and buyers to reward sellers' cooperative behavior. Reputation transferability also arguably limits the effect of law enforcement operations targeted at a single cryptomarket – if users are able to carry over crucial reputation information to new contexts, they can continue exchanging in new cryptomarkets without increased uncertainty.

Secondly, this means that reputation cascading (Frey and van de Rijt, 2016) might become an important challenge for actors in cryptomarkets. Since buyers prefer to exchange with sellers who have a good reputation, most sales might concentrate in the hands of few successful sellers, making the entry barrier increasingly high for trustworthy newcomers. This effect is likely to be amplified in cryptomarkets when only the more successful sellers move from market to market. The long-tailed distribution of sellers' market success has been observed in every chapter of this dissertation.

Chapters 5 and 6 revealed the importance of two other forms of embeddedness for trust in cryptomarkets. We found that social embeddedness might be an important aspect in sustaining cooperation between buyers and sellers. Although actors in online markets are typically assumed not to be socially embedded (Diekmann *et al.*, 2014), which seems an even more convincing assumption in fully anonymous cryptomarkets, this might not be true. There are now multiple studies showing that buyers and sellers actively engage in various discussions, seek help and information regarding drug use, help new members or discuss political ideals (Martin, 2014; Munksgaard and Demant, 2016; Aldridge and Askew, 2017; Bancroft and Reid, 2017). We complement these findings by showing that sellers' engagement in such discussions might create a spillover effect, making buyers more willing to trust active community members in the marketplace.

Based on our findings, sellers' communication with buyers is generally a signal of trustworthiness that yields market benefits. Sellers, however, not always use it strategically to maximize revenue. It might be a fruitful theoretical approach to analyze cryptomarkets as online communities, rather than a group of actors driven solely by individual monetary motives. The rational choice theoretical approach used throughout this study is not necessarily incompatible with this assumption. The rationality assumption can be maintained, while the selfishness assumption could be modified (Buskens and Raub, 2008). Actors could be assumed to have other-regarding preferences and receive utility from engaging with other community members. More generally, the analysis of cryptomarket discussion forums might reveal social norms and hierarchies among users that could be important when analyzing trust relations in the market.

Another finding that was evident in several chapters of this dissertation is the asymmetrical impact of negative ratings. We found that exchanges that end up with buyers' dissatisfaction and negative ratings, have a larger absolute effect on sellers' market outcomes in Chapter 2. Chapter 3 showed that buyers are more likely to leave the cryptomarket after such experiences instead of retaliating against the seller and choosing another one. We argued that buyers, after getting their trust abused, might possibly look for alternatives outside of cryptomarkets. Chapter 5 showed that sellers are also more likely to leave the analyzed cryptomarket after receiving negative ratings than to engage in damage control and communicate with their buyers. It is possible that sellers re-enter the marketplace with a new alias, especially if the reputation history is short and there is little to lose. Together these findings show that abuses of trust, be they due to sellers' intentions, a lack of competence or events out of sellers' control, such as package interceptions, have a detrimental effect on future cooperation. This finding also shows that market exit is an important behavioral alternative in empirical settings, which should be incorporated into theoretical models when analyzing cooperation in empirical settings, where the cost of exit is relatively low.

Finally, in Chapter 6 we showed that risks and uncertainties that cryptomarket users face might in turn lead to macro-level structural outcomes. We found that buyer-seller exchanges are not only embedded in terms of buyer-seller dyads, but also show strong patterns of geographical embeddedness. Although theoretically cryptomarkets might be able to globalize retail drug trade by providing buyers and sellers with quick access to worldwide markets, we find that the network structure is shaped by geographical borders. Taken together with findings in Chapter 3, we can conclude that cryptomarket networks are highly structurally fragmented, similarly to "closed" offline retail drug trade networks analyzed in previous research.

LIMITATIONS AND FUTURE RESEARCH

There are several limitations that should be addressed in future research on the subject. As discussed in the introduction of this chapter, the empirical analyses of this dissertation rely on the information that is available in cryptomarket websites, collected during the study or before the study by other authors. While this approach of data collection can be considered a strength of this study, it also has several drawbacks. First, in many cases the data are “wide”, but “shallow”. In other words, the data from cryptomarket websites typically contain information about tens or hundreds of thousands of users, but provides very little information about each one of them. For example, we rarely had detailed information about cryptomarket buyers, such as their nicknames in different cryptomarkets, which would have allowed to test our hypotheses more rigorously. We also had to rely on feedback messages to operationalize exchanges between buyers and sellers, which inevitably omits those exchanges that never result in a feedback message by the buyer. Ideally, future studies could rely on data from website databases that have been seized during the law enforcement operations. Data coming from these sources are more complete, since it contains information that is not publicly displayed for the users. The data could be sufficiently anonymized and released to study fundamental social scientific problems, as we do here.

The second limitation is that the design of this study does not allow to make strong causal inference claims. We identified specific mechanisms that increase trust and cooperation between cryptomarket users using longitudinal observational designs. Where possible, we used fixed-effects models that account for unobserved heterogeneity in the data and to some extent mitigate the problems related to causal inference in observational research designs. However, in many cases, for example with regards to the role of reputation systems or discussion forums in trust creation, a stronger design could involve seeking for counterfactual cryptomarkets that have no reputation systems or discussion forums and comparing the relevant market outcomes of actors in both cases. At the time of this study, to the best of our knowledge, there were no such cases available.

Third, we did not focus on several mechanisms that are important for gaining and maintaining trust (Barratt and Aldridge, 2016; Bartlett 2014: Ch. 5; Morselli et al., 2017; Moeller et al., 2017). For example, escrow systems hold buyer’s money in a centralized cryptomarket account before he receives the good. While it does not solve product quality uncertainty, it alleviates the problem of a seller running away with the buyer’s money. However, it also shifts the risk from the seller to the cryptomarket administrators who might equally successfully disappear with all the money in the

escrow account⁴. Additionally, sellers face currency risk – cryptocurrency values are volatile and might drop quickly while it is locked in the escrow account. As a result, sellers incentivize buyers not to use escrow, especially those with good reputation (Moeller et al., 2017). This creates a tension between buyer's trust in the seller and his trust in the marketplace – a problem that is beyond the scope of this study, but remains an important problem to analyze empirically using cryptomarket data.

Another important mechanism that was not included in this study is conflict resolution and the activities of cryptomarket administrators. While administrators might not completely substitute centralized governance that legal systems embody outside of cryptomarkets, they might exert influence on cooperation between buyers and sellers by either sanctioning opportunistic sellers or awarding cooperative sellers. Theoretically, the problem could be formulated at a very fundamental level – to what extent is *some* form of governance necessary in cryptomarkets to ensure cooperation? Are poorly moderated cryptomarkets as successful as those with more involved administrators, or are the technical solutions, such as the reputation and escrow systems, sufficient preconditions for the emergence of social order?

Future studies could also build on the findings of this dissertation. For example, the strong dyadic embeddedness analyzed in Chapter 3 creates an opportunity for sellers to scam first-time buyers selectively by not sending them the ordered goods, once a sufficiently large group of loyal repeat buyers is secured. Selective scamming has been documented in cryptomarket buyers' forum messages (Munksgaard and Demant, 2017). On the other hand, the occurrence of opportunistic behavior in general, let alone selective scamming specifically, is a difficult phenomenon to measure and analyze quantitatively on a large scale. Discussion forum messages that report scamming, allegedly posted by buyers, might in fact be authored by competing sellers. Digital footprints of opportunistic behavior are scarce – there are relatively few negative feedback ratings left by buyers with comments that indicate such behavior, while identified scammers often disappear without leaving a trace on the websites. Focusing specifically on opportunistic behavior instead of cooperation could yield important insights about conditions under which the mechanisms identified in this study do not work sufficiently well.

Finally, we encourage future research to focus on the social embeddedness aspect of cryptomarket communities. Cryptomarket discussion forums are a rich source of information about social interactions between marketplace actors. The results of this study, as well as some qualitative findings in previous studies (see Chapter 5 for an

4 See, for example, the case of Evolution market that disappeared with \$12 million of user funds: <https://thehackernews.com/2015/03/evolution-drug-market-bitcoin.html>

overview) indicate that these interactions do not necessarily revolve around market-related topics. Community building might be an important building block of trust in cryptomarkets and their resilience to external shocks. While qualitative studies have already collected a lot of information about online communities in cryptomarkets (van Hout and Bingham 2013, 2014; Barratt et al., 2016b; Maddox et al., 2016; Ladegaard, 2017a; Masson and Bancroft, 2018), quantitative content analysis in future studies could reveal the relation of social and market interactions between cryptomarket users and shed more light on the creation of trust between anonymous actors in highly risky environments.

PRACTICAL IMPLICATIONS

There are several practical implications that can be derived from the findings of this study. As mentioned previously in the discussion section of this chapter, we argue that law enforcement operations aimed at closing specific cryptomarkets might result in unintended consequences that are not necessarily desirable. Our findings show that sellers, specifically the more successful ones, often migrate to new environments after market closures. Moreover, we found that these migrating sellers gain competitive advantage against new sellers in the new marketplaces. Given that new cryptomarkets typically open soon after the closure of old ones, the effectiveness of such operations should be carefully weighed against the fact that they centralize profits in the hands of few a selected group of drug sellers.

Trust problems are detrimental for market efficiency beyond cryptomarkets. We believe that there are several lessons that legal e-commerce platform owners could learn from the findings of this study. Based on the findings in Chapter 5, we could stress that e-commerce websites might benefit from introducing discussion platforms for their users, where actors can communicate directly and not necessarily on strictly platform-related topics. Social cues and signaling effects might help users build up trust, where this problem is relevant.

Online market platform owners should put all efforts to reduce the amount of noise in the reputation systems of their websites (e.g., put effort in preventing retaliation and fake reviews). We find that buyers are more inclined to repeatedly exchange with the trusted seller than to choose the cheapest seller or one with the best reputation. A possible explanation to this finding is that reputation systems might not be perceived by the buyers to have a sufficiently high signal/noise ratio. After a buyer's trust is abused by an opportunistic seller, the perceived inaccuracy of reputation systems might make buyers more likely to look for alternatives outside of the website than to look for a better seller within the marketplace.

Finally, the problem of reputation transferability studied in Chapter 4 suggests that a system for inter-platform identity verification might help buyers and sellers trust each other in different contexts. This might be an increasingly important problem in the light of the popularity of sharing platforms (e.g. ter Huurne et al., 2017), where individuals have accounts and accumulated reputations in different websites. Scattered reputation cannot be observed by users in different platforms, making it more costly to build trust between users in every new sharing or market platform. Relevant solutions for this problem could include blockchain-based developments (e.g., Ontology⁵), where each individual's identity and reputation information from different platforms are stored on the blockchain that is immutable and decentralized, allowing users to transfer and verify their reputation between contexts, introducing additional costs of opportunistic behavior and helping users build up trust quicker.

5 Ontology - <https://ont.io>

2

Order without law:

Reputation promotes cooperation in a
cryptomarket for illegal drugs

ABSTRACT

The emergence of large-scale cooperation in humans poses a major puzzle for the social and behavioral sciences. Reputation formation – individuals' ability to share information about others' deeds and misdeeds – has been found to promote cooperation. However, these findings are mostly based on small scale laboratory and field experiments or on data gathered from online markets embedded in functioning legal systems. Using a unique dataset of transactions in a cryptomarket for illegal drugs, we analyze the effect of buyers' ratings of finished transactions on sellers' business success. Cryptomarkets are online marketplaces in the so-called dark web, which can only be accessed by means of encryption software that conceals users' identities and locations. The encryption technology makes it virtually impossible for law enforcement to intervene in these market exchanges. We find that sellers with a better rating history charge higher prices and sell their merchandise faster than sellers with no or a bad rating history. Our results demonstrate how reputation creates real incentives for cooperative behavior at a large scale, in the absence of law enforcement and among anonymous actors with doubtful intentions. Our results thus challenge the institutional and social embeddedness of actors as necessary preconditions for the emergence of social order in markets.⁶

6 This chapter was co-authored by Wojtek Przepiorka and Rense Corten. A version of this chapter is published as: Przepiorka, W., Norbutas, L., and Corten, R. (2017). Order without law: Reputation promotes cooperation in a cryptomarket for illegal drugs. *European Sociological Review*, 33(6), 752-764.

INTRODUCTION

Humans' ability to overcome individual self-interest to create a larger benefit for the collective has received considerable attention in the social and behavioral sciences in the last three decades (Axelrod, 1984; Bowles and Gintis, 2011; Nowak, 2006). A simple mechanism that has been shown to promote cooperation in humans is our ability to share information about our peers' deeds and misdeeds with third parties. Such information sharing contributes to the formation of individuals' reputations (Dunbar, 2004; Feinberg, Willer and Schultz, 2014; Sommerfeld *et al.*, 2007). Individuals with a reputation to lose have a strong incentive to behave cooperatively and are therefore attractive partners in social and economic exchange (Milinski, 2016; Kollock, 1994; Shapiro, 1983; Sylwester and Roberts, 2013). More generally, it has been argued that reputational incentives provide a more efficient means to uphold norm compliance and order in society than other forms of sanctioning (Ellickson, 1991; Grimalda, Pondorfer and Tracer, 2016; Milinski, Semmann and Krambeck, 2002; Willer, 2009; Wu, Balliet and van Lange, 2016).

Throughout human history, reputation mechanisms have also facilitated mutually beneficial economic exchanges. In the absence of formal institutions protecting property rights and enforcing contractual commitments, the transfer of reputation information through dense social networks has promoted good business conduct (Hillmann, 2013). For example, Greif (1989) describes how Maghribi traders in medieval Europe organized in coalitions in which they exchanged information about their agents' reputations to reduce the trust problems arising in long-distance trade. Hillmann and Aven (2011) describe the role reputation played in the development of corporate capitalism in Russia around the turn of the nineteenth century. At that time, entrepreneurs faced the trade-off of limiting their interactions to local partners to ensure compliance and interacting with partners beyond their social networks offering more profitable but riskier businesses.

These historical examples illustrate how the lack of formal institutions promoting economic exchange are substituted by informal institutions at work in social groups in which information about actors' deeds and misdeeds is exchanged and selective incentives upheld (Nee 2005). However, there are several historical accounts of centralized reputation systems which facilitated economic exchange without requiring actors to be closely connected via a social network. Also in the early middle ages, the Champagne Fairs in France became a meeting point for traders from all over Europe. Promoted by the use of bookkeeping and cashless payment, a private adjudication system evolved that allowed tracking fraudulent traders and excluding them from future fairs (Milgrom *et al.*, 1990). In the late nineteenth century, so-called credit

bureaus started to emerge, which collected and shared information about borrowers' credit histories creating reputational incentives for timely debt repayment (Japelli and Pagano, 2002; Carruthers, 2013). These examples are prototypical for the centralized reputation systems that are today's standard for governing online market exchanges (Dellarocas, 2003; Diekmann and Przepiorka, 2019).

In online markets such as eBay, thousands of anonymous buyers and sellers trade with each other every day across large geographic distances. Via an electronic feedback system, traders can comment on each other's conduct after finished transactions with positive or negative ratings and short text messages, and these ratings constitute online traders' reputations. The advent of the internet and the emergence of online markets have created ample opportunities to study the effectiveness of reputation systems to promote cooperation among anonymous traders at a large scale (Bolton, Greiner and Ockenfels, 2013; Dellarocas, 2003; Diekmann *et al.*, 2014; Kollock, 1999; Resnick and Zeckhauser, 2002). In particular, it has been shown how electronic reputation systems create incentives for traders' cooperative behavior without requiring these traders to be embedded in social networks (Granovetter, 1992; Diekmann *et al.*, 2014). However, the working of the reputation mechanism has thus far only been established under favorable conditions. The majority of online markets are embedded in functioning legal systems attracting and backing up trades among individuals with mostly good intentions. It is thus an open question whether reputation formation net of legal and moral assurances is sufficient to promote cooperation in a large group of strangers.

Here we study the functioning of the reputation mechanism in a cryptomarket for illegal drugs. Cryptomarkets are online marketplaces in the dark web, which can only be accessed by means of encryption software that conceals users' identities and locations (Martin, 2014). Trades in cryptomarkets include forged personal documents, hacked user accounts, weapons, etc., with illegal drugs constituting the largest proportion of trades (Christin, 2013; Soska and Christin, 2015). Globally, almost 10% of drug users reported ever buying drugs from cryptomarkets (Global Drugs Survey, 2016). The encryption technology makes it virtually impossible for law enforcement to intervene. Hence, given the lack of legal deterrent, traders' good intentions are highly uncertain at best. This creates severe trust problems between buyers and sellers as it makes buyers vulnerable to sellers' fraudulent transactions (Coleman, 1990; Dasgupta, 1988). However, in the same way as online markets for licit goods, cryptomarkets use electronic reputation systems which allow buyers to rate sellers after finished transactions (Bartlett 2014; Hardy and Norgaard, 2016). This makes cryptomarkets

the ideal settings to test the potential of the reputation mechanism to bring about “order without law” (Ellickson, 1991).⁷

In the next section, we describe the reputation mechanism, previous approaches to its studying, the set-up of the cryptomarket that we study, and state our hypotheses. In the Data and Methods section, we describe the data and data gathering process, the variables we used in our analyses, and our model estimations. Thereafter we present our results, and, in the final section, we conclude with a discussion of our findings.

REPUTATION IN MARKETS AND THE PROBLEM OF EMBEDDEDNESS

Acquiring a good seller reputation in online (and offline) markets is costly because it can only be achieved through good business conduct over an extended period of time. Sellers who lack trustworthy-making properties, such as long-term business interests or honest intentions, will not bother to enter the market and build a good reputation by behaving cooperatively. Hence, based on sellers’ reputations, buyers can infer these sellers’ trustworthiness and choose the sellers they prefer to buy from. However, trustworthy sellers who enter the market and, therefore, have not yet built their reputation, are indistinguishable from their untrustworthy competitors. New, trustworthy sellers must therefore allow prices to compensate potential buyers for the risk they take when trading with “unknown” sellers. Once these sellers have built their reputations, they can charge higher prices, which will compensate them for their initial investment in reputation (Friedman and Resnick, 2001; Przepiorka, 2013; Shapiro, 1983).⁸ From this reasoning it follows that sellers with a better reputation

7 In his seminal book, “Order without Law: How Neighbors Settle Disputes,” Ellickson (1991) describes how cooperation and social order is maintained in a close-knit community of cattle farmers in Shasta County, California. In his accounts, Ellickson repeatedly emphasizes the importance of gossip and reputation for promoting cooperative behavior (e.g., p. 232): “The residents of rural Shasta County gossip all the time. Indeed, any close-knit group is likely to have procedural norms that ask members to help spread truthful information about the prior prosocial or antisocial behavior of other members. By facilitating the flow of reputational information, these norms deter future uncooperative behavior by increasing an actor’s estimates of the probability that informal enforcers would eventually catch up with him.” Although we study a “community” of anonymous traders that engage in illegal market exchanges without ever meeting each other in person, the mechanisms by which cooperation is maintained are the same albeit digitalized in form of an electronic reputation system.

8 Note that this is different from the “reputation” model put forward by Kreps et al. (1982). Kreps et al. (1982) start from the observation that in finitely repeated prisoners’ dilemma (PD) games players cooperate more than the Nash equilibrium would predict. They explain this observation by suggesting that if players assume that with a small probability their interaction partner prefers to cooperate as long as they do, it may be rational for them to cooperate as well. In other words, a self-regarding player, who would defect in the one-shot PD, mimics a cooperative type in order not to forgo the higher benefits that result from several rounds of mutual cooperation as compared to mutual defection. Only once the sequence of interactions approaches the end, it becomes beneficial to defect and thereby reveal one’s true type. Kreps and Wilson (1982) call this initial phase of mimicry “reputation effect.” In contrast, we argue that reputation can be conceived as a costly signal because it is costly to acquire, which deters untrustworthy sellers to enter the market (Przepiorka and Berger, 2017).

will achieve higher prices because buyers are willing to pay higher prices for these sellers' products.

This conjecture has been corroborated in more than two dozen studies, most of which analyze the effect of sellers' reputations on the probability of product sale and selling price using eBay auction data (for a review see, Diekmann *et al.*, 2014). Although the costliness of building a good reputation constitutes an important deterrent for fraudulent sellers, the legal system in which online markets are embedded deters fraud and promotes trust and large-scale cooperation in its own right (Bakos and Dellarocas, 2011; Beckert, 2009; Diekmann and Przepiorka 2019; Fliegstein, 2001; Güth and Ockenfels, 2003; Pavlou and Gefen, 2004). First, the legal system maintains a non-negligible threat that fraudulent business conduct will be prosecuted and punished. Second, online market platforms can be made accountable for sellers' misconduct by their community of buyers, who can easily turn to alternative platforms. As a consequence, platform providers have a strong incentive to protect buyers from fraud by, for example, monitoring sellers' activities and sanctioning bad behavior (e.g., by banning sellers). However, unlike online markets for licit goods, cryptomarkets cannot work with law enforcement to combat fraudulent behavior (Calkins *et al.*, 2008). Third, buyers are insured against fraud to a certain extent if they use credit card payment. Although such insurances do not eliminate the trust problem, they reduce the material losses buyers may expect when trading in online markets. In sum, legal assurances preselect sellers with good intentions, incentivize platform providers to enforce cooperation, and reduce the risk of large monetary losses. As a consequence, buyers will have high *a priori* expectations as to online sellers' trustworthiness (Güth and Ockenfels, 2003; Lindenberg, 2017).⁹

In the light of these considerations, it is an open question whether the reputation mechanism, as instituted in many electronic rating systems, promotes trust and cooperation in online markets net of their embeddedness in well-functioning legal systems. Backed by legal and moral assurances, reputation may function as a mere coordination device, which facilitates buyers' choices among the plethora of sellers offering the same products, rather than solving cooperation problems (Beckert, 2009; Frey and van de Rijt, 2017; Przepiorka and Aksoy, 2017). More importantly, in the absence of legal and moral assurances, reputation systems may fail to attract a critical

9 Legal systems do not completely prevent scamming behavior of online sellers, especially for transactions of small value, where potential costs of litigation become relatively high compared to potential losses for buyers. It has been estimated, based on buyer survey data, that 1-2% of transactions in eBay contain fraudulent seller behavior (Bauerly, 2009). While embeddedness of licit markets in legal systems cannot fully eradicate opportunistic behavior, it provides strong assurances for buyers, which might account for a large part of trust facilitation that has been attributed to reputation systems in previous research.

mass of traders because they may be regarded as an insufficient safeguard of mutually beneficial economic exchange.

One way to address this question is to study the functioning of the reputation mechanism in an extra-legal context, for example, as we do, in a cryptomarket for illegal goods. If we still find reputation effects even in the absence of legal and social conditions that deter opportunistic actors and promote trust, this would strongly reinforce the idea that reputation systems enable the bottom-up emergence of cooperation in large groups of self-regarding actors. We thus re-evaluate the claim from earlier research that reputation affects market outcomes of sellers in the context of cryptomarkets for illegal drugs, and derive hypotheses for our specific study context, the cryptomarket Silk Road 1.0.¹⁰

The cryptomarket Silk Road 1.0

We use data from the first cryptomarket, Silk Road 1.0 (Christin 2012), to study in how far sellers reap the benefits of a good reputation and in how far buyers take into account sellers' reputations when deciding which seller to buy from. The data were collected by crawling the Silk Road website and making daily offline copies of item and seller pages. Webpages that had already been copied were updated on each crawling session, appending the data set with new pages that had not been observed before. Silk Road 1.0 started operating in February, 2011 and was closed after its owner was arrested in October 2013 (Barratt and Aldridge, 2016). Our data contain information on all item listings that were online between February 3, 2012 and July 24, 2012, including item names and descriptions, categories, prices and item specific feedback messages. Since each item listing contains an encrypted vendor identifier, feedback can be attributed to individual sellers who were active during this period.

A typical transaction on Silk Road is initiated by the seller, who decides on the number of items and the item price of his or her product and posts the offer online. Buyers can then buy the item at the specified price as long it is available. A buyer first sends the

10 Another way to address this question is to conduct laboratory experiments, in which a basic market environment can be staged, and the main tenets of the reputation mechanism can be put to an empirical test under controlled conditions (Falk and Heckman, 2009; Greiner and Ockenfels, 2009). The effectiveness of the reputation mechanism to promote trust and cooperation in social and economic exchange has been corroborated in a number of experiments (e.g., Abraham et al., 2016; Bolton et al., 2004; Kuwabara, 2015; Yamagishi et al., 2009; although see Corten et al., 2016). However, this approach still resembles the setup of online markets for licit goods in many relevant respects. First, participants are recruited from a selective sample of mostly university students motivated to participate in experimental research. Second, although decisions in the lab are financially incentivized, the stakes are relatively low and potential losses limited to the opportunity costs of participation. Third, at the end of the day, participants are socially embedded in the environment of their universities which, in most cases, are embedded in well-functioning legal systems. In other words, actors are less likely to be blackmailed or even killed as a consequence of participating in experimental as compared to illegal markets.

money to an escrow service, which releases the money and transfers it to the seller when the buyer confirms receipt of the item. Although the escrow service mitigates the trust problem to a certain extent as it protects the buyer from spending the money without receiving anything in return, the trust problem remains with regard to the quality of the product and the competence of the seller. Buyers cannot withhold payment because of quality reasons as this would require using or testing the product. Moreover, there is more to a transaction than the money and the product. A seller's good reputation also stands for his or her professional handling of the transactions. Since buyers have to provide a postal address the seller can send the product to, buyers have to trust the seller to wrap the product inconspicuously, send it to the right address and maybe provide a refund should the product get lost on its way to the buyer (Bartlett 2014: Ch. 5).

In Silk Road 1.0, a finished transaction receives the highest rating (i.e. 5 stars) by default. Buyers can change the default rating to a 4-, 3-, 2- or 1-star rating and add a text comment. The sum of these seller ratings establishes a seller's reputation in the market. The information about a seller's reputation is conspicuously displayed and can be considered by buyers deciding which seller to buy from. We use the sum of a seller's 5-star ratings and non-5-star ratings as an indicator of this seller's reputation and keep track of sellers' rating history over time (see Data and Methods). We use item prices, which are set by the sellers, as an indicator for sellers' cashing in the premium for their good reputation or giving a discount in case of no or a bad rating history. We use the speed at which items are sold, which is determined by buyers, as an indicator for the trust buyers have in sellers with a certain rating history. Based on the theoretical argument in the first paragraph of the previous section and the setup of Silk Road 1.0 we can formulate the following four hypotheses:

H1: *The more 5-star ratings a seller has, the more he or she will charge for his or her items.*

H2: *The more non-5-star ratings a seller has, the less he or she will charge for his or her items.*

H3: *The more 5-star ratings a seller has, the more items he or she will sell per day.*

H4: *The more non-5-star ratings a seller has, the less items he or she will sell per day.*

DATA AND METHODS

Data

We use a dataset containing 24,385 items collected by Christin (2012) on Silk Road 1.0 between February 3, 2012 and July 24, 2012. To avoid bias due to unobserved item heterogeneity, we select a subset of illegal drug items for our analyses (Diekmann *et al.*, 2014). Some types of drugs (e.g., LSD) are sold in different forms (e.g., pills, powder, blotter), which vary in weight and substance concentration, making the calculation and comparability of item prices per gram more difficult. Our subset comprises 7 categories of illegal drugs: weed, hash, cocaine, ketamine, MDMA, heroin and meth. We limit our analyses to these categories because of their size in terms of the number of item listings and the comparability of items within each category. Item listings in these categories account for 24.6% (6005) of all item listings and 37.3% of all feedback messages. To this sample we add 211 items listed in the general categories “Drugs” and “Cannabis”, which we could identify as also belonging to one of the seven categories specified above. This results in a total of 6216 items.

Information on item weight is not available in a standardized form in the original dataset. Item weight information is only provided as part of the item name or item description. We extract item weight from the item name or description manually and exclude items which have no information on weight or have weight information not comparable with the majority of items in the category (e.g., pre-rolled joints of marijuana in category “weed”, where the majority of items is sold in grams of loose marijuana). At this stage we exclude 430 items. Moreover, we exclude 111 items that are given away (e.g., as “freebies”, “samples” or “lotteries”) or are included as custom listings for a specific buyer. This leaves us with 5675 items offered by 550 different sellers.

Of these 5675 items, 2522 (44.4%) received no feedback messages during the time of data collection. Since we use the number of feedback messages an item received in total as a measure for the number of item sales (see below), we have no evidence that these items generated any sales. Note that 67% of these items were online for five days or less, whereas only 11% of the items for which at least one sale was recorded were online five days or less. In other words, a large majority of the items without recorded sales were online for a relatively short time. We cannot be sure that the sellers posting these 2522 items had the intention to sell them as specified. These sellers may have offered these items but not reacted to any buyer requests or taken the items offline before completing any transactions. We therefore exclude these items from our main analyses. Our main analyses are based on 3153 items, for each of which at least one sale was recorded. These items were offered by 445 different sellers. However, in the

online supplementary material we also discuss the results of logistic regressions that are based on all 5675 items and estimate the probability that at least one sale was recorded conditional on covariates. The results of this analysis are consistent with the results reported here.

Variables and model estimations

The unit of analysis is an item offered by a seller. Our two target variables are item price per gram (in USD) and number of item sales per day. We calculate item price per gram by dividing item price by item weight. Since no direct information on the number of sales per item is available in Silk Road 1.0, we derive the number of item sales from the total number of ratings a seller received for a particular item. Since a 5-star rating is automatically awarded after a finished transaction, this approach provides an accurate estimate of the number of item sales (Décary-Héту, Paquet-Clouston and Aldridge, 2016; Soska and Christin, 2015). To obtain the number of item sales per day, we divide the number of item sales by the time in days the item was observed online.

To test our first two hypotheses, we use a regression model with the log-transformed item price per gram (in USD) as the dependent variable; to test hypotheses 3 and 4, we use a regression model with the log-transformed number of sales per day as dependent variable. Here and further, we use log-transformed variables to account for skewed distributions (see Table 2.1). In both models, we use the same explanatory and control variables with two exceptions. In our model of item price, we use the log number of total item sales as a measure for the quantity of an item initially in the seller's possession. Recall that item prices are set by the sellers. Since sellers are likely to pass on quantity discounts to their customers, the quantity of an item in the seller's possession will be negatively associated with item price. For obvious reasons, we do not use the log number of item sales as an explanatory variable in our models of sales per day, but we use log item price per gram for it will negatively affect item sales per day.

Our main explanatory variables are sellers' positive and negative reputation scores. We calculate a seller's reputation scores by summing up the number of 5-star ratings and non-5-star ratings the seller has received by the time his or her item is first listed online. Note that we aggregate the 5-star and non-5-star ratings across all items of a seller, also the items not included in our analyses. This is done to replicate the aggregated seller reputation score displayed in Silk Road 1.0 as closely as possible. We use the log number of 5-star ratings as a measure of positive seller reputation and the log number of non-5-star ratings as a measure of negative seller reputation. Five-star ratings account for 95.8% of all ratings in our sample; non-5-star ratings are given in extraordinary cases and might have negative impact on a seller's reputation irrespective of the actual number of stars.

We include several control variables in our models. To reduce the number of control variables, we pool the 7 categories of illegal drugs in three price categories: Low price (weed and hash), medium price (cocaine, ketamine and MDMA) and high price (heroin and meth). We use a set of three dummy variables to account for the three different categories with low price items as the reference category. Items in Silk Road 1.0 are offered in quantities ranging from .05 grams to 1000 grams (see Table 2.1). We use log-transformed item weight (in grams), which we expect to have a negative effect on item price because of quantity discounts offered by sellers. Item weight will also have a negative effect on the number of sales per day, because of a lower demand for bulk offers (Aldridge and Décary-Héту, 2016). We also use dummy variables for shipping locations of each item as offered by the sellers. Since sellers who ship their items internationally face additional risks (Décary-Héту *et al.*, 2016), these sellers might charge a price premium. For most sellers we have information on their country of origin and the countries and regions these sellers ship their items to. Based on this information, we distinguish between sellers who only ship domestically (i.e. within their country of origin), sellers who also ship their items abroad and sellers with unknown shipping preferences. Sellers who only ship domestically constitute the reference category. One dummy variable accounts for items of poor quality, an attribute sometimes specified in the titles of low-price items only. Finally, since the data are right-censored, we include a dummy variable to mark items that were listed online on the last two days of data collection. Table 2.1 contains the descriptive statistics of the main variables used in our analyses.

We do not have information on sellers' ratings from before the start of data collection. Since feedback messages were collected from item pages, the changes in item feedback data could be updated with each daily crawl during the collection. The items that were removed by sellers before the beginning of data collection, however, could not be observed. We therefore calculate sellers' reputations by summing up the number of 5-star ratings and non-5-star ratings these sellers receive throughout the observation period. Since we perform our data analysis at the item level, we use the sum of ratings a seller received by the time an item was first listed in the market as an indicator of the seller's reputation (also see above). In other words, our data allow us to capture the change in sellers' reputations over time; our ability to compare sellers based on their number of 5-star and non-5-star ratings is rather limited. We therefore estimate regression models with seller fixed effects (FE), which are solely based on the within-seller variation in dependent and explanatory variables (e.g., Allison, 2009). These models estimate how changes in seller's reputation, compared to seller's average reputation across all observations, affect changes in seller's item prices and number of sales.

Table 2.1. Descriptive statistics of the main variables used in our analyses.

	N	Mean	SD	Median	Min	Max
Item sales and duration online						
# item sales	3153	20.72	58.94	5	1	1501
item online in days	3153	50.44	56.17	28	0.5	382
# item sales per day	3153	0.45	0.69	0.25	0.01	10.83
Seller ratings at time item was first seen						
# 5-star ratings	3153	148.3	279.9	43	0	2615
# non-5-star ratings	3153	4.89	12.36	0	0	149
Low price products (weed, hash)						
weight in g	2297	18.15	63.57	5	0.25	1000
price in USD per g	2297	15.50	7.30	14.61	1.46	115.8
Medium price products (ketamine, MDMA, cocaine)						
weight in g	562	7.17	45.00	1	0.05	1000
price in USD per g	562	92.26	57.52	80.58	8.41	464.1
High price products (meth, heroin)						
weight in g	294	1.40	3.87	0.5	0.10	56
price in USD per g	294	217.6	140.4	173.8	33.72	992

Note: The data comprise N = 3153 items which were online for 50 days and generated 21 sales on average. Only items for which at least one transaction was recorded are considered in this analysis (see Data and Methods).

RESULTS

Table 2.2 shows the regression model estimations with seller fixed effects. In both the model of item price (M1) and the model of sales per day (M2), the coefficient estimates of the log number of 5-star ratings are positive and the coefficient estimates of the log number of non-5-star ratings are negative. The four coefficients are statistically significant providing first evidence in support of our hypotheses.

Recall from Table 2.1 that the range in the number of 5-star ratings in our data is considerably larger than the range in the number of non-5-star ratings. In what follows, we use 10-fold increases in 5-star ratings (e.g., 50 vs 500) and 3-fold increases in non-5-star ratings (e.g., 7 vs 21) to calculate the effect of sellers' rating histories on item price and selling speed.

In model M1, if the number of 5-star ratings increases by a factor 10, sellers increase the item price by $100 \times [\exp(0.029 \times \ln(10)) - 1] = 6.8\%$, and if the number of non-5-star ratings increases by a factor 3, sellers decrease the item price by $100 \times [\exp(-0.044 \times \ln(3)) - 1] = (-)4.7\%$. Based on the average selling price of a medium-price item of USD 92.26 (see Table 2.1), these changes correspond to USD 6.29 and USD -4.35, respectively. These results clearly support our first two hypotheses (H1 and H2) and show that sellers' price adjustments in response to changes in their reputation can be substantial. These results are visualized in Figure 2.1A.

The coefficients of the control variables point in the expected directions. The higher its product category and the higher its quality, the higher is the price the seller asks for the item. The negative and statistically significant coefficients of the log number of sales and item weight both indicate that sellers give quantity discounts to buyers. Although sellers who also ship their items abroad tend to charge higher prices than sellers who only ship domestically, the difference is statistically insignificant.

Setting the price of an item is a deliberate choice made by sellers. Therefore, changes in item price do not directly tell us whether buyers infer trustworthiness from sellers' reputations and act accordingly. Given sellers' reputations and item characteristics, it is mainly the buyers who determine how quickly an item sells. Selling speed thus constitutes a better measure for how sellers' reputations help buyers to overcome the trust problem.

In model M2, we find similar results in terms of item sales per day as we found in our model for item price (M1). The coefficient estimates of the log number of 5-star ratings and log number of non-5-star ratings can be interpreted as follows. If the number of 5-star ratings increases by a factor 10, item sales per day increase by $100 \times [\exp(0.060 \times \ln(10)) - 1] = 14.7\%$, and if the number of non-5-star ratings increases by a factor 3,

item sales per day decrease by $100 \times [\exp(-0.188 \times \ln(3)) - 1] = (-)18.7\%$. Based on these changes, a median seller, who sells one item in four days (see Table 2.1), would need three and a half days or five days, respectively, to sell that item. These results clearly support hypotheses H3 and H4. These results are visualized in Figure 2.1B. The control variables exhibit the same effects as in our model of item price. Unsurprisingly, item price has a significantly negative effect on the number of sales.

The effects of sellers' reputation on selling speed appear relatively small. To a large extent, this is a result of our accounting for differences in unobserved, time-constant seller characteristics in our model estimations (Allison, 2009). However, buyers choosing a seller compare offers from different sellers (Snijders and Weesie, 2009). Therefore, we also estimated ordinary least square regression models, which take between-seller variability of seller and item characteristics into account (see online supplementary material). Based on these estimations, the effects of 5-star ratings on selling speed are up to three times larger than the effects shown in Figure 2.1B, but these effects can only partly be interpreted causally.

Table 2.2. Regression models of item price and sales per day with seller fixed effects.

	Log(item price per g in USD)	Log(# item sales per day)
	M1	M2
Const.	2.974*** (0.036)	1.402*** (0.259)
<i>Item variables</i>		
Log(item price per g in USD)		-0.823*** (0.089)
Log(weight in g)	-0.208*** (0.009)	-0.502*** (0.079)
Low price	(ref.)	(ref.)
Medium price	1.506*** (0.065)	0.908*** (0.218)
High price	2.035*** (0.095)	1.271*** (0.310)
Poor quality (weed & hash)	-0.756*** (0.078)	0.190 (0.196)
Last two days	0.114*** (0.027)	0.174* (0.077)
<i>Seller variables</i>		
Log(# 5-star ratings + 1)	0.029*** (0.007)	0.060* (0.028)
Log(# non-5-star ratings + 1)	-0.044** (0.016)	-0.188*** (0.057)
Log(# item sales)	-0.035*** (0.006)	
<i>Seller ships to</i>		
unknown	-0.012 (0.064)	-0.006 (0.207)
domestic only	(ref.)	(ref.)
foreign	0.035 (0.036)	0.063 (0.130)
N_1	3153	3153
N_2	445	445
adj. R^2	0.77	0.22

Note: The table lists coefficient estimates and cluster-robust standard errors (***) $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, for two-sided tests) of fixed effects regression models. The target variable in model M1 is the log-transformed item price per g in USD. The target variable in model M2 is the log-transformed number of item sales per day. N_1 denotes the number of cases (items) and N_2 denotes the number of clusters (sellers). Both models include seller fixed effects. Figures 2.1A and 2.1B are based on model M1 and M2, respectively.

Figure 2.1. The changes in item price (A) and selling speed (B) due to changes in the number of 5-star and non-5-star ratings of a seller.

CONCLUSIONS AND DISCUSSION

We study how cooperation is established between anonymous individuals in a cryptomarket for illegal goods. We use longitudinal data on market transactions from the first major cryptomarket, called 'Silk Road', to test whether reputation formation can promote cooperation between buyers and sellers in an environment of high uncertainty and in the absence of a centralized authority. We use all available market transactions in the seven largest categories of illegal drugs to test whether high (low) buyer ratings increase (harm) sellers' market success in terms of pricing and sales. We find that sellers' rating histories are associated with changes in the behavior of both sellers and buyers. Seller item price changes are associated with the changes in their reputation. Well-reputed sellers reap market benefits by increasing prices, while sellers with lower reputations decrease their prices to compensate potential buyers for the risk they take when buying from them (Friedman and Resnick, 2001; Przepiorka, 2013; Shapiro, 1983). We also find that sellers with better reputations sell more goods over the same period of time. Although we do not observe buyers' choices of particular sellers, the higher selling speed of well-reputed sellers' items suggests that buyers choose sellers based on these sellers' rating histories. Finally, we find that negative ratings have a larger absolute effect on sellers' prices and sales than positive ratings. Negative asymmetry, or a large impact of negative information about partner's trustworthiness on withholding trust, has been observed previously in online markets and experimental settings (Bozoyan and Vogt, 2016; Standifird, 2001). Our findings suggest that in cryptomarkets too damaged reputations are hard to repair (Matzat and Snijders, 2012).

Our research contributes to the agenda of the new institutionalism in economic sociology (Beckert, 2009; Hillmann, 2013; Nee 2005) in at least two ways. First, we show that reputation formation is a robust mechanism to foster trust and cooperation in online markets net of legal assurances, verifiable identities or a positive self-selection of mostly law-abiding citizens. In online markets for licit goods, the trust problem inherent in economic exchanges is mitigated but not entirely dissolved by legal and moral assurances. Our results thus suggest that reputation systems in general could be an essential organizational assurance which, if well-designed, could protect online traders from being cheated or in other ways dissatisfied by their peers. Second, in a historical perspective, cryptomarkets constitute a next phase in the evolution of market institutions. In this study, we describe a case that illustrates how cooperative market exchanges are possible at a large scale in the absence of formal institutions established by nation states and informal institutions at work in small social groups (Nee 2005). In fact, formal and informal institutions such as legal systems and social

norms, respectively, have not disappeared, but they have lost their influence in the governing of online market exchanges (Przepiorka and Aksoy 2017).

Our findings also illustrate more generally the potential of data generated by the hidden corners of the World Wide Web for studying fundamental social processes. Since the shutdown of Silk Road 1.0, many new cryptomarkets have emerged, which have developed a wide range of institutional arrangements that promote trust between buyers and sellers, but also online traders' trust in cryptomarket platforms. Traders' trust in marketplace platforms has become essential for establishing cooperation on the dark web, since absence of law enforcement and full anonymity also brought uncertainty with regard to trustworthiness of cryptomarkets as institutions. After several cases of large-scale fraud committed by owners of major cryptomarkets, more recent marketplaces signal their trustworthiness to potential traders by investing in technical innovations. Such innovations include, for example, multi-signature escrow systems that prevent marketplaces from abusing funds in the escrow system (Barratt and Aldridge, 2016; Bartlett 2014: Ch. 5), more complex website code bases that require cryptomarket owners to have higher levels of technical knowledge (Branwen, 2016) or finances to start and maintain the marketplace, but also in social innovations. The latter is exemplified by some cryptomarkets' introduction of hierarchical systems among buyers and sellers, where only well-reputed buyers can gain access to goods of well-reputed sellers. In other words, only after having engaged in some illicit transactions are buyers trusted with transactions for higher stakes (Gambetta, 2009). Such institutional arrangements have an effect on how traders in a particular cryptomarket perceive the shadow of the future and, accordingly, on their strategies when interacting with each other (Axelrod, 1984; Guala, 2012).

On the one hand, these developments show that cryptomarket traders can never fully rely on platform providers to take the role of rule enforcers, making trust between buyers and sellers an essential part of maintaining cooperation in the dark web. On the other hand, such developments open avenues to analyze how institutional innovations affect cooperation between individuals in an otherwise largely de-centralized and unregulated environment. The ongoing growth and diversification of cryptomarkets (Soska and Christin, 2015) thus makes these dark web marketplaces particularly interesting for studying issues of cooperation and institutional evolution (Beckert and Wehinger, 2013).

3

Believe it when you see it:
dyadic embeddedness and reputation effects
on trust in cryptomarkets for illegal drugs

ABSTRACT

Large-scale online marketplace data have been repeatedly used to test sociological theories on trust between strangers. Most studies focus on sellers' aggregate reputation scores, rather than on buyers' individual decisions to trust. Theoretical predictions on how repeated exchanges affect trust within dyads and how buyers weigh individual experience against reputation feedback from other actors have not been tested directly in detail. What do buyers do when they are warned not to trust someone they have trusted many times before? We analyze reputation effects on trust at the dyadic and network levels using data from an illegal online drug marketplace. We find that buyers' trust decisions are primarily explained by dyadic embeddedness - cooperative sellers get awarded by repeated exchanges. Although buyers take third-party information into account, this effect is weaker and more important for first-time buyers. Buyers tend to choose market exit instead of retaliation against sellers after negative experiences.¹¹

11 A version of this chapter is submitted to an international scientific journal. This chapter was co-authored by Stijn Ruiter and Rense Corten.

INTRODUCTION

Reputation is key for establishing trust between individuals in social interactions and market exchanges in which information about partner's trustworthiness or true quality of goods and services is hard to obtain (Akerlof, 1978; Axelrod, 1984; Granovetter, 1985; Coleman, 1990; Dellarocas, 2003; Diekmann *et al.*, 2014). When uncertainty is high, people can rely on their social networks to exchange with someone they already know (DiMaggio and Louch, 1998). Social ties can also be used to get information about trustworthiness of potential partners, or sanction them after opportunistic behavior (Buskens, 2002; Buskens and Raub, 2002).

When economic exchanges take place between many anonymous actors, such as in large online marketplaces, social network effects are often substituted by reputation systems (Resnick and Zeckhauser, 2002; Dellarocas, 2003). These systems allow buyers to rate sellers' trustworthiness and product quality after exchanges. The information is then disseminated to all market actors. Reputation information allows buyers to select cooperative sellers without having individual experience with any one of them. While opportunistic sellers have no incentive to cooperate in one-shot exchanges, buyers can use the reputation system to sanction uncooperative behavior by informing others, which introduces a shadow of the future (Axelrod, 1984). Previous studies of online marketplaces found that reputation systems incentivize cooperative behavior by increasing sales and selling price of highly-reputed sellers, and simultaneously driving those with poor reputation out of the market (Dellarocas 2003; Diekmann *et al.*, 2014; Kollock 1999; Przepiorka 2013).

Trustors' decisions on whom (or whether) to trust can also be based on their own experience with particular trustees when exchanges are repeated over time; reputation can work at both the dyadic and network levels (Buskens and Raub, 2002). Actors might base their decisions on their own experience with an exchange partner (dyadic learning) or on other actors' experiences (network learning). Dyadic and network learning effects have been studied extensively in experimental studies of trust games (for an overview, see Buskens and Raub, 2013). When these two effects are studied in isolation, it is typically found that trustors use both sources of information, and positive or negative experiences or feedback affect how much they trust particular trustees (e.g., Bolton, Katok and Ockenfels, 2004). The results are less clear, however, when the two are studied simultaneously and their relative importance for trust is evaluated. Barrera and Buskens (2009) found that individual experience affects trustors' decisions on whether to trust, but trustors do not consider the behavior of exchange partners with other trustors. In a repeated trust game of two trustors and a trustee Buskens *et al.* (2010) found evidence for both effects.

Individuals in online markets face similar dilemmas to those experimentally analyzed using trust games. In many cases buyers must evaluate trustworthiness of competing sellers, considering information from their previous exchanges and feedback from other buyers. These environments are therefore convenient to test reputation effects observationally on a large scale. However, previous studies on reputation effects in online marketplaces and sharing economy platforms have rarely distinguished between information at the dyadic and network levels. Studies employing data from eBay (e.g., Kollock, 1999; Resnick and Zeckhauser, 2002; Diekmann *et al.*, 2014), Taobao (e.g., Ye *et al.*, 2013), accommodation- (e.g., Teubner *et al.*, 2017) or meal-sharing platforms (ter Huurne *et al.*, 2018) typically used the seller as the unit of analysis for the effects of aggregated feedback ratings on item prices and volume of sales. Such research designs do not shed light on the actual decision-making process that buyers face and cannot distinguish between dyadic and network learning effects. To the best of our knowledge, there are few studies of online markets that differentiate between third-party feedback and individual experience in their analyses (Przepiorka, 2013; Snijders and Weesie, 2009). Also in these studies, however, buyers' past experience with a seller was used as a proxy for the seller's overall reputation, and the two mechanisms were not studied in detail.

Information that individuals obtain from their own experience can complement or contradict information that they receive from others. What does a buyer do, when other market participants report being scammed by their favorite seller? Does a negative individual experience with a seller get ignored as a misunderstanding if other buyers in the marketplace leave only positive feedback? Answers to these questions can inform theories of dyadic and learning effects in repeated exchanges – which effect is stronger when both of them affect actors' decisions at the same time, or how buyers weigh negative against positive evaluations depending on the source of this information. Such questions can only be answered by using a research design that focuses on buyers' decisions rather than sellers' market outcomes.

In this chapter we analyze under what conditions buyers' individual experience and reputation information from third parties affect choices of sellers in an online marketplace for illegal drugs. Marketplaces on the Dark Web, or cryptomarkets, are online platforms that enable individual buyers and sellers to exchange in full anonymity by employing an anonymizing internet browser (TOR), cryptocurrencies for transactions and other technical means (Barratt and Aldridge, 2016). In their structure and layout, these websites copy major legal online marketplaces, such as eBay – buyers choose from a list of categorized items that are photographed and described by sellers, including standard information on price and shipping options (Christin, 2013). Ordered drugs are typically sent to buyers by regular mail and payments

are handled in digital currencies. Cryptomarkets, like typical online marketplaces, also use 5-star rating systems, where buyers rate their experience with sellers after exchanges. Previous research shows that reputation has positive effects for sellers' market outcomes, similar to those found in legal online marketplaces (see Chapter 2; Przepiorka, Norbutas and Corten, 2017; Hardy and Norgaard, 2016). In contrast, however, cryptomarkets are mostly used for selling consumable goods – illegal drugs such as cannabis products, cocaine or heroin (Barratt and Aldridge, 2016). As a result, buyers are likely to exchange repeatedly with the same partners (Décary-Héту and Quessy-Doré, 2017).

Additionally, cryptomarkets are environments of extreme uncertainty – next to the usual problem of information asymmetry between buyers and sellers, contracts in cryptomarkets are not secured by the legal system, while the actors are at constant risk of being exposed to law enforcement. As a result, these drug marketplaces provide an excellent test bed for studying dyadic and network learning effects on trust simultaneously.

We analyze data on 10,234 exchanges between 282 sellers and 3,192 buyers of drugs over a period of 7 months. We first explore patterns of buyer-seller interactions in an online environment. Secondly, we use a buyer's choice model and construct which sets of alternatives were available for buyers at the time of the transactions to study how buyers' own experience with each available seller and their reputation in the marketplace affect buyers' choices.

THEORY

The problem: cryptomarket exchanges and uncertainty

Cryptomarkets are peer-to-peer market platforms, where drug vendors trade directly with end users, bypassing local distributors and other middle-men that typically operate in offline drug supply chains (Martin, 2014; Barratt and Aldridge, 2016). Although buyers do not know the true identity of their exchange partners, they can identify specific sellers not only from their online nickname, but also from the person-specific encryption keys that sellers use to encrypt and secure their messages (PGP; Broséus *et al.*, 2016). As a result, drug buyers in cryptomarkets can choose to repeatedly exchange with the same seller.

Typically, a cryptomarket exchange between a buyer and a seller has the following structure (see also Christin, 2013). Sellers list the goods they offer, often with textual descriptions, images and other details important for an exchange, such as price and weight. A buyer chooses a listing, contacts the seller directly and transfers money to the seller (or uses an escrow system, see below). The drug is then shipped to the buyer, concealed in a vacuum sealed packages or other type of masking (Aldridge and Askew, 2017).

This structure of exchanges makes buyers vulnerable to opportunistic behavior. Buyers choose a seller and are typically required to trust her with their money before actually receiving the goods. Contracts made in cryptomarkets are not secured by law enforcement, hence there are limited means to enforce them (Martin, 2014; Barratt and Aldridge, 2016). Buyers must also choose based on limited information about the truthfulness and professionalism of the seller, and quality of their goods. In such situations, buyers face high risk of getting a good of inferior quality than advertised, or not receiving the good at all (Aldridge and Askew, 2017). In the worst-case scenario, buyers face the risk of arrest due to seller's negligence¹².

To reduce asymmetry in information between buyers and sellers, cryptomarkets employ several safety mechanisms. Most cryptomarkets offer escrow systems, which make the marketplace itself a financial intermediary in an exchange between a buyer and a seller (Barratt and Aldridge, 2016; Christin, 2013). Cryptomarkets charge a fixed percent for each transaction, which leads sellers to offer a reduced price for goods in exchange for trading directly without the escrow (i.e. finalizing early; Moeller, Munksgaard and Demant, 2017). Buyers can also abuse the escrow system by claiming

¹² See, for example: Branwen, G. (2018). DNM-related arrests, 2011–2015 (Updated 08 Jun, 2018). Retrieved 3rd October 2017 from: <https://www.gwern.net/DNM-arrests>

they never received the item, which leads some sellers to require a direct transfer of money from the buyer (Morselli *et al.*, 2017; Moeller *et al.*, 2017).

Another mechanism that sustains cooperation is the reputation system, where buyers provide feedback about the seller and the quality of goods (Przepiorka *et al.*, 2017; Kollock 1993; Resnick and Zeckhauser 2002). Buyers can observe seller's history of feedback messages, which reduces information asymmetry. Reputation systems allow buyers to make informed decisions not only based on their own trial-and-error process, but also on information from the experience of all other buyers. Sellers with high reputation have been found to sell more drugs for a higher price, compared to their lower-reputed competitors (Hardy and Norgaard, 2016; Przepiorka *et al.*, 2017).

Reputation, embeddedness and learning

There are several theoretical mechanisms that have been argued to influence actors' trust under uncertainty, when information about partners' trustworthiness can be exchanged in a network of individuals (Buskens, 2002; Buskens and Raub, 2013; Barrera, 2008). In a dyadic exchange between a buyer and a seller, the buyer can control the seller by retaliating after opportunistic behavior. Assuming that actors exchange repeatedly over a sufficiently long period of time, buyer's retaliation imposes potential future costs of opportunistic behavior on the seller, which incentivizes the seller to cooperate in the present. In an online environment, where identities are not fixed, the seller has an incentive to exit the market after receiving buyer's money and re-enter under a new alias, avoiding buyer's punishment, or simply to look for a new buyer.

Reputation systems provide an incentive for sellers to refrain from opportunistic behavior by embedding buyers and sellers in an information network¹³. Buyers can exchange information about seller's trustworthiness, choose trustworthy sellers and avoid the opportunistic ones. Sellers face a larger cost of leaving the market, because reputation is costly to build, and buyers choose sellers based on good reputation (Bolton *et al.*, 2004; Diekmann *et al.*, 2014; Przepiorka *et al.*, 2017). Sellers also receive a larger premium for cooperation, since a good reputation might attract new buyers.

From the buyer's perspective, reputation systems enable network control and learning effects. Since reputation information is disseminated between all market actors, buyers can punish uncooperative sellers by leaving negative feedback. With a reputation system present, buyers can also learn from other buyers' feedback and evaluate

13 Note that the network learning theory used throughout the chapter does not assume any particular network structural effects. In online markets with a reputation system, information on sellers' past behavior is available to all buyers. It can be argued that buyers are embedded in a fully-connected information network, where everyone can exchange information with everyone else.

trustworthiness of a seller with no individual transaction history. This effect might be especially relevant for buyers entering the market, when no individual experience is present, and other buyers are the only source of information to guide decisions.

Dyadic- and network learning and control effects have been studied in experimental settings, using trust games and survey studies (see Barrera, 2008; Raub and Buskens, 2008; Buskens, Frey and Raub, 2018 for reviews). It is generally found that both repeated dyadic exchanges and embeddedness within a network of information sharing increases trust placed in trustees. Evidence for both control and learning effects have been found, although it is often difficult to disentangle these effects, even in experimental designs (Buskens, Raub and van der Veer, 2010).

We expect that cryptomarket buyers will not be different and act conditional on own experience and information they retrieve from other buyers via the reputation system. Although we cannot disentangle control and learning effects in this environment, we expect that net of item price and other item properties, buyers will be more (less) likely to choose sellers that they have positive (negative) history of transactions with. We expect them to also be more (less) likely to choose sellers that have positive (negative) reputation based on third-party information.

H1: *The likelihood that a buyer chooses a vendor increases (decreases) with the number of successful (unsuccessful) exchanges they had before.*

H2: *The likelihood that a buyer chooses a vendor increases (decreases) with the number of successful (unsuccessful) exchanges reported by other buyers.*

Dyadic vs. network learning

Studies that analyzed dyadic and network learning effects simultaneously (e.g., Snijders and Weesie, 2009; Barrera and Buskens, 2009; Barrera and van den Bunt, 2009; Buskens *et al.*, 2010) often assumed that these two sources of information are complementary. However, in situations where actors exchange repeatedly and receive information about their partners from third parties, situations might occur in which individual experience contradicts that of other actors (Buskens *et al.*, 2018). For example, a buyer in a cryptomarket might have to choose whether to trust a seller in a situation, where the seller receives negative ratings from multiple buyers, even though the individual experience with that seller is extensive and only positive. Alternatively, buyer's trust might be abused by a seller, who is reported to be perfectly trustworthy by other buyers.

There are several theoretical reasons to believe that the two sources of information might not be perfect substitutes for buyers making trust decisions. It has been argued

that individual experience is always more salient than information gained from third parties (Granovetter, 1985; Gluckler and Armbruster, 2003). Individual experience might have a larger impact on partner's choice because the information is more detailed and accurate. Granovetter (1985) also argued that individual experience is the more important source, because information is cheaper to obtain than network-based experience. The latter argument might not apply in the case of online reputation systems, where information sharing is virtually costless as the reputation system effectively disseminates information on past exchanges to all users.

Noise, on the other hand, might be particularly important in the context of online marketplaces and cryptomarkets in particular (Utz, 2009). Buyer feedback messages in online markets typically contain a numeric score (e.g., 1-5 stars) and, less frequently, a short text comment (Hijikata *et al.*, 2007). Feedback messages might provide insufficient information for a buyer, since they usually refer to a particular aspect of an exchange, like product quality or reliability of the seller, and are therefore hard to summarize when the number of feedback messages and sellers is large (Hijikata *et al.*, 2007; O'Donovan *et al.*, 2007).

Exchanges in illegal marketplaces also contain an additional element of risk for both parties, namely, that goods might be confiscated during the shipping stage (Décary-Héту *et al.*, 2016; Aldridge and Askew, 2017). Cryptomarket buyers cannot be certain that sellers are not responsible for such events, which would lead to increased prevalence of noise in feedback messages due to uncontrollable exogenous events (Kollock, 1993). As a result, information from other buyers might be considered noisy and less important than individual experience when choosing a seller.

Repeated economic relations might also develop into social bonds, which could diminish the relevance of third-party information (Granovetter, 1985). Individual experience might increase affect towards the person and reduce objectivity when evaluating third-party information (Sorenson and Waguespack, 2006; Lawler, 2001). Although users in online marketplaces are anonymous and the strength of social bonds in online marketplaces could be questioned (Diekmann *et al.*, 2014), buyers and sellers in cryptomarkets frequently engage in non-market related conversations in discussion forums (Chapter 5; Munksgaard and Demant, 2016; Barratt and Aldridge, 2016). Sellers' engagement in such discussions that could be considered cheap talk have been found to increase their market outcomes, regardless of their market reputation (Chapter 5).

These theoretical arguments point towards the same prediction, namely, that buyer's individual experience, whether positive or negative, will have a stronger effect on their choice of exchange partners than information from other buyers' feedback.

H3: *The effect of buyer's own successful (unsuccessful) experience with a seller on the likelihood of choosing the seller is larger than that of other buyers.*

Negative asymmetry

It has been argued that negative information about an exchange partner has a stronger impact than positive information (Peeters and Czapinski 1990; Taylor 1991). While positive social relations, such as friendships, develop gradually over time, the strength of negative relationships develop much faster, resulting in quick categorizations of a person as “rival”, compared to more detailed ranking of acquaintances and friends based on their closeness (Labianca and Brass, 2006).

Although social and market relations might not necessarily be directly comparable, negative asymmetry has also been observed in online market exchanges. Studies on reputation effects in online marketplaces also show that the impact of negative ratings on buyer's trust is much larger than the trust-building effect of positive ratings (Standifird, 2001; Przepiorka *et al.*, 2017). Although negative ratings are typically rare, they carry much more weight on actors' decisions.

There are also cryptomarket-specific reasons to expect a stronger effect of negative information on buyers' trust. Sellers are assumed to act cooperatively if the cost they face for abusing buyer's trust is larger than the expected benefit from future exchanges (Axelrod, 1984; Buskens and Raub, 2008). The number of repeated exchanges with buyers has to be sufficiently high to outweigh the benefits of scamming for the seller. Experimental research shows that in finitely repeated trust games, cooperative behavior of both actors decreases in the last rounds of the game, since trustors (i.e. buyers, in the case of online markets) know that trustees (i.e. sellers) no longer have an incentive to honor trust (e.g., Buskens *et al.*, 2010; Barrera and Buskens, 2008).

The end-game effect takes place when parties know about the approaching end of the game. In case of online markets, however, buyers can never be sure when a seller might be willing to leave the market. When a seller decides to leave, it becomes beneficial to abuse buyer's trust and take the money, since they no longer face potential costs of such actions. In legal online marketplaces, such seller's behavior is costly due to the threat of legal enforcement. In illegal marketplaces, on the other hand, occurrences of such behavior might be more frequent. Such cases where cryptomarket sellers build up a good reputation and suddenly disappear, also called ‘exit scams’, have been observed in multiple cryptomarkets (Moeller *et al.*, 2017).

As a result, regardless of a seller's reputation, buyers cannot be certain about the shadow of the future. Negative feedback messages from third parties could be more

informative in those cases than individual positive experience in the past, since they can reveal seller's intentions of leaving the market.

Based on these arguments, we expect that negative feedback messages will diminish the positive effect of buyer's positive individual experience with a seller. The increased likelihood of choosing a vendor with whom already successful exchanges were made, will diminish with every negative rating reported by other buyers. This leads to our interaction effect hypothesis.

H4: *The positive effect of the number of buyer's successful past transactions with a seller on choosing the seller is weaker with the number of negative transactions reported by other buyers.*

DATA AND METHODS

We use a dataset from the cryptomarket “Abraxas”, collected by Branwen *et al.* (2015). The dataset contains semi-daily copies of the marketplace, collected over 7 months, using a website content retrieval package called ‘wget’. The dataset and the methodology of data collection are available publicly (Branwen *et al.*, 2015). The first copy of the marketplace website in the dataset was collected before the first customer purchase in 2015. The last scrape in the collection is dated approximately 3 months before the marketplace was closed. The marketplace was mostly used for trading illegal drugs (see also Chapter 6).

The structure of the website resembles that of other major online marketplaces and cryptomarkets. Sellers post items on the website, include a picture of the product, a description, price, possible shipping destinations and other information. Buyers can observe the list of items on sale, categorized by the type of drug they contain. A purchase is made by contacting item’s seller and transferring the money directly to the seller or via the escrow system. All drug items are sent to buyers using regular postal services. When the package arrives, buyers can leave 0-5 stars rating and a comment about their experience. This information is then instantly published on the website – a list of all item-specific feedback can be observed in the webpage of each drug item; an aggregated list of feedback about all seller’s items is provided in sellers’ profile pages. An average reputational score of is also displayed next to sellers’ nicknames wherever they are displayed.

In total, the data contain 7,971 unique items, 463 seller profile pages, 3,542 buyer profile pages, and 10,898 feedback messages. We use all items in the “Drugs” category to ensure comparability in our analyses. Excluded items contain digital goods (eBooks, software, etc.), which are difficult to compare to drug items, since digital goods contain no shipping stage and are sent directly to the buyer. After deletion, the dataset contains 79.9% (6,374/7,971) of all items on Abraxas.

Feedback messages that were edited by the buyers were deleted, keeping only the most recent feedback message for every transaction. We do not expect this to have any effect on the results, since edits were typically made to add textual comments and were mostly made within 1-2 days after the original message had been posted. Buyers could not see the original messages after they were edited, which makes our final dataset similar to what most buyers were likely to observe on the website. After deletion of feedback messages, the subset contains 84.8% feedback messages (9,244/10,898), 84.23% seller profiles (390/463) and 90.11% buyer profiles (3,192/3,542).

Item weights were provided by sellers in the title of each item. Since these data are highly unstandardized, item weights were recoded manually. For some items, weights were not available in the name or the description, resulting in missing values. We excluded these items from our analyses. After this deletion, the subset contains 43.78% of all items in Abraxas (3,490/7,971) in 10 sub-categories, 53.93% of seller profiles (259/463), 74.05% of buyer profiles (2,623/3,542) and 70.17% of all feedback messages (6,487/10,898).

The statistical models used to test the hypotheses require a dataset that represents buyers' choices at the time of each purchase. We derive this dataset by using details of the items that buyers actually purchased and adding all other items of the same drug type, within 200% margin of weight that were available online at least 2 days before the date of buyer's purchase. Here we assume that it takes at least 2 days from the time a buyer places an order to the time the buyer receives the good via mail and leaves a feedback message. For example, if a buyer bought 1g of marijuana on the 15th of June, we assume that a buyer chose from a set of all marijuana items that are 0.5g-2g in weight, were posted before 13th of June and last observed after 15th of June. We create these choice sets for every purchase in the data, which results in a nested dataset where item alternatives are nested in choice sets with 1 item actually selected by the buyer per set (see Figure 3.1). These choice sets are further nested in buyer profiles and represent all transactions they made. Finally, we aggregate the alternatives to the seller-level, since sellers might offer multiple similar items and be over-represented in each set. We excluded 46 sets, where the buyer had only 1 option. The final dataset contains 6,441 choice sets (69.68% of all feedback messages), 181,423 total seller alternatives for 2,614 unique buyer profiles and 258 unique seller profiles.

It is important to note that we derive buyer-seller exchanges based on buyers' feedback messages. Since buyers can only post feedback after a purchase is made, we can be certain that each feedback message corresponds to an exchange. There can be, however, cases where the buyer leaves no feedback message. Previous research on cryptomarket feedback messages found that 88% of all sales are reported by feedback messages (Aldridge and Décary-Hétu, 2014). We will address this limitation further in the Conclusions section.

1. Item-level alternatives

Buyer ID	Choice set	Seller ID	Drug type	Item weight (g)	Date	Selected
1	1	1	A	1	Bought on Feb 18	1
1	1	1	A	0.75	Feb 16-Mar 30	0
1	1	2	A	1.25	Jan 27-Feb 27	0
1	1	2	A	5	Jan 5 – Jul 30	0
1	2	3	B	4	Bought on Mar 9	1
1	2	3	B	5	Mar 8 – Jul 26	0
1	2	4	B	5	Jan 1 – Jul 20	0
1	2	4	B	5	Feb 20 – Dec 6	0

Item

Items selected based on similarity
to the selected item

2. Seller-level alternatives

Buyer ID	Choice set	Seller ID	Selected
1	1	1	1
1	1	2	0
1	2	3	1
1	2	4	0

Alternative (seller)

Dependent variable

Figure 3.1. Structure of the dataset used in the analyses. Choice sets are constructed by selecting similar alternatives for every buyer’s purchase (top). Item-level alternatives are then aggregated to the seller level (bottom).

Variables used in the models

The dependent variable, selected alternative, is a binary variable, indicating which seller alternative was selected by the buyer in each choice set (see also Table 3.1). Every set contains one selected seller and reflects one transaction in the marketplace (based on feedback messages; see Figure 3.1).

Positive and negative individual experience with a seller were measured using the number of 5-star and non-5-star feedback ratings a buyer had awarded a particular seller before the time of exchange. These variables have different values for each seller alternative in the choice sets. If a buyer never had an exchange with a seller, both variables are equal to 0. We use 0-4 stars as a measure of negative experience, since reputation scores in online marketplaces, including cryptomarkets, tend to be extremely highly skewed with few ratings below 5 stars (Przepiorka *et al.*, 2017). In the subset used in the analyses, 5-star ratings account for 96.12% of all feedback messages, while 0-4-star ratings account for 0.7-1.3% of feedback messages each. This suggests that ratings below the maximum value are posted in extraordinary cases. It also shows that sellers’ average rating scores might not be helpful for buyers to differentiate sellers’ quality, especially when the number of seller’s total sales is high and the impact of each additional sub-5-star rating on the average reputation score decreases. The number of 0-4-star ratings could therefore be considered an indicator of buyers’ negative experiences, regardless of the actual number of stars awarded.

We test sensitivity of the results to different measurements in the section “Additional analysis”.

Positive and negative third-party ratings reflect, respectively, the number of 5-star and non-5-star feedback ratings from all exchanges for each seller alternative, at the time of observation. This variable reflects each seller’s market reputation at the time a buyer chose between alternatives. The variable is constructed using all feedback ratings, including items that have been excluded from the analyzed subset ($N = 10,898$ feedback messages). Since both buyers’ individual experience and third-party ratings, are strongly left-skewed, we use a log-transformed version of the 4 variables. The correlation between positive individual experience and positive third-party ratings is 0.16, while correlation between negative experience and third-party ratings is 0.05.

To control for price differences across alternatives, we used two types of price variables. First, a dummy variable ‘lowest price seller’ indicates which seller offered the lowest priced item in the choice set. Secondly, we used an “average price (USD)” continuous variable, which indicates the average price of each seller’s items in the marketplace at the time of buyer’s selection. Since items in cryptomarkets can be sold multiple times, sellers who run out of stock for an item have been found to artificially increase item price (e.g., to 9999\$ per gram) to keep the item visible until they restock and are able to sell again (Décary-Héту and Paquet-Clouston, 2016). We excluded such “holding” items with artificially high prices when calculating the average price for the “average price (USD)” variable. To account for the fact that such items might still affect buyers’ choices via visibility of these items in the website, we included a variable for the “number of holding items” each seller had online in each choice set. A total of 42.14% choice sets (2,714/6,441) had at least one seller with holding items posted (2% of all alternatives).

We add dummies for seller’s offered shipping destinations, since this might limit buyers’ choices (see also Chapter 6 for effects of shipping destination on buyer-seller exchanges). We use a dummy variable that represents whether a seller offered shipping Worldwide, or to a limited set of countries (baseline category). 32% of items that are not shipped worldwide, ship only to European countries, 18% ship only to EU and 10% only to Australia. Additional 22% of items with restricted shipping locations are sent to multiple countries, while about 18% are being shipped to all but 1 continent.

It is possible that in some cases buyers’ choices are constrained by few domestic sellers in a given country. Even if there are competing sellers who offer worldwide shipping, buyers might be unwilling to choose them, because they ship from a distant location, which might increase shipping fees and risk of detection. Since we cannot observe buyers’ geographic locations, we use sellers’ provided shipping origin and

destination locations to control for geographic constraints. We measure “geographic monopoly - origin” and “geographic monopoly - destination” using dummy variables that show whether each seller is the only one shipping to or from a country. Destination monopoly variable controls for cases where a seller is the only one that offers shipping to a country. Origin monopoly controls for cases where there is only one alternative that ships from a country, regardless of shipping destinations. For example, multiple sellers might offer shipping to Australia, but only one alternative might be shipping from Australia, which would make that alternative much more attractive to Australian buyers.

We control for the number of items each seller choice sets had posted online at the time of each exchange, to account for differences in visibility of items. Sellers use different strategies to increase their visibility on the website, such as making multiple listings of the same type with slightly different weights or posting similar items under different names.

Table 3.1. Variables used in the regression models.

Variable	N	Mean (Std. dev)	Min-max
Selected alternative	181,423	0.035	0/1
Positive individual experience	181,423	0.042 (0.45)	0-29
Negative individual experience	181,423	0.0007 (0.02)	0-1
Positive 3 rd -party ratings	181,423	36.626 (72.47)	0-605
Negative 3 rd -party ratings	181,423	1.000 (2.55)	0-33
Lowest price per gram	181,423	0.021	0/1
Average price per gram (USD)	181,423	34.476 (95.74)	0.15-22528
Ships worldwide	181,423	0.301	0/1
Geographic monopoly (destination)	181,423	0.048	0/1
Geographic monopoly (origin)	181,423	0.134	0/1
Number of seller's items	181,423	2.840 (3.96)	1-46
Number of holding items	181,423	0.021 (0.15)	0-2
N(Buyers)		2,614	
N(Sets)		6,441	

Analytical strategy

We estimate conditional fixed effects logistic regression model (clogit in Stata; McFadden, 1974) to model the likelihood an alternative is selected. These models treat choice among alternatives as a function of characteristics of the alternatives and not the individual making the choices. The model estimates the likelihood an alternative is selected conditional on other available alternatives in the set. By definition, the model does not estimate effects of buyer-specific predictors (constant across alternatives),

since the analysis is done “within” choices by comparing alternatives. We use clustered standard errors to account for correlated standard errors in repeated choices made by the same buyer. A similar model was used in Snijders and Weesie (2009) to analyze a programmer’s market.

We estimate 3 models. The first model includes only the first exchange of every buyer in the cryptomarket to estimate the effect of third-party information when buyers have no individual experience. Model 2 uses all remaining exchanges of the buyers (i.e. the second and subsequent exchanges). This is the full model with repeated exchanges and is used to test hypotheses 1-3. Model 3 adds an interaction effect and tests hypothesis 4. Finally, we report sensitivity of the main results to assumptions used throughout the models.

RESULTS

Descriptive findings

In this section, we first focus on descriptive results of finalized buyer-seller exchanges, that is, alternatives in the choice sets that were selected by each buyer ($N = 6,441$). The results show that 46.22% of all analyzed transactions (2,977/6,441) are the first transactions for the buyers (market entrants). Accordingly, more than a half of all exchanges are made by returning buyers (see Figure 3.2). Out of the 3,464 exchanges that are made by returning buyers, 51.24% (1,775/3,464) are made between buyers and sellers who had already exchanged in the past. On average, buyers who made at least two purchases on the market bought from 2.26 sellers and made 65.3% of their exchanges with a single seller. These figures show a much stronger dyadic embeddedness between buyers and sellers of illegal drugs than found previously in another cryptomarket – on average 15 vendors per buyer and 31% of exchanges with the most popular vendor (Décary-Hétu and Quessy-Doré, 2017). The difference might be caused by the data used in Décary-Hétu and Quessy-Doré (2017) that contained partially anonymized buyer nicknames. This could have led to an underestimation of the number of buyer accounts (i.e. multiple accounts with similar nicknames analyzed as a single account) and an overestimation of the number of sellers per buyer.

Figure 3.2. Cumulative distribution of buyers' repeated exchanges in the marketplace.

Buyers make choices that are almost entirely conditional on positive individual history with that seller. Out of the analyzed 3,464 repeated exchanges, only 0.78% (or 0.42% of all exchanges) are made with sellers, who buyers have reported having negative experience with in the past, which shows that buyers very rarely come back to a seller after posting negative feedback. This is almost perfectly in line with the expected rational retaliation behavior. In contrast, buyers have up to 29 repeated exchanges with sellers they had positive exchanges with in the past. Interestingly, buyers are likely to repeatedly exchange with the same seller even if the seller has negative ratings reported by other buyers - buyers exchange more than once with sellers that have up to 25 negative ratings reported by other buyers (2.64 negative ratings on average).

In dyads where the same two actors exchange repeatedly ($N = 1,119$), 73.64% of exchanges are made for the same drug type, while in a quarter of these exchanges buyers return to the same seller for a different type of drug. This result indicates that buyers return to sellers not only because of the quality of a specific product, but possibly due to trust in the seller.

The number of seller-alternatives varies substantially across the analyzed choice sets. In the 6,441 choice sets, buyers on average choose from 28 different sellers, ranging from 2 to 75 alternatives per set. The number of alternatives varies by drug category due to differences in popularity of these drugs. Buyer purchases of items in the “Weed” category have the largest average number of alternatives (43 alternatives per set), followed by “Cocaine” (26.5 alternatives per set), while choice set sizes in “Ketamine” and “Mushrooms” categories are significantly lower (3.8 and 4.1 seller-alternatives respectively).

Strong embeddedness in buyer-seller dyads cannot be fully explained by a lack of seller alternatives. When making the first exchange, buyers on average select out of 28 seller alternatives. Returning buyers with 1-3 exchanges on average choose out of 13 alternatives. Finally, buyers who have more than 3 exchanges choose from 16 alternatives.

Hypotheses testing

Table 3.2. Conditional fixed-effects logistic regression models. Buyers' choices of sellers.

Independent variables	Model 1 1 st exchange	Model 2 Full model (all subsequent exchanges)	Model 3 Model 2 + interaction
Positive individual experience (log)		33.530** (3.24)	44.168** (4.93)
Negative individual experience (log)		1.391 (0.86)	1.713 (0.93)
Positive 3 rd -party ratings (log)	1.470** (0.02)	1.202** (0.02)	1.188** (0.02)
Negative 3 rd -party ratings (log)	0.878** (0.03)	1.047 (0.03)	1.151** (0.04)
Positive individual experience (log) *			0.724** (0.06)
Negative 3 rd -party ratings (log)			
Lowest price per gram	1.176 (0.11)	1.368* (0.16)	1.367* (0.16)
Average price per gram (USD; log)	0.611** (0.03)	0.522** (0.03)	0.515** (0.03)
Ships worldwide	0.872** (0.03)	0.980 (0.05)	0.969 (0.05)
Geographic monopoly (origin)	0.734** (0.05)	0.810** (0.05)	0.817** (0.05)
Geographic monopoly (destination)	1.490** (0.10)	1.343** (0.13)	1.338** (0.13)
Number of seller's items	1.050** (0.00)	1.033** (0.00)	1.035** (0.00)
Number of holding items	0.935 (0.13)	1.065 (0.17)	1.094 (0.17)
N obs.			
Level 1: Alternatives	76,976	104,447	104,447
Level 2: Choice sets	2,977	3,464	3,464
Level 3: Buyers	2,614	1,199	1,199
Explained variance (Pseudo R ²)	0.075	0.355	0.357

* - $p < 0.05$; ** - $p < 0.01$. Odds ratios reported, standard errors in parentheses.

The results of Model 1 (see Table 3.2) are based only on buyers' first exchanges and exclude individual experience effects. The results show that the number of positive feedback messages positively affects the likelihood a seller is chosen (OR = 1.470, $p < .01$), while the effect of negative feedback decreases the odds a seller is chosen (OR = 0.878, $p < .01$). For the first exchange, buyers choose based on both positive and negative ratings of each seller, as reported by previous buyers. Results also show that reputation considerations might be more important than price, as the seller who offers an item for the lowest price in the set is not significantly more likely to get selected at buyers' first exchange (OR = 1.176, $p > .05$). On the other hand, price still plays a role, as sellers with higher average price are significantly less likely selected (OR = 0.611, $p < .01$). Sellers that are the only ones shipping from a particular country in a choice set are less likely selected (OR = 0.734, $p < .01$). For buyers' first exchange,

sellers who are the sole option for shipping to a particular country are more likely selected ($OR = 1.490, p < .01$). These geographic effects remain significant throughout all models. The odds of being selected also rises with the number of items the sellers had posted in the marketplace ($OR = 1.050, p < .01$), which could be related to seller's visibility in the website.

Results in Model 2 include only buyers' second and subsequent exchanges, when the effect of individual experience becomes possible. The model shows that buyers are overwhelmingly likely to choose sellers with whom they interacted in the past. Every positive experience with a seller increases the odds that same seller is chosen by a factor of 33.5 ($p < .01$), which is in line with Hypothesis 1. Interestingly, negative individual experience does not significantly affect the likelihood of (not) choosing the same seller in the future ($OR = 1.391, p > .05$). We therefore find only partial evidence for Hypothesis 1. Once buyers' individual experience is taken into account, the effect of positive third-party information decreases only slightly ($OR = 1.202, p < .01$), while the effect of negative feedback becomes statistically insignificant ($OR = 1.047, p > .05$). These results are in line with Hypothesis 2 only for positive third-party experience.

The two variables that measure individual experience increase the explained variance in Model 2 by 24.4%. This figure is based on comparing Model 2 with the same model that excludes the two individual experience variables (not shown). The pseudo- R^2 of this model is equal to 11.1%. The results of a likelihood ratio test that compares the fit of the two models also shows a significant improvement of Model 2 over the model, which excludes the two individual experience variables. These results are in line with Hypothesis 3.

Finally, Model 3 includes the interaction effect, which tests Hypothesis 4. Although negative 3rd-party ratings do not directly affect buyers' choices as shown in Model 2, it decreases the effect of buyer's positive experience with a seller ($OR = 0.724, p < .01$). While buyers are not less likely to choose sellers with more negative ratings based on findings in Model 2, they are less likely to come back to the same seller after positive exchanges if other buyers report negative experiences with that seller. These results are in line with theoretical expectations and confirm Hypothesis 4.

Additional analyses

The previous analyses were made under an assumption that only 5-star ratings are considered a positive signal, while 0-4-star ratings are a signal of negative or poor reputation. This assumption was based on the skewed distribution of ratings. In the following analyses, we test this assumption by varying the operationalization

of negative ratings and changing it to 0-3-star, 0-2 star and 0-1-star ratings, while keeping the positive ratings at 5 stars.

Figure 3.3 shows the results of Model 2 repeatedly run with the different operationalizations of negative ratings. The estimated odds ratios for different operationalizations are marked by different colors. The results show, that as the operationalization of negative ratings becomes more extreme (i.e. approaches 0-1 ratings), the estimated odds ratios change towards the hypothesized directions. The effects of positive individual experience and third-party ratings become larger, while the effects of negative experience and third-party feedback become even lower. The results for negative third-party ratings are only statistically insignificant for the original operationalization (0-4 ratings) and become negative and statistically significant in all other models. This shows that buyers might not consider all 0-4-star ratings a negative signal, or there might be individual heterogeneity in these considerations. These results provide further support for Hypotheses 1 and 2.

Figure 3.3. Estimated Model 2 odds ratios by different operationalizations of negative ratings.

Figure 3.4 shows the same procedure of alternative operationalizations applied to the interaction effect tested in Model 3. The top left panel shows the interaction effect in

the original model, which shows that buyers are slightly more likely to choose sellers with whom they have no positive experience, the more negative ratings these sellers have. These results are counter-intuitive and in line with the previous interpretation – it is possible that buyers consider a fraction of “negative” 0-4-star ratings as a positive signal. The same interaction effect becomes increasingly more negative for all groups once more extreme operationalizations of negative ratings are taken into account. The interaction effects are statistically significant throughout the 4 different operationalizations in Figure 3.4. The direction of the effects is stronger in the hypothesized direction, the more extreme the measure of negative ratings is used, which provides further support for Hypothesis 4.

Figure 3.4. Estimated Model 3 interaction effects by different operationalizations of negative ratings.

Finally, the previous models used in the analyses cannot account for the fact that buyers, after receiving negative ratings are likely to leave the marketplace, instead of switching to another alternative within the marketplace (e.g., switch to buying drugs offline). This strategy could provide an alternative explanation for the null results of negative individual experience on seller’s choice. We estimated a Cox proportional hazard model to analyze whether buyers are more likely to leave the market after at least one negative experience with any seller (see Figure 3.5). Time is operationalized as the number of buyer’s exchanges. Failure is operationalized as the date of the final

observed exchange, if the feedback message was left at least 4 weeks before the end of data selection. We operationalize market exit as not making any orders for one month or more. The results show that buyers who have negative experience have a larger hazard of leaving the market, especially during initial exchanges in the marketplace (haz. ratio = 1.344, $p < .05$). The gap becomes smaller in subsequent exchanges.

Figure 3.5. Cox proportional hazards model of buyer leaving the marketplace based on having negative experience with at least 1 seller.

CONCLUSIONS AND DISCUSSION

In this chapter, we analyzed how reputation affects buyers' trust in sellers, in a highly uncertain environment – a cryptomarket for illegal drugs. We add to the previous literature on reputation in online markets by focusing on decisions of buyers, instead of sellers' market outcomes. This allowed us to distinguish between two different levels of reputation effects - buyers' individual experience and third-party information effects. We add to the literature on embedded trust by studying dyadic and network learning mechanisms simultaneously in an empirical setting on a large scale.

Our results are generally in line with the main predictions of dyadic and network learning effects (Buskens and Raub, 2002). Buyers are more likely to trust sellers with whom they had positive experience in the past, or if they observe positive feedback from other buyers. The evidence is relatively weaker for negative experience - although buyers react to negative ratings from other buyers before making their first purchase, the effect of negative information on trust becomes less pronounced in subsequent exchanges.

Perhaps more importantly, we find that dyadic embeddedness effects on trust are stronger than those of network learning. Buyers' individual history of exchanges is a stronger predictor of their subsequent trust decisions than the third-party reputation information they observe. Despite having a rich set of seller alternatives and a significant amount of information about trustworthiness of each option on the market, buyers tend to repeatedly exchange with the same sellers they trusted in the past. Although cryptomarkets enable unprecedented access to multiple sources of illegal substances to end-users, it might be that high uncertainty pushes buyers to choose exchanges with few trusted sellers, much like they do in offline drug markets (Beckert and Wehinger, 2013; Chalmers and Bradford, 2013; Jacques *et al.*, 2014).

This finding echoes those of Romero, Uzzi and Kleinberg (2016), who showed that the structure of communication networks between stock traders tends to “turtle up” when uncertainty increases – individuals cluster and focus their communication on strong ties and trusted company insiders, instead of reaching out to weak ties to obtain as much information as possible. In our case, similarly, buyers have the option to reduce their reliance on a single source of drugs, which is relevant given the reported police arrests and seller scams (Décary-Héту and Quessy-Doré, 2017). Instead, online drug exchanges tend to “turtle up” as well, as buyers focus on few individually trusted market ties. Even though analysis of whether this tendency becomes stronger as uncertainty increases (e.g., after law enforcement marketplace shutdowns) is outside the scope of this study, cryptomarkets offer a wide variety of

cases where the effect of external shocks on trust and exchange network structure could be analyzed empirically.

Although, in line with dyadic learning theory, buyers reward cooperative sellers by choosing them repeatedly, we do not find the predicted retaliation effect after negative experiences. Instead of choosing a different seller, buyers become more likely to exit the marketplace. The use of the term ‘exit’ in this chapter slightly differs from the one used in experimental research on Trust games (e.g., Buskens and Raub, 2002; Buskens, 2003) or Prisoner’s dilemma games (e.g., Schuessler, 1989; Yamagishi *et al.*, 1984) played in networks of actors, where it refers to the ability to select a different partner within a game. In our case, instead of choosing another partner, buyers opt out of the game for good. It is possible that after facing an abuse of trust, buyers turn to less risky sources for the same product. Given that online drug markets constitute a relatively small portion of global drug trade (Global Drug Survey, 2016), buyers might turn to offline sources, which could be interpreted as an ‘exit’ by selecting an offline drug dealer, instead of an online drug seller. It is difficult to test predictions about such behavior in this environment, since we cannot observe product and search costs of offline alternatives that buyers have (Yamagishi, 1988). An interesting future research avenue could be a test of whether cryptomarket buyers in countries with high “street” prices of specific drugs are less likely to leave cryptomarkets after negative experiences.

Interestingly, a tendency to leave the marketplace after receiving a negative rating has been found for sellers in a similar online environment (see Chapter 5). Sellers have an incentive to leave the marketplace early on if they receive a negative rating, since re-entering with a new nickname is less costly than rebuilding damaged reputation. This tendency might also partially explain why we do not find strong effects of negative third-party ratings on buyers’ behavior – the ‘worst’ sellers might leave the market and no longer show up on buyers’ list of alternatives. Taken together, these findings show that the ‘exit’ option is an important behavioral alternative to consider when analyzing reputation effects in risky environments.

We also find that negative signals from third parties can erode buyer’s ongoing trust relation with a seller. The trust-decreasing effect of observed negative ratings is stronger for those, who have a positive exchange history with a given seller. We show that network learning not only directly affects trust of the buyer towards specific sellers, but also by moderating the effect of dyadic learning. Positive individual experience still outweighs the effect of information from other actors, however, since buyers are highly likely to return to a trusted seller with up to 15 observed negative ratings.

Taken together, our findings show that reputation effects play a crucial role in establishing trust in an uncertain market environment. However, not all reputation information is equally important when making trust decisions – individual history of exchanges plays a much stronger role than third-party information, and subsequently translates into strong dyadic embeddedness of actors in the exchange network. Negative experiences can be especially detrimental and lead actors to leave the market, instead of looking for alternatives. We show that cryptomarkets are a useful empirical environment with high uncertainty and non-trivial risks for the actors involved, excellent for testing social theories on trust and cooperation.

Limitations

As mentioned previously, our analysis relies on a measure of transactions that is based on buyers' feedback messages. This measure is conservative, since feedback cannot be posted without an exchange taking place. It has been used in previous research, showing a high correlation between the websites' reported actual number of sales and total items of feedback per seller (Aldridge and Décary-Héty, 2014; Przepiorka *et al.*, 2017; Hardy and Norgaard, 2016). Nevertheless, it might not reflect all exchanges, since some buyers might choose not to leave feedback for different reasons. Based on previous research, we could expect that the missing exchanges would only strengthen the effects of dyadic embeddedness, since some buyers in online markets are reluctant to leave feedback for the same seller more than once (Diekmann *et al.*, 2014)

Due to the nature of the TOR network, we also could not identify cases where individuals use several accounts. Although this problem holds for most analyses of online marketplaces, the use of multiple accounts for security purposes could be somewhat more prevalent in illegal contexts. This could also partially explain the high number of single-exchange buyer accounts found in the results. Future research should ideally obtain exchange data from cryptomarkets or other online marketplaces, to analyze the scope of this shortcoming in more detail.

4

Reputation transferability across contexts:

Maintaining cooperation among anonymous crypto-market actors when moving between markets

ABSTRACT

Buyers and sellers of illegal drugs in cryptomarkets have been found to overcome trust issues created by anonymity and the lack of legal protection with the help of reputation systems. It has also been observed that cryptomarkets rarely operate for longer than one year before closing or getting shut down due to external shocks, such as law enforcement operations. This results in large flows of users migrating between market platforms. An important question to address in order to better understand why cryptomarkets recover quickly after external shocks is: to what extent can reputation be carried over by online drug sellers to different markets? This problem is non-trivial given the anonymity of cryptomarket users and the fact that reputation is always tied to a user's online identity. In this chapter, we analyze conditions under which cryptomarket sellers choose to migrate with the same identity and whether reputation history from the previous cryptomarket yields market benefits in the new context. We analyze sellers' migration in three cryptomarkets and follow their reputation history to answer the research questions. We find that it is predominantly successful sellers with a large number of sales and high reputation that choose to migrate and verify their identity using cryptographic methods after market closures. Additionally, we find that reputation history from the previous markets creates a competitive advantage to these migrants, compared to new market entrants. We conclude that reputation transferability embeds cryptomarket users beyond a single market platform, which extends the "shadow of the future" and further incentivizes cooperative behavior. The results also suggest that reputation transferability might contribute to a quick recovery of online drug trade after shutdowns, potentially limiting the effectiveness of law enforcement operations aimed at specific marketplaces.¹⁴

14 A version of this chapter is submitted to an international scientific journal. This chapter is co-authored by Stijn Ruiter and Rense Corten.

INTRODUCTION

Recent years have seen rapid growth of online user-to-user drug marketplaces, or cryptomarkets (Barratt and Aldridge, 2016; Martin, 2014). Individual buyers and sellers of illegal drugs have been able to successfully conduct business online due to technical innovations employed by cryptomarkets, which ensure online anonymity, such as the TOR network and cryptocurrencies (Martin, 2014). As a response, coordinated international law enforcement operations were conducted, aimed at closing these illegal online markets. Numerous cryptomarkets were closed down and their administrators were arrested in several large operations, such as Operation Onymous (Décary-Héту and Giommoni, 2017; van Buskirk *et al.*, 2017; Europol, 2014) or Operation Bayonet (Afilipoaie and Shortis, 2018; van Wegberg and Verburch, 2018).

Despite these collective actions, the cryptomarket ecosystem remains a viable space for drug trade, with multiple new cryptomarkets starting operations after each shock (Soska and Christin, 2015; van Buskirk *et al.*, 2017). Previous research has found that drug sellers operate in multiple cryptomarkets (Soska and Christin, 2015; Broseus *et al.*, 2016) and tend to migrate to new marketplaces once their current cryptomarkets get shut down (Ladegaard, 2019).

A key question to understanding cryptomarkets' resilience is how market actors – buyers and sellers – maintain trust in each other over time in an environment where every user is fully anonymous, and marketplaces are likely to disappear due to sting operations, website administrator scams or voluntary exits (Aldridge and Décary-Héту, 2016; Barratt and Aldridge, 2016; Branwen, 2019). Anonymity of online identities in the TOR network, despite its effectiveness in enabling illegal online trade, also creates uncertainty for market users, and creates a trust problem (Buskens, 2002; Buskens and Raub, 2013). Buyers of drugs cannot be certain about the quality of goods and true intentions of an anonymous seller, while sellers have every incentive to run away with buyers' money, keeping their goods to themselves. Even if willing buyers are able to find trustworthy sellers and cooperate, it is yet unclear what happens when these anonymous buyers and sellers are made to migrate to new venues of exchange.

Illegal online marketplaces, in order to remain operative, have to reduce the uncertainty and provide additional incentives for their users to cooperate or increase costs of opportunistic behavior (Beckert and Wehinger, 2013; Reuter, 1983). It has been found that one of the key aspects in creating and maintaining trust between cryptomarket users is the reputation system (see Chapters 2, 3, 5; Hardy and Norgaard, 2016; Przepiorka *et al.*, 2017; Nurmi *et al.*, 2017; Bakken *et al.*, 2018). Reputation systems disseminate buyers' feedback on trustworthiness of sellers and their product quality to all users on the marketplace. Public availability of information about past deeds

provides sellers additional benefits for being cooperative via attracting new buyers and increases the cost of defection. It has also been found that dyadic embeddedness plays a crucial role in maintaining trust over time, since buyers tend to repeatedly interact with the same seller (see Chapter 3; Décary-Hétu and Quessy-Doré, 2017).

Reputation effects on cooperation in cryptomarkets have been analyzed under stable conditions, that is, by analyzing buyer-seller exchanges within a single cryptomarket. It is unclear to what extent these effects extend beyond the boundaries of a single exchange environment. Can seller's reputation in one market translate to market outcomes in another and help explain why cryptomarkets recover after interventions so quickly? We propose that reputation transferability in cryptomarkets should be tested by analyzing two underlying processes, largely neglected in previous research. First, conditions under which sellers choose to maintain their online identity in a new cryptomarket should be analyzed, followed by the extent to which buyers take incomplete or noisy reputation from previous markets into account when complete reputation information is available in the present market.

The first research problem is related to the total anonymity of cryptomarket users. Buyers cannot be certain that they are dealing with the same seller in a new environment, even if they observe a user with the same nickname and identical offers on the market. For this purpose, cryptomarket users have employed a text encryption method (PGP), which allows them to conceal their interpersonal communication, and, more importantly, to verify the author of the message (Christin, 2013; Afilipoaie and Shortis, 2018). While the TOR network ensures that all personally identifying information of each user, such as an IP address and geographic location, are securely hidden, PGP encryption enables unique identities, and allows users to identify specific individuals, even if anonymous, in different contexts. This also allows users to attribute reputation histories of sellers from one market to sellers in another.

The use of PGP encryption is optional and not all cryptomarket sellers choose to use it (Soska and Christin, 2015). Reputation is a strong signal of trustworthiness which is costly to build, and it can be expected that sellers with a good reputation will choose to maintain their identity and display their accumulated reputation in a new environment (Przepiorka and Berger, 2017). On the other hand, law enforcement operations create non-trivial risks for sellers, such as leaked information on their identity, and they might weigh this risk against the cost of reputational loss when choosing whether to continue using the same online identity. To our knowledge, there are no previous findings on the extent to which sellers choose to maintain their identity and specific conditions under which they do so. In this chapter, we will study this question by analyzing seller migration between cryptomarkets and the extent to which sellers'

history of transactions and reputation increase the odds of a seller to maintain the same PGP-verified identity in a new environment.

The second research problem relates to buyers' response to sellers' reputational information from previous cryptomarkets. Buyers might be aware of trustworthiness of sellers who migrate to a new cryptomarket with the same identity due to having observed them in the past or having had bought from them already (see Chapter 3). In both cases, the transferred reputation information is imperfect in the sense that buyers might not perfectly recall seller's reputation from the previous marketplace, or have perfect information about few but not all sellers (Bolton, Katok and Ockenfels, 2004). It is unclear to what extent buyers actually take such noisy information into account when choosing a seller, especially when complete information about sellers' trustworthiness is available from the reputation system in the current market. Questions related to reputation transfer have attracted some attention in studies related to online sharing economy platforms, where trust issues are also relevant, reputation systems are present and userbases overlap between platforms much like they do in the cryptomarket ecosystem (ter Huurne *et al.*, 2017; Teubner *et al.*, 2019). At the time of writing, however, there is little-to-none empirical research on the subject (for an exception on a related problem in online freelance platforms, see: Kokkodis and Ipeirotis, 2015).

In this chapter, we aim to answer the question of the extent to which reputation mechanisms effectively contribute to ensuring cooperation across different environments by analyzing conditions under which cryptomarket sellers choose to maintain their identity (research problem 1), and market outcomes of such sellers in comparison to those that operate with a new one (research problem 2). We use data from one of the largest cryptomarkets to date, AlphaBay, which was opened in late 2014 and was closed in 2017 after a joint operation of FBI and Europol (Europol, 2017). The data contain around 2.4 million purchases of illegal items that were sold by more than 7,500 sellers. We link accounts of these sellers to those in 2 cryptomarkets that closed shortly after AlphaBay opened, resulting in user migration to the new AlphaBay market. We use these data to analyze sellers' movement between marketplaces after shutdowns and measure the extent to which sellers' reputation in previous marketplaces shape their success in AlphaBay.

THEORY

Trust problems in online drug sales

The illegal nature of cryptomarkets creates several sources of uncertainty that market actors aim to minimize in order to increase exchange efficiency (Beckert and Wehinger, 2013; Beckert, 2009). Information about the true quality of products on the market is unequally distributed between buyers and sellers. Buyers cannot be certain about the quality of the product before making a purchase. In order to avoid being detected, market actors need to remain fully anonymous. It is not only important for users to conceal their physical location, which is facilitated by the TOR network and cryptocurrencies (Martin, 2014; Barratt and Aldridge, 2016), but also avoid sharing any other self-disclosing social cues, such as details about one's demographic details or interests, that – if shared – would increase perceived trustworthiness in the eyes of potential customers in legal peer-to-peer marketplaces (ter Huurne *et al.*, 2017; Ert *et al.*, 2016; Bente *et al.*, 2012; Ma *et al.*, 2017). Finally, even if a buyer decides to order a product of uncertain quality from an anonymous seller, the contract is not secured legally, which exposes buyers and sellers to additional risks of being defrauded. As a result, exchanges on cryptomarkets take place without the state, against the state and among users who cannot easily trust one another (Beckert and Wehinger, 2013).

To compensate for the lack of legal assurance and reduce uncertainty, cryptomarket platforms typically offer informal conflict resolution and rule enforcement mechanisms. Perhaps one of the most widely analyzed and effective mechanisms are the reputation or rating systems that allow buyers to exchange information about sellers' product quality and their trustworthiness after exchanges. These systems enable reputation effects by attracting buyers to cooperative sellers and introducing costs for behaving opportunistically at the same time (Przepiorka *et al.*, 2017; Hardy and Norgaard, 2016; Tzanetakis *et al.*, 2016). Information about sellers' trustworthiness reduces information asymmetry between buyers and sellers, which makes buyers more likely to place trust in sellers.

Reputation or rating systems can thus reduce the trust problem between buyers and sellers by facilitating information exchange and incentivizing cooperation. On the other hand, there are several underlying conditions for reputation effects to work in online environments. Reputation is tied to actor's online identity, not the actual person behind it (Wibral, 2015). Actors with an accumulated reputation history must therefore have stable online identities. Sellers theoretically have an incentive to maintain their identity, since reputation is costly to build (Friedman and Resnick, 2001). Empirical evidence from cryptomarkets show that even though the majority of

sellers are active for 7 months or less, about 10% of analyzed drug sellers have been active for multiple years (Soska and Christin, 2015).

While users have incentives to maintain their online identities and secure their market reputation, the unlawfulness of cryptomarkets and their anonymity might create conditions where sellers' online identity changes could be inevitable. Namely, cryptomarket platforms themselves have a short average lifespan, which requires users to migrate frequently. The first cryptomarket, Silk Road, was opened in February, 2011 and was closed after the arrest of its owner in October, 2013 (Christin, 2013). The ecosystem of cryptomarkets expanded significantly after Silk Road's closure, and more than 10 cryptomarkets were online on January, 2014. Around 100 cryptomarkets have been opened and closed or are still active since then, with an average lifespan of less than 2 years (Branwen, 2019). While some illegal marketplaces are closed by coordinated law enforcement operations, many of them closed voluntarily due to high risks, got hacked by competitors, or disappeared with users' funds in large-scale frauds (e.g., see van Buskirk *et al.*, 2017).

Volatility in terms of market lifespans creates an environment, where overlapping sets of actors exchange in different contexts and reputation information might get lost across contexts. In order to attribute the reputation of seller 'John' in Market A to seller 'John' in Market B, buyers need to verify that both 'Johns' are the same actor. This is a non-trivial task, given that all users are fully anonymous.

Movement across contexts presents additional risks for market actors. Sellers, in cases where their identity cannot be verified, face the risk of losing their reputation. Buyers, exchanging with non-verified sellers, risk getting exposed to deceptive mimicry (Gambetta, 2005; Bacharach and Gambetta, 2001). Reputation of cryptomarket sellers can be exploited by untrustworthy pretenders who could mimic successful sellers' online identities and defraud convinced buyers. Although no quantitative research exists on the scope of sellers' identity theft in cryptomarkets, sellers' discussion forum posts used in related literature provide examples of sellers changing their online identities and publicly distancing themselves from actors with similar or identical nicknames in other cryptomarkets (Broséus *et al.*, 2016; see also Ladegaard, 2019).

Identity verification and market migration

A possible technical solution for the problem of online identity verification across contexts is a cryptographic encryption protocol, called PGP (Pretty Good Privacy; Zimmerman, 1995). This tool allows users to encrypt their text messages using a person-specific private key. The encrypted text can then be decrypted using that person's public key, which is shared publicly. PGP encrypted messages can be used

to verify that the same author is sending messages using different pseudonyms, or the same pseudonym in different cryptomarkets (Broseus *et al.*, 2016; Bancroft and Reid, 2016).

Cryptomarket users adopted this tool only gradually. Based on estimates from multiple marketplaces, Soska and Christin (2015) found that only approximately two-thirds of active sellers had employed PGP encryption by January, 2012, followed by a decrease to 25% in July, 2013, and a gradual increase to 90% by January, 2015. After the closure of Silk Road, cryptomarket users created vendor encryption key databases that enabled buyers to match vendors and their public keys before and after market shutdowns (Ladegaard, 2017b).

PGP encryption provides a technical solution, a proof of identity which is virtually impossible to fake for potential opportunistic actors than online aliases. However, the conditions under which market actors choose to maintain their identities between contexts are unclear. As mentioned previously, market actors have an incentive to maintain their identity and reputation history, since it is costly to build. In fact, the ability to change one's identity without cost often results in less trust placed in market newcomers (Friedman and Resnick, 2001; Resnick and Zeckhauser, 2002), who have to turn to alternative measures, such as lowering prices or making additional time investments in communicating with buyers (see Chapter 5).

On the other hand, the benefits of maintaining one's identity after a market shutdown might be outweighed by associated risks. Previous research shows that a large portion of sellers who migrate between marketplaces, change their aliases, PGP keys or both (Soska and Christin, 2015; Broseus *et al.*, 2016; van Wegberg and Verburch, 2018). It is unlikely that sellers do this in order to shed bad reputation (Wibral, 2015), since sellers could as easily change their identity before market shutdown, that is, within the same cryptomarket before closure. A possible explanation for the utility of identity change is that sellers might aim to decrease the risk of getting deanonymized. Publicly known arrests of cryptomarket users show that arrests can take place after multiple years of evidence collection, in some cases long after a seller's nickname was observed online (Branwen, 2019). In case sellers get deanonymized, a longer history of operation from multiple cryptomarkets could also lead to more severe sentences.

We therefore hypothesize that seller's decision to migrate to a new marketplace using the same online identity depends on the reputation accumulated in a previous marketplace. We expect a trade-off, where sellers with a higher number of sales or a better reputation will be more likely to maintain their identity in the new marketplace, since benefits of having a long history of exchanges will be more likely to outweigh perceived risk of getting exposed.

H1: *Sellers who migrated to a new marketplace will be more likely to maintain identity of the old marketplace, the higher reputation or the more sales they had in the old market place.*

Reputation transferability

Sellers, who choose to maintain their identity when migrating between marketplaces, might benefit from transferring their reputation history and becoming more likely to be trusted by buyers in the new context. In order for these effects to take place, buyers must be aware of the reputation a verified seller had in the previous marketplace. This might happen if buyers themselves migrate between marketplaces and observe seller's reputation scores before the prior gets shut down. Empirical evidence from cryptomarkets show that the total number of new users and generated feedback messages typically grow rapidly after marketplace shutdowns (van Wegberg and Verburch, 2018; Décary-Héту and Giommoni, 2016). This suggests that at least theoretically, buyers might be able to observe sellers' histories in multiple cryptomarkets.

Alternatively, buyers could rely on a now closed third-party vendor search engine Grams, which was created to aggregate sellers' reputations from different cryptomarkets and match accounts using their PGP public encryption keys (Masson and Bancroft, 2018). Buyers could search a vendor by their nickname and observe all feedback messages with textual comments, posted items and other properties that the aggregator had collected since the beginning of its operation.

As a result, buyers who had observed reputation history in cryptomarkets that got shutdown, could evaluate seller's trustworthiness in a new market based on that information. It can be expected, however, that transferred reputation history does not have the same effect on seller's market success in a given context as it did in the previous one. In cases, where buyers evaluate seller's trustworthiness based on observed reputation information in the past, they might no longer have perfect information about all migrating sellers. Buyers might recall reputation information about some of the actors, or the reputation information about specific sellers might be imperfect. In such cases, buyers' willingness to cooperate might not be as strongly affected by transferred reputation as it is by perfectly observable reputation in the current context (Bolton, Katok and Ockenfels, 2005). Sellers' transferred reputation information could then be discounted by buyers when making trust decisions.

The degree to which buyers are able to observe sellers' reputation in previous cryptomarkets depends on sellers' visibility (Bockstedt and Huat Goh, 2012; Paquet-Clouston *et al.*, 2018). Since many cryptomarkets contain hundreds or thousands

of sellers, buyers could be more likely to have seen the seller in the past if a seller was active in multiple cryptomarkets. Opening accounts in multiple cryptomarkets simultaneously might not be an unexpected strategy from online drug sellers, since this might help them hedge against closures, downtimes and other unexpected events (Soska and Christin, 2015). This might also be seen as a strategy to increase one's visibility and get exposure to more potential clients. Empirical evidence shows that a large fraction of sellers operates in multiple cryptomarkets, although some choose to focus on specific platforms (Soska and Christin, 2015; Ladegaard, 2019; Broseus *et al.*, 2016).

It is unclear to what extent buyers observe sellers' past reputation and to what extent it is discounted against reputation that sellers have in the current context. However, if reputation is indeed transferable between contexts, we can expect that market entrants who have a history of sales in previous markets will be trusted more often than market entrants with no history or a changed identity and therefore get more sales on average. We can also expect that this effect will be moderated by the migrating seller's visibility – the more cryptomarkets a seller was active in, the stronger should the effect be of past reputation on the number of sales be in the current context. A comparison of migrating market entrants to market entrants with no history should provide a conservative test of reputation transferability – since market entrants do not have a reputation in the new context, the result should not be biased by possible discounting effects of sellers' exchange history.

H2: *The more sales/higher reputation a market entering seller had in previous cryptomarkets, the higher sales in the current market compared to those with no previous accounts*

H3: *The positive effect of market entrant's history of sales/reputation on the number of sales in the current market, compared to those with no previous accounts, is stronger the more cryptomarkets a seller had been active in the past*

Additionally, reputation transferability can occur in several different ways. Drugs sold on cryptomarkets are consumable goods, which results in possibilities for sellers and buyers to interact repeatedly (see Chapter 3; Décary-Héту and Quessy-Doré, 2017). Theoretically, repeated interactions within the same buyer-seller dyad can be expected, since buyers can learn from seller's previous actions and infer information about further exchanges. Sellers are more likely to honor trust of buyers in repeated exchanges, since buyers can switch between sellers and also punish or award them by posting feedback messages (Buskens and Raub, 2013). Previous studies on dyadic embeddedness of buyer-seller exchanges in cryptomarkets show that buyers are highly likely to repeatedly select the same buyer, instead of switching between alternatives

(see Chapter 3; Décary-Héту and Quessy-Doré, 2017). Reputation information from other buyers is therefore useful for buyers mostly when selecting a seller for the initial exchange in the market. Afterwards, the uncertainty is minimized by buyer's own experience with a seller and reputation effects mostly occur within the dyad.

It is therefore possible that reputation transferability not only occurs when buyers observe sellers' reputation in previous contexts, but also when buyers follow the sellers they already trusted in the past to a new environment. In other words, we might distinguish two types of effects – dyadic reputation transferability, when repeated dyadic exchanges extend into a new context, and network reputation transferability, when buyers infer trustworthiness of a seller they never interacted with from reputation information provided by others in previous contexts. It can also be expected, that dyadic reputation transferability has a stronger effect on seller's market success in the new context, since it does not depend on buyers' ability to observe and recall reputation information from previous contexts.

Literature on cryptomarket individual buyers' trust decisions and between-platform migration patterns is generally scarce. While buyer profiles and their activity can be easily observed on licit online marketplaces, such as eBay (Przepiorka, 2013; Diekmann *et al.*, 2014), buyer profiles in cryptomarkets are typically hidden (see Chapter 6). This makes a direct analysis of repeated dyadic exchanges across platforms problematic – it is not only necessary to link multiple exchanges to individual buyer profiles within a single platform, but also to link buyer profiles between platforms.

A possible proxy for the dyadic reputation transferability effect could be the behavior of buyers who enter a new market shortly after the closure of an old one. As mentioned previously, the number of new users and buyer feedback messages typically spike after cryptomarket closures (van Wegberg and Verburch, 2018; Décary-Héту and Giommoni, 2016). If new buyers enter a new market after closure of another one only to follow their trusted seller who operated in the old marketplace, we should observe that such buyers are more likely to trust the new sellers that also migrate after the shutdown, or those that are already operating in the new context, but also operated in the one that was closed.

H4: *Buyers who enter a new cryptomarket after the closure of another market are more likely to buy from sellers who also entered the market after the closure and had an account in that market*

DATA AND METHODS

Four data sources were used in our study to test the hypotheses. We analyzed drug vendor movements from two cryptomarkets, Abraxas and Agora, to a third marketplace, AlphaBay. AlphaBay was one of the largest cryptomarket to date, which started its operation in late December, 2014 and was seized during an international law enforcement operation in July, 2017. Agora started its operation a year earlier, while Abraxas was opened at the same time. Both marketplaces were shut down in late 2015, almost a year after AlphaBay opened. This resulted in a spike in the number of sellers and feedback messages in AlphaBay shortly after (Paquet-Clouston *et al.*, 2018). This provided a good environment to observe which Abraxas and Agora drug sellers maintained their identity in AlphaBay, and how or whether their reputation and history of sales affected subsequent success in the new market.

We collected data from AlphaBay in two takes, in June and July, 2017, shortly before the cryptomarket was seized. The data collection contains a copy of the website, including item pages, users' profile pages and drug item pages. Item listings in AlphaBay, as in most cryptomarkets, can be deleted by their sellers over time, which introduces a large number of unobserved items. Each item listing in AlphaBay was numbered with a unique identifier - starting from ID1 and ending with ID381593 for the most recent item. This provided an opportunity to try out every identifier in-between and accurately assess the coverage of our data. Our data contain 145,724 listings out of 381,593 that ever existed in AlphaBay (38.2%), the coverage being more complete for more recent items (65.1% for items posted in 2017). These items were sold by 7,593 sellers, who received a total of 2,419,628 feedback messages from their buyers. Since sellers' feedback messages for both deleted and existing item listings, were stored in their profiles, these data can be considered highly complete for the sellers that we were able to observe during our data collection.

In addition to sellers' data, we collected any available buyer profile pages from AlphaBay. Typically, buyer nicknames and profiles are hidden from the public view of cryptomarket websites, which makes it difficult to link individual customers to sellers' feedback messages. AlphaBay was not an exception and buyer IDs were hidden. However, buyers' user profiles could be accessed in the website if a buyer's nickname was entered in the URL address of a profile page. Since the website contained no list of buyer nicknames, we used the nicknames of users in the discussion forum AlphaBay, to collect all buyer profiles with a matching nickname in the marketplace website. In total, we were able to obtain 35,381 buyer profiles and 390,603 feedback messages that these buyers had left to sellers. This accounts for 16.1% of all collected feedback messages in AlphaBay's seller profile pages. While this is not a random sample of the

marketplace's buyers, it is, to our knowledge, the largest collection of information on cryptomarket buyers.

The data for Abraxas and Agora markets were collected by Branwen *et al.* (2015; see also data description in Chapter 6) and Soska and Christin (2015) respectively. Abraxas data set contains daily copies of the website, including item and user profile pages from the marketplace's start of operation until July, 2015. The aggregated data contain information on 463 sellers, 11,814 unique item listings and 10,898 buyer feedback messages. Agora data by Soska and Christin (2015) were available, among other marketplaces, as an aggregated database, that contained data on 27,974 item listings posted by 1,960 sellers, and a total of 234,372 feedback messages. The original non-aggregated data contained 161 snapshots of the website collected between December, 2013 and December, 2015.

We used the three cryptomarkets to collect information about all available sellers, specifically the type of goods they sold on the market, their reputation and the number of sales based on buyers' feedback messages, and their provided shipping locations. To link vendor accounts between marketplaces, we used the final data source, a database from the Grams website, which operated between 2014 and 2017. The website was hosted on TOR and provided cryptomarket buyers with aggregated information on 38,415 accounts of 22,356 unique sellers in more than 15 largest cryptomarkets at the time. The service used vendor PGP keys to link accounts between marketplaces. The database was published by the website administrator shortly before the website went offline.

After cleaning the missing cases on item- and user profile information, we derived 3 data sets used for testing our hypothesis. The first data set contains aggregated information on Abraxas and Agora sellers and was used to test the association between their reputation in the respective markets and whether they maintained their identity in AlphaBay. The data contains 1,960 sellers from Agora and 432 out of 463 sellers in Abraxas. 31 sellers were removed due to missing information on sellers' item listings.

The second data set contains information on AlphaBay's sellers' weekly reputation and sales. We grouped sellers' market data into weekly windows since the individual date each of them registered in the website. We tested whether each seller migrated from another market, and whether their history affects their market success in comparison to non-migrant sellers who had spent a similar amount of time on AlphaBay. The data contains 341,223 weekly timepoints of all 7,593 sellers.

The final data set was used to test whether AlphaBay buyers who entered the market after Abraxas' or Agora's shutdowns are more likely to buy from sellers who entered

AlphaBay from those marketplaces. The data contain 237,636 feedback messages of 16,941 buyers. 18,440 buyer accounts with 152,967 feedback messages were removed from the original buyers' data, since our data contained no information about either the item that these buyers bought, or the seller that had posted the item.

Variables used in the analyses

We used several dependent variables to test the hypotheses (see Table 4.1 for descriptive statistics). In the first set of models we tested whether *sellers from Abraxas and Agora cryptomarkets registered in any other cryptomarket* after the shutdown of each one of them. The dummy variable was constructed using the Grams database by looking for accounts of each Abraxas and Agora seller available in our data and their accounts registered after the shutdown dates.

In the second set of models the dependent variable is the *weekly number of sales*, calculated by summing up all feedback messages left for the seller by their buyers each week. This measure has been used in previous research (Przepiorka *et al.*, 2017; Soska and Christin, 2015; Décary-Héту, Paquet-Clouston and Aldridge, 2016) and can be considered a conservative proxy for the number of sales – feedback can only be left after a purchase, but not all purchases receive a feedback message.

In the third set of models, we used 2 dummy variables that indicate whether a *buyer in AlphaBay bought from a migrant from Agora or Abraxas*. The dependent variables were measured for every transaction and are equal to 1 if a buyer's chosen seller registered in AlphaBay within 1 month after their respective shutdown dates and if the selected seller had an account in that market.

Our main independent variables in the first set of models measure the *total number of sales* of each seller in Agora and Abraxas, and the *average reputation*, calculated as the mean of ratings received in all feedback messages in the corresponding cryptomarket. The total number of sales was constructed by summing up all feedback messages for each seller account in their respective market. Ratings in both Agora and Abraxas range between 0 and 5.

The main independent variables in the second set of models are the *number of sales*, *average reputation* in feedback messages each seller had before joining AlphaBay, and the *number of cryptomarkets* a seller had been active in before joining. The number of sales and average reputation were calculated by linking AlphaBay seller accounts to accounts in Agora and Abraxas using the Grams database. As in previous cases, the number of sales contains the sum of feedback messages each seller had received in either one of Agora or Abraxas, or both if a seller had accounts in both markets. Average reputation was calculated by taking the mean of all available ratings. The number of

cryptomarkets for each AlphaBay seller was constructed by using the Grams database, and counting the number of accounts in different marketplaces, registered before AlphaBay's registration date.

The main independent variables in the third set of models are dummy variables that indicate whether each buyer *migrated after Agora/Abraxas shutdowns*. These dummy variables were constructed using date of registration from buyer profiles in AlphaBay, and equal to 1 if a buyer registered in AlphaBay within 1 month of Agora or Abraxas shutdowns.

For all sets of models, we used several types of control variables. *Percentage of listings in 2nd-4th category price quartiles* were constructed by calculating price quartiles for each item category (see below) and counting what percentage of total number of seller's listings belong to each price quartile. The reference category, 1st quartile, contains cheapest items in each category. Percentages are calculated for each seller separately (i.e. these 4 variables sum up to 100% for each seller), which leads the means across all sellers to slightly deviate from 25% in Table 4.1. In the third set of models that uses buyers' data, this variable indicates which quartile an item that was bought belongs to.

We classified items in *8 drug categories*, including Cannabis & Hashish, Stimulant, Ecstasy, Opioid and other categories. Most categories in this scheme were originally used in the 3 analyzed cryptomarkets. We recoded mismatching items manually, to reflect the categorization used in previous research (Soska and Christin, 2015). The baseline category in each model are non-drug and mixed-drug items. We use this control variable to account for differences in popularity of items, that might affect both seller market outcomes and their willingness to migrate.

In each set of models, we controlled for the *destination of shipping* that sellers provide in their listings. We used a set of dummy variables that reflect the 5 most frequent shipping destinations across the analyzed markets: USA, United Kingdom, Australia, EU, and Worldwide shipping. Note that the categories are not mutually exclusive – sellers who ship worldwide also ship to the US. The baseline category are the remaining country-specific locations.

The second and third sets of models use *number of months since market opened* as a control for calendar time, to account for the trend of user growth in cryptomarkets over time. Buyers or sellers who enter the market at different time-points might also face different market conditions in terms of competition, item diversity, etc., which need to be taken into account. In the second set of models we also control for *number of weeks since seller's market entry*, which is individual for each seller. The variable counts how many weeks have passed since the seller registered an account in AlphaBay, to

control for seller-specific timeline differences (e.g., experience, accumulated visibility of posted items, etc.).

Finally, we used several control variables specific to model sets. In the first set of models, a dummy variable *Abraxas cryptomarket* marks seller accounts that were observed in Abraxas, with seller accounts from Agora as the reference category. In the second set of models *no sales before AlphaBay* is a dummy variable that controls for sellers that had no sales before AlphaBay. This is necessary, since these sellers have an average pre-AlphaBay reputation equal to zero, which also has a substantively different meaning for sellers who had a very low reputation and actual sales. This variable “compensates” for sellers who have 0 average reputation only due to not having sold any items before AlphaBay. *No markets before AlphaBay* is equal to 1 for AlphaBay sellers that had no accounts before registering there, to differentiate between sellers who are really new, and those who are not new but might have made no sales in previous cryptomarkets.

Table 4.1. Descriptive statistics of variables used in the analyses.

Variable name	Model set 1		Model set 2		Model set 3	
	Mean (SD)	Range	Mean (SD)	Range	Mean (SD)	Range
<i>Dependent variables</i>						
Migrated	0.53	0/1				
Weekly # of sales			6.56 (22.38)	0-1,039		
Seller migrated from Agora					0.005 (0.07)	0-1
Seller migrated from Abraxas					0.025 (0.15)	0-1
<i>Main predictors</i>						
Total # of sales	102.37 (209.57)	0-2,729				
Average reputation	4.76 (0.69)	0-5				
Total # of sales (Abrx.+Agr.)			17.72 (115.71)	0-2,310		
Avg. reputation (Abrx.+Agr.)			0.40 (1.34)	0-5		
# Markets before AlphaBay			0.77 (1.37)	0-14		
Buyer entered after Agora					0.066 (0.24)	0-1
Buyer entered after Abraxas					0.130 (0.33)	0-1

Table 4.1. (Continued)

Variable name	Model set 1		Model set 2		Model set 3	
	Mean (SD)	Range	Mean (SD)	Range	Mean (SD)	Range
<i>Control variables</i>						
Total # of listings	16.63 (33.99)	1-937				
% of listings in Q1 price	(ref.)		(ref.)		(ref.)	
% of listings in Q2 price	0.24 (0.23)	0-1	0.22 (0.24)	0-1	0.31 (0.46)	0/1
% of listings in Q3 price	0.24 (0.23)	0-1	0.24 (0.23)	0-1	0.26 (0.43)	0/1
% of listings in Q4 price	0.23 (0.28)	0-1	0.23 (0.29)	0-1	0.09 (0.29)	0/1
Number of items in:						
Mixed drug- and non-drug	(ref.)		(ref.)		(ref.)	
Cannabis	4.58 (12.23)	0-161	4.79 (17.98)	0-344	0.21 (0.40)	0/1
Stimulant	2.14 (4.44)	0-48	2.28 (6.85)	0-181	0.16 (0.36)	0/1
Ecstasy	1.91 (6.04)	0-109	1.72 (6.99)	0-148	0.08 (0.26)	0/1
Opioid	1.04 (3.15)	0-36	1.30 (5.79)	0-165	0.08 (0.27)	0/1
Psychedelic	1.25 (4.90)	0-101	1.17 (6.10)	0-126	0.05 (0.21)	0/1
Benzo	0.79 (3.38)	0-52	1.07 (5.85)	0-109	0.06 (0.23)	0/1
Prescription	0.98 (7.00)	0-214	0.88 (6.11)	0-190	0.02 (0.15)	0/1
Dissociative	0.24 (1.16)	0-16	0.30 (1.65)	0-26	0.02 (0.13)	0/1
Ships to:						
Other countries/continents	(ref.)		(ref.)		(ref.)	
Worldwide	0.33	0/1	0.64 (0.47)	0/1	0.57 (0.49)	0/1
U.S. only	0.28	0/1	0.26 (0.44)	0/1	0.22 (0.41)	0/1
Europe only	0.10	0/1	0.14 (0.35)	0/1	0.13 (0.33)	0/1
U.K. only	0.05	0/1	0.09 (0.29)	0/1	0.12 (0.32)	0/1
Australia only	0.08	0/1	0.07 (0.25)	0/1	0.06 (0.24)	0/1
Cryptomarket (= Abraxas)	0.18	0/1				
Average reputation (AlphaBay)			0.63 (0.46)	-1 - 1		
No sales before AlphaBay			0.68 (0.46)	0-1		
No accounts before AlphaBay			0.65 (0.47)	0-1		

Table 4.1. (Continued)

Variable name	Model set 1		Model set 2		Model set 3	
	Mean (SD)	Range	Mean (SD)	Range	Mean (SD)	Range
Weeks since market entry			36.63 (28.19)	1-133		
Months since market opened			20.10 (7.70)	1-32	19.03 (7.19)	1-29
	N(sellers)	2,392	N(sellers)	7,593	N(buyers)	16,941
			N(sellers* weeks)	341,223	N(buyers* feedbacks)	237,636

RESULTS

Descriptive statistics

Before focusing the analysis on Agora, Abraxas and AlphaBay, the three cryptomarkets where we test the hypotheses, we provide an overview of the scope of seller movements between all largest cryptomarkets documented in the Grams database. Based on the database, AlphaBay was the largest cryptomarket in terms of the number of sellers during the observed period between 2014 and 2017. The marketplace had 10,942 seller accounts, followed by Dream Market with 5,912 seller accounts, and Evolution, with 3,838 (see Figure 4.1B).

On average, each unique PGP address, which can be assumed to correspond to unique sellers, had 1.52 accounts associated with it in 1.47 cryptomarkets. 73.2% of all PGP keys were associated with a single account, some keys having up to 10 accounts in 9 marketplaces associated with them. This shows that while a large majority of sellers operated in a single cryptomarket, a quarter of all observed sellers operated in multiple markets, in some cases - in all of them.

We operationalized a seller's movement between two marketplaces if a seller had an account open in one marketplace *before* he or she opened an account in a different one. These directed movements of unique sellers are depicted in Figure 4.1A. The figure represents only those sellers that moved between marketplaces at least once. Sellers could move more than once and have active accounts in more than one marketplace simultaneously. Colors of the circle border represent the number of sellers in each marketplace, while the colors of flows represent the "source" marketplace of moving sellers (e.g., Agora sellers moving to AlphaBay are depicted by an orange flow towards green circle border area). The seller flows are directed, which means that sellers in 2 markets can move in 2 different directions (e.g., unequal number of sellers moving from Dream to AlphaBay and vice versa).

In total, 10,643 cases of seller migration were observed. The largest flow of sellers was observed after AlphaBay's closure in 2017 – there were 1,633 sellers who opened accounts in Dream Market. 515 AlphaBay sellers opened accounts under the same identity in Valhalla. Both Dream and Valhalla marketplaces are still functional at the time of writing. In terms of seller inflow, the largest number of sellers migrated to AlphaBay from Dream (N = 415), Abraxas (N = 401), Evolution (N = 276) and Agora (N = 270). Majority of these sellers, with an exception of Dream Market, opened accounts in AlphaBay following the closure of the cryptomarkets they had operated in.

Figure 4.1 A, B. Seller migration patterns between cryptomarkets (left; direction is indicated by color, e.g., Agora sellers moving to AlphaBay are depicted by an orange flow towards green circle border area). Cryptomarket lifetimes and seller account statistics (right).

Based on data in the Grams database, 18.89% of observed seller accounts with provided PGP keys were already active in other markets before joining AlphaBay. 63.02% of unique sellers in AlphaBay were only ever observed to be active in AlphaBay and did not maintain the same identity after its closure. This roughly corresponds to the figures of sellers in the entire database – around 20% of sellers actively migrate between marketplaces, while the majority of sellers either operate in a single cryptomarket or constantly change their identities.

Seller inflow from different marketplaces directly reflects in the subsequent number of sales in AlphaBay (see Figure 4.2). During the first 3 months of operation, AlphaBay had virtually no feedback messages posted by buyers. The first surge in the number of sellers and subsequent feedback messages was observed after the shutdown of Evolution market. Similarly, after Agora and Abraxas shutdowns, the number of daily feedback messages increased, roughly doubling after each event. In 2016, AlphaBay was already the dominant cryptomarket in the space, with a constant average of 10 new sellers per day, and constantly increasing number of feedback messages from 1787 in January, 2016 to 5581 in April, 2017.

Figure 4.2. The number of daily new seller accounts and number of feedback messages in AlphaBay.

Hypothesis testing

Sellers' identity maintenance

The first set of models (see Figure 4.3) test hypothesis 1 and uses data on sellers from Agora and Abraxas. The three logistic regression models test whether sellers' sales and reputation had a positive impact on their likelihood to maintain the same identity and move to a different cryptomarket after the shutdown of their respective marketplaces. Each case represents a seller in either Abraxas or Agora. Figure 4.3 depicts results of the models (odds ratio coefficients and standard errors). Only the effects of the main independent variables are shown in the figure (for the complete table of results including control variables, see Appendix 2A).

In the first model, to observe the effect without control variables, we only included the variable with sellers' aggregate sales count and a dummy for the marketplace an account was observed in. In Model 2 we added sellers' total number of listings, their prices and categories, and the shipping destinations each seller offered. In the final model, we added the reputation effect. We kept this variable for the final model, since sellers with 0 sales had no information on reputation ($N = 127$), therefore dropped out, which decreased the sample size in the final model.

Logistic regression Model 1 shows that sellers' accumulated total number of sales increases the odds that the seller migrates to a new cryptomarket with the same identity ($OR=1.005$, $p < .001$). Every 10 sales increase the odds of a seller to migrate by

about 5%. We also observed the expected positive effect of the seller being registered in Abraxas, since a relatively larger proportion of all sellers did so, as discussed in the descriptive results section.

The hypothesized effect of the number of sales remained statistically significant in Model 2, once sellers' listing- and shipping controls were taken into account. Based on the results, a seller's decision to move to a new market is not associated with the type or price of goods they sell, or the market they ship their products to. Sellers who ship items to Australia only are the only exception - these sellers are more likely to migrate than others (OR = 1.568, $p < .01$). Australia is known to be a relatively isolated niche in cryptomarkets, in terms of having mostly domestic shipments and high prices, primarily due to geographic location, strict border controls and high offline drug prices (see Chapter 6; Cunliffe *et al.*, 2017; Norbutas, 2018).

Model 3 shows that on top of the positive effect of sales, high reputation is also strongly positively related to the odds of a seller migrating with the same identity (OR = 1.689, $p < .001$). Both of these effects show that it is primarily the successful and well-reputed sellers who migrated maintaining their identity after cryptomarket shutdowns and maintained their identity. These results are in line with Hypothesis 1¹⁵.

Reputation transferability and market outcomes

The second set of models (Figure 4.4; for full results see Appendix 2B) are multi-level random intercept negative binomial models, with weekly observations of sellers nested in seller IDs. Here we test whether sellers' history of sales and reputation in previous cryptomarkets (if any) had an effect on their market success in AlphaBay. These models test hypotheses 2 and 3. The dependent variable, number of sales, is at the weekly level. The main independent variables, reputation and sales in Abraxas and Agora are constant at the seller-level (level 2 effects). Reputation effects in Abraxas vary at the seller*week level (lagged level 1 effects). The remaining controls for item categories and shipping locations are measured at the seller level (level 2).

In these models we only used data on sellers that migrated from Abraxas and Agora, since we only had sales data available for these 2 markets. We used data on sellers who were new in AlphaBay (or had changed their identity) as the comparison group.

15 We also tested a quadratic and cubic effects of sales on the probability of migration, adding them to Model 2. The results show a non-linear (inverse u-shape) effect – sellers with no sales have the lowest probability to migrate, which increases rapidly for those with 100-600 sales and somewhat decreases for those with >600 sales.

Figure 4.3. The main results of logistic regression models of seller properties on odds of migrating to a new market with the same identity (for full results, see Appendix 2A).

In models 4 and 5, we added the main effects of the number of markets a seller had been active in before AlphaBay, the number of sales and average reputation in Abraxas and Agora and analyzed whether it had an impact on sellers' subsequent weekly number of sales in AlphaBay (hypothesis 2). In the third and fourth models we added control variables to check the robustness of these effects. In the models 6 and 7 we tested the interaction effect between the main variables (hypothesis 3).

The results of Models 4 and 5 show that both the pre-AlphaBay accumulated number of sales ($IRR = 1.001, p < .001$) and reputation ($IRR = 1.198, p < .001$) of seller migrants with maintained identity are positively associated with weekly number of sales in AlphaBay. In this model we also observe that the number of markets migrating sellers had been active in have a positive effect on weekly sales (M4: $IRR = 1.310, p < .001$; M5: $b = 1.256, p < .001$).

Models 6 and 7 show that the effects of pre-AlphaBay number of sales and reputation remain statistically significant once control variables are accounted for. The effect of the history of number of sales and positive reputation score are both in line with hypothesis 2. We therefore find substantial evidence in favor of this hypothesis.

Figure 4.4. The main results of multi-level negative binomial regression models on weekly number of sales (for full results, see Appendix 2B).

The control variables in Models 4 and 5 show similar results to those observed in previous studies on cryptomarket vendors (Chapters 2, 3, 5, 6). We find that sellers’ lagged reputation in AlphaBay positively affects the number of sales in the current week ($IRR = 1.043, p < .001$). Interestingly, the effect size of reputation from previous marketplaces, and the current marketplace are similar, the latter being slightly weaker, even though the range of the latter is much smaller – ratings in AlphaBay ranging from -1 to 1, while those in Agora and Abraxas from 0 to 5. We also find a similar effect of time to that found in previous studies – sellers tend to gradually make fewer weekly sales over time ($IRR = 0.994, p < .001$), and those, who joined or were active later in terms of calendar time, had on average more weekly sales ($IRR = 0.031, p < .001$). The former might be explained by sellers’ relative inactivity before exiting the market and increased competition due to a growing number of sellers. Having controlled for this, sellers who joined later got more sales since they could sell to a larger pool of buyers. We also found that sellers who ship specifically to the United States, United Kingdom, Australia and the EU get more weekly sales than sellers who ship to fewer specific locations or other countries (IRRs between 1.226 and 1.749 in Models 4 and 5, $p < .001$). We also find that seller with a higher number of items within the highest

price quartile in respective item categories have fewer weekly sales, compared to those with more items in the first price quartile ($IRR = 0.605$, $p < .001$).

Models 6 and 7 include the interaction effects and test hypothesis 3. We expected that the effects of the number of marketplaces a seller had been active in before AlphaBay, would significantly increase the effects of the history of sales and reputation on current weekly sales due to increased visibility. We found no statistically significant interaction effect in either Model 6 ($IRR = 0.999$, $p = .11$) or Model 7 ($IRR = 1.004$, $p = 0.71$). In other words, the results suggest that it does not matter how many markets a seller had been active in. What matters is the seller's reputation and sales in those markets - this leads us to reject hypothesis 3. For an additional analysis of how transferred reputation effects vary over time, see Appendix 3.

Reputation transferability and dyadic embeddedness

The third set of models are multi-level random intercept multinomial logistic regression models, with buyers' feedback messages (exchanges) nested in buyer IDs. These models test hypothesis 4. The models estimate the likelihood that a specific category of a 3-category nominal dependent variable is chosen. The relative risk ratios of selecting a specific category are estimated in contrast to the baseline category. In our case, we estimated the likelihood that a buyer chooses a seller, who had migrated from either Agora or Abraxas cryptomarket, compared to the baseline category, which is an AlphaBay seller who did not have an account in these 2 marketplaces. We analyzed whether these likelihoods depend on whether the buyers themselves migrated from one of those two marketplaces (measured by time of registration), controlling for time and selected item properties.

Model 8 (for a full table of results, see Appendix 2C) shows that buyers that entered AlphaBay within one month after Abraxas' closure are significantly more likely than those who entered earlier or later to select both Abraxas migrant sellers ($RRR = 2.028$, $p < .001$) and Agora migrant sellers ($RRR = 1.685$, $p < .001$). Buyers that migrated earlier, within one month after Agora closure, are significantly more likely than other buyers to select Abraxas migrant sellers rather than other sellers ($RRR = 1.568$, $p < .001$). We did not find any evidence of post-Agora buyers being more likely to select Agora migrant sellers ($RRR = 1.229$, $p = 0.15$). The same results hold in Model 9 (see Figure 4.5), once control variables are taken into account. We also find that buyers are less likely to select migrant sellers later in time (M9 Agora: $RRR = 0.972$, $p < .001$; Abraxas: $RRR = 0.976$, $p < .001$), which is in line with sellers' sales trajectories depicted in Figure A3 (see Appendix 3). Although we find evidence that buyers who entered AlphaBay after Abraxas' closure are more likely to select Abraxas migrant sellers than Agora sellers, or any other sellers, we do not find the same consistent pattern for

buyers who entered after the Agora closure. We therefore find only partial evidence for hypothesis 4.

Figure 4.5. The main results of multi-level random-intercept multinomial logistic regression models of buyer migration history on migration-based seller selection (for full results, see Appendix 2C)

CONCLUSIONS AND DISCUSSION

In this chapter, we aimed to analyze cryptomarket sellers' reputation transferability by answering two related research questions: under what conditions do sellers choose to maintain their online identities in new environments, and, for those who do, to what extent does reputation from previous marketplaces increase market outcomes in a new one.

Regarding the first research question, the results show that sellers with higher reputation and a longer history of sales are more likely to keep their online identity when migrating to new marketplaces. There is virtually no difference between sellers in different geographic locations, sellers specializing in different types of items and price brackets. We conclude that at a certain point the future market benefits of having a good reputation history might outweigh potential risks related to the risk of getting exposed to the law enforcement, making sellers with an established reputation more likely to migrate using the same online identity.

This finding relates to an important observation made by van Wegberg and Verburch (2018), namely, that some cryptomarket vendors choose to "throw away" their reputation and change their identity upon migration. Our study suggests that these sellers might not have much to throw away in the first place. It is the more successful sellers that choose to maintain their "brand" or identity, while the less successful ones, having less to lose, might choose to start with a clean slate and avoid any additional risks.

Our second finding relates to whether reputation from previous contexts yields market benefits in new cryptomarkets for sellers who choose to maintain their online identities. We find strong support for reputation transferability effects – history of sales and a good reputation significantly increased sellers' sales in a new marketplace - AlphaBay, compared to other sellers with previously unverified identity. The positive effects of "transferred" reputation are of comparable size to those of reputation that sellers accumulated in the new market. These findings suggest that while sellers' reputation in previous markets might no longer be perfectly observable for buyers in the current context, it is still relevant in shaping their decisions when choosing a seller in new contexts, which eventually triggers further reputation benefits for migrating sellers.

The first two findings have an important implication when considering the distribution of market success across cryptomarket sellers. Although we focused on only three cryptomarkets (AlphaBay, Abraxas and Agora), descriptive results from the Grams database show that around 20% of sellers with cryptographically verified identities migrate and have multiple accounts in different markets. This tendency and our previously discussed findings suggest that law enforcement operations aimed at closing

down specific cryptomarkets might have unintended consequences and contribute to accumulation of profit in the hands of a relatively small number of successful sellers. If it is the top sellers that choose to maintain their identity, over time this might lead to an increased competitive advantage over market entrants, also known as reputation cascading (Frey and van de Rijt, 2016). This might be further strengthened by reputation transferability effect found in this study and further consolidate the market advantage of already successful drug sellers.

Our findings also stress the importance of reputation systems as a mechanism that sustains trust across contexts. Reputation transferability embeds actors beyond cryptomarket boundaries, which prolongs the “shadow of the future” and buyers’ ability to control opportunistic sellers. Reputation scores that buyers post in the websites impact sellers’ market prospects beyond any specific market. This aspect might increase sellers’ incentives to cooperate and further strengthen the positive effect of reputation systems on cooperation (see Chapters 2 and 3; Hardy and Norgaard, 2016).

Another consequence of reputation transferability is its impact on cryptomarkets resilience to disruptions. Since well reputed sellers are more likely to migrate and maintain identity, and buyers take sellers’ history of reputation into account, exchanges in cryptomarkets after disruptions do not start from scratch. Established trust and cooperation between market actors can simply transfer to new venues, limiting the uncertainty that would otherwise increase drastically after market closures.

Our third finding relates to repeated dyadic exchanges between buyers and sellers, previously observed in other cryptomarkets (see Chapter 3; Décary-Hétu and Quessy-Dore, 2017). It has been found that buyers typically limit their exchanges to one or a few trusted sellers instead of looking for cheapest or highest quality alternatives in the market. We find that buyers who enter a new market after market closures, likely migrating users themselves, are much more willing to choose a migrant seller than a new seller, compared to buyers who enter before or after that. This result suggests that reputation transferability effects might be partially driven by dyadically embedded buyers and sellers who migrate to new contexts and continue exchanging there. It could be that buyers follow their trusted sellers to new venues, or at least look for sellers that are familiar from the previous context.

On the other hand, we do not find that buyers who register after the closure of a specific market are more likely to select sellers from that same market. Abraxas migrant buyers are more likely to select Abraxas migrant sellers, but also Agora migrant sellers. One possible explanation could be indirect migration - our descriptive findings revealed complex migration patterns, including sellers that migrated more than once between

Agora, Abraxas and AlphaBay. It could be that migrating buyers had interacted with the same seller in more than one marketplace.

In summary, we find that reputation effects in cryptomarkets are transferable across marketplaces – more highly reputed online drug sellers choose to maintain their online identity in different contexts, while buyers take their past reputation into account when considering exchange partners in current contexts. We observed an interesting tension between anonymity and embeddedness when it comes to sellers' success. Trust in cryptomarkets is consolidated by reputation and repeated exchanges. Market closures and the risk of getting arrested, however, make sellers balance the trade-off between remaining fully anonymous on the one hand, and maintaining their identity and reputation across contexts on the other.

LIMITATIONS

There are several limitations in this study that could be addressed in future research. Firstly, we have limited information on identity maintenance. Specifically, we defined “maintaining identity” as users having the same PGP key in multiple cryptomarkets. There might be cases when sellers change the key or drop the encryption and use non-technical/informal alternatives to prove their identities to other users (e.g., private messages to buyers, vouching of trusted third-parties). While these identity signals are weaker than PGP encryption and we do not expect them to take place often, especially when the number of migrating sellers is so high, this might mean that some of the sellers we analyzed as “new” were actually those that maintained identity by different means.

The data on buyers we obtained is a relatively selective sample of all buyers. We obtained this sample by a trial-and-error process of trying out nicknames of individuals active in discussion forums. It is therefore not necessarily representative of all buyers in AlphaBay. Sadly, the lack of data on individual buyers is common for all cryptomarkets, as user profile pages are typically hidden (see Chapter 6). To our knowledge, our AlphaBay buyers dataset and the unique Abraxas dataset used in Chapter 6 are the biggest samples of cryptomarket buyers to date. Future studies able to match buyers between marketplaces could use more advanced research approaches, such as an analysis of buyer/seller exchange network structure (for a similar approach, see Chapter 6). Network models, such as random graph models, allow to test hypotheses about relational changes between a set of actors over time and as a function of some predictors. For example, such an approach would allow us to directly test whether buyers and sellers who exchanged in a previous cryptomarket are also more likely to exchange with these sellers in a new venue.

5

“Cheap talk” signaling in full anonymity:

An empirical study of seller behavior
and success in a drug cryptomarket

ABSTRACT

Trust is essential for cooperation between anonymous individuals in the absence of central authority. We analyze how signaling, or intentional behavior of sellers aimed at convincing buyers of their trustworthiness, emerges as an additional strategy to facilitate cooperation in an illegal online market for drugs, when reputation systems might not suffice. We investigate whether sellers use communication strategically to signal their trustworthiness and whether these signals substitute for lacking or damaged reputation. We analyze longitudinal data from a cryptomarket that include 137,077 sales and 13,003 discussion forum messages by 1,062 drug sellers spanning over a period of 6 months in 2012. We use hybrid regression models to analyze under what conditions sellers become active in the forums and whether that affects success in the marketplace. Our findings suggest that communication signaling leads to increased sales regardless of seller's reputation. Drug sellers post market-related messages strategically, along with price discounts, to compensate for lacking market reputation. In contrast, general discussion messages with other users are posted relatively constantly over time. We argue that trust between illegal online market actors might emerge as a by-product of non-market related social interactions.¹⁶

¹⁶ A version of this chapter is submitted to an international scientific journal. This chapter is co-authored by Rense Corten and Stijn Ruiter.

INTRODUCTION

Cooperation in social exchanges characterized by high uncertainty is one of the key puzzles in social sciences (Axelrod, 1984; Coleman, 1990, Nowak, 2006). Although cooperation can be beneficial for collectives, individual short-term gain from opportunistic behavior provides incentives to act uncooperatively (Raub, Buskens and Corten, 2014). Individuals often lack sufficient information about the true intentions of their interaction partners, which makes trust, or willingness of an individual to cooperate at a risk of being abused, a prerequisite for cooperation (Arrow, 1974).

Trust plays an important role in virtually any economic exchange (Arrow, 1974; Granovetter, 1985; Buskens, 2002). If buyers and suppliers cannot trust that goods will be delivered, and money will be paid on time, costlier written agreements and contract enforcement measures will be necessary to prevent opportunism. Trust, therefore, reduces the need for inefficient contracting measures in exchange situations.

Trust, however, may not always lead to socially desirable consequences. It can also increase efficiency of cooperation and economic exchanges in illegal settings, such as online marketplaces for drugs (see Chapter 2; Przepiorka, Norbutas and Corten, 2017; Beckert and Wehinger, 2013). In recent years, the growth of online marketplaces for illegal drugs (cryptomarkets) has attracted increasing attention of sociologists, economists and criminologists (Barratt and Aldridge, 2016). Cryptomarkets are online platforms that enable individual buyers and sellers to exchange in full anonymity by employing an anonymizing internet browser (TOR), cryptocurrencies for transactions and other technical means (Barratt and Aldridge, 2016). The estimated global volume of monthly cryptomarket drug exchanges was between \$12 and \$21 million dollars in 2016, a figure that had doubled in three years despite several large, internationally coordinated law enforcement actions to disrupt operations (Kruithof *et al.*, 2016; van Buskirk *et al.*, 2017; Décary-Héту and Giommoni, 2017).

Trust plays a key role in such settings, since actors not only face uncertainty, typical in licit online markets (Diekmann *et al.*, 2014; Przepiorka, 2013), but are also not protected by the legal system (Hardy and Norgaard, 2016; Przepiorka *et al.*, 2017; Duxbury and Haynie, 2018a). Buyers cannot be certain about the true quality of the products they consider or about the trustworthiness of their exchange partners. Although drug buyers typically have more information about the drugs they order compared to retail drug trade offline, the accuracy of the information provided by the sellers cannot be fully verified in advance. If buyers get scammed by an opportunistic seller, there is typically no institution or formal safety net to rely upon. Nevertheless, cryptomarket buyers and sellers find ways to cooperate, and opportunistic behavior is relatively rare (Christin, 2013; Soska and Christin, 2015). Understanding how

anonymous market actors come to trust each other in such environments of extreme uncertainty can be informative not only to law enforcement agencies, who seek to disrupt such markets, but also to social scientists, who seek to understand the social mechanisms that ensure trust between individuals in situations with no central coordination or authority.

In this chapter, we analyze the emergence of trust between buyers and sellers in a cryptomarket for drugs, specifically focusing on the effect of direct communication between buyers and sellers. While research on cryptomarkets often aims to compare this environment to offline or “street” markets in terms of structure or safety (e.g., Martin, 2014; Barratt, Ferris and Winstock, 2016; Aldridge and Décary-Héту, 2016), our aim here is to focus on online-specific mechanisms that might affect trust between buyers and sellers of drugs.

Previous research on trust in cryptomarkets, and online marketplaces in general, were based on a premise that sellers’ actions speak louder than their words (Bracht and Feltovich, 2009; Duffy and Feltovich, 2000), focusing mainly on the effect of reputation systems, where buyers provide public feedback about sellers’ past actions (Kollock 1999; Resnick and Zeckhauser 2002; Dellarocas 2003; Diekmann *et al.* 2009; Przepiorka 2013; Diekmann *et al.* 2014; Hardy and Norgaard, 2016; Przepiorka *et al.*, 2017). Reputations are costly to build and can therefore serve as a signal of trustworthiness (Gambetta, 2009; Przepiorka and Berger, 2017). Communication with customers, on the other hand, can be considered “cheap talk”, which is non-binding, costless and should therefore have limited or no effect on buyers’ trust in a particular seller (Gambetta, 2009).

This theoretical prediction is in contrast with consistent empirical findings from laboratory experiments, which show that direct communication in both face-to-face and written forms before an interaction can lead to large increases in cooperation in social dilemma situations, including trust games (for meta-analytic reviews, see Sally, 1995; Balliet, 2010). On the other hand, when both mechanisms are compared, the ability to observe one’s reputation has a stronger effect on cooperation and trust than the ability to hear one’s promise, or “cheap talk” (Bracht and Feltovich, 2009; Duffy and Feltovich, 2000).

We test the effect of communication between buyers and sellers in an empirical setting, namely a cryptomarket for illegal drugs. We use signaling theory as a framework (Gambetta, 2009; Przepiorka and Berger, 2017) to derive hypotheses on what kind of sellers’ messages and under what conditions communication on cryptomarket discussion forums can increase buyers’ trust and, accordingly, sellers’ market success. We test whether sellers’ communication with buyers positively affects their market

outcomes net of their market reputation. Additionally, we argue that seller's strategic signaling by communication with buyers can be a substitute for market reputation.

We use longitudinal data on more than 135,000 sales of illegal drugs by 1,062 vendors in a cryptomarket called Silk Road (Christin, 2012). We link sellers' market and forum accounts to analyze, on the one hand, under what conditions market sellers actively use discussion forums and, on the other hand, whether these investments lead to increased prices of their goods and larger sales. Silk Road was the first major cryptomarket, which operated as a monopoly of online drug sales between 2011 and 2013. This allows us to answer our questions without having to worry about possible effects of unobserved seller reputation from competing online marketplaces or out-of-market communication between buyers and sellers. Our data include sellers' activity spanning over a period of 6 months in 2012.

THEORY

Online marketplaces and the trust dilemma

Cryptomarkets, like most online marketplaces, are characterized by high information asymmetry between buyers and sellers (Akerlof, 1970; Christin, 2013). Buyers cannot estimate the real quality of goods and must rely on information provided by sellers. If buyers agree to send money before receiving the goods they ordered, they also risk never receiving the items (Diekmann *et al.*, 2009). Sellers have an incentive to act opportunistically by not sending the goods or sending goods of inferior quality, if no institutions are present to enforce cooperative behavior, because it is more profitable. It is also always possible to re-enter the market under a new alias in case abused buyers escalate the issue publicly. Buyers cannot estimate the willingness of a particular seller to act cooperatively, because users in cryptomarkets are fully anonymous.

Such conditions create the so-called the trust dilemma (Coleman, 1990; Raub, Buskens and Corten, 2014). If buyers and sellers act rationally, no transactions will take place in such a situation, because the potential cost of being abused would be too high for any buyer to place trust. The problem of trust is arguably even more severe in cryptomarkets than in legal online markets, since a much higher level of user anonymity is guaranteed by the Tor network and anonymous digital currencies (Bradbury, 2014; Nakamoto, 2008). Market contracts are not secured by law enforcement, which leads to a higher risk for buyers, and potentially a higher number of fraudulent sellers in the market, who would otherwise be deterred by the risk of punishment. Furthermore, since all goods purchased in cryptomarkets are sent via regular mail, buyers risk being arrested if a seller is unprofessional and a mail package gets intercepted.¹⁷

In cryptomarket platforms, like in many licit online marketplaces, sellers' ability to disappear with buyers' funds is somewhat limited by escrow systems, conflict resolution interventions by administrators and other mechanisms (Barratt and Aldridge, 2016). Despite these attempts to implement endogenous institutional regulation at the platform level, buyer complaints about both product uncertainty and losing money to fraudulent sellers, are abundant (Moeller *et al.*, 2017). Furthermore, users' reliance on marketplace's mechanisms that are implemented to alleviate the trust problem, presents other sources of risk. Escrow systems, for example, that lock buyers' funds in a marketplace account, until buyers receive the goods, make it possible for marketplace administrators to steal funds. There have been multiple instances of

¹⁷ In most cases where Dark Web users were arrested, it happened after mail packages were intercepted and not by de-anonymizing their online identity. See: <https://www.deepdotweb.com/2015/11/23/dunedin-students-arrested-for-importing-drugs-from-dark-net/>, also see: <http://www.cnet.com/news/one-man-arrested-another-indicted-in-ebay-fraud-schemes/>

cryptomarket platforms disappearing with users’ funds, the largest of which to date stole \$12 million (Moeller *et al.*, 2017).

Costly signaling of trustworthiness in online markets

To overcome such constraints and minimize risk, buyers need to be able to identify trustworthy sellers. To convince buyers of one’s trustworthiness, a seller must produce a signal that would be too costly for an opportunistic seller, but not a cooperative one (Gambetta, 2009). Signals are any form of costly behavior or observable features of an actor, which are intentionally displayed for raising the probability a receiver assigns to a certain state of affairs – seller’s trustworthiness, in our case (Gambetta, 2009; Przepiorka and Berger, 2017). A successful signal is type-separating – only trustworthy sellers will be able to produce such a signal and will make it sufficiently informative of seller’s true nature for the buyer to make a decision.

The seller’s market reputation is the most analyzed type of costly signal in the context of licit online marketplaces and cryptomarkets (Diekmann *et al.*, 2014; Przepiorka *et al.*, 2017; Hardy and Norgaard, 2016). Every cryptomarket contains a centralized reputation system, where buyers can leave feedback on sellers’ trustworthiness after an exchange. Good reputation is costly to build – too costly for untrustworthy sellers, reaching for short-term gains. Reputation therefore serves as a costly signal, affects buyers’ choices and eventually allows trustworthy sellers to trade at premium prices, while pushing opportunistic sellers out of the market (see Chapter 2; Przepiorka *et al.*, 2017).

Seller’s reputation is not the only source of information about sellers that cryptomarkets buyers evaluate before making a choice. Before making purchases, cryptomarket buyers have been found to consult discussion forums for available information about sellers and their goods, which is often provided by sellers themselves (Bancroft and Scott Reid, 2016; van Hout and Bingham 2013; 2014; Martin, 2014).

Discussion forums are a part of every cryptomarket and are designed to enable direct communication between marketplace buyers and sellers. Whether and how such communication can affect users’ market behavior is not straightforward. Topics discussed between buyers and sellers range from product advertisements, requests and reviews (Martin, 2014), to political debates about privacy, philosophy and sharing of drug-related experiences (Maddox *et al.* 2016; Martin, 2014; Munksgaard and Demant, 2016). Additionally, the cost of seller’s engagement in online discussions with buyers is near-zero, and a signal produced in such environment could in many cases be emulated by untrustworthy sellers (Gambetta, 2009).

“Cheap talk”: strategic market-related signals and non-strategic signs of kindness

The distinction between “signals” and “signs” is important when analyzing communication between sellers and buyers (Przepiorka and Berger, 2017; Gambetta and Przepiorka, 2014; Gambetta, 2009). While signals are by definition displayed intentionally, the production of signs need not be strategic. Signs can be informative of actor’s trustworthiness, although not having been produced for that purpose. They can be produced because of an actor’s intrinsic properties that are related to trustworthiness – for example generosity or guilt aversion (Przepiorka and Berger, 2017; Gambetta and Przepiorka, 2014). While strategically displayed signals need to be costly to be type-separating, signs can be informative while actually being “cheap” – the cost of production being identical for both trustworthy and untrustworthy actors.

Since signs are produced non-strategically due to actor’s intrinsic properties related to trustworthiness, they can become a credible signal when the actor is asked to *display* the sign. Trustworthy actors, who had been producing a sign due to generosity or another related intrinsic trait, will be able to display it, while an actor who does not possess such trait will need to fabricate the signs (Przepiorka and Berger, 2017).

In the context of communication between cryptomarket sellers and buyers, sellers can be expected to produce both strategic market-related signals and engage in naturally occurring general discussions with like-minded users. Cryptomarket discussion forums are structured thematically, the two main categories typically being market and non-market related discussions.

Market-related sections are devoted to discussions about quality of sellers and the goods they sell, reviews and recommendations. In these sections, sellers typically advertise, engage in marketing or “branding” of their products, and otherwise maintain communication with their customers (Martin, 2014; Tzanetakis *et al.*, 2016). Such communication is produced strategically to maximize profit in the marketplace. Based on signaling theory, it should be unlikely to affect buyers’ decisions, unless there are additional costs that would make such messaging too costly for opportunistic sellers. To signal their credibility and trustworthiness sellers have been found to provide evidence of the quality of their goods by publishing laboratory test results, offering personal and “freebie” testing or disclosing their reputable suppliers (Van Hout and Bingham, 2014). While sellers incur costs to generate such messages and such messages are likely to increase the quality of sellers’ market-related signals, not all messages on the forums are costly to generate and many can be considered “cheap talk”.

Individuals are not always strategic in their actions and might produce signs of their trustworthiness for other reasons (Przepiorka and Berger, 2017). The general

conversations between buyers and sellers regarding non-market related topics can be regarded as such signs. Discussions between cryptomarket users in “General discussion” sections of the forum usually revolve around topics such as drug use, privacy, politics and other topics that do not necessarily relate to market exchanges (Martin, 2014). As an illegal community, buyers and sellers rely on the diffusion of technical knowledge and risk reduction strategies within the community in order to avoid getting arrested (Martin, 2014; Aldridge and Askew, 2017). Users turn to cryptomarket discussion forums to seek and share advice on harm-reducing ways of using various substances (Bancroft and Scott Reid, 2017). Cryptomarket members have also been found to actively engage in political discourse, mostly related to libertarian views and individual’s right to non-interference (Munksgaard and Demant, 2016).

Some sellers contribute to such discussions and help other members with technical security and harm reduction, while others mainly engage in market-related activities. Those that engage in such discussions should have other, non-market related motivations to do so, such as group identity or other-regarding preferences. While the costs of producing such signs are identical to both trustworthy and untrustworthy sellers, only the former receive benefits for doing so (Fehrler and Przepiorka, 2013; Przepiorka and Berger, 2017). As a result, regardless of identical costs for both types of actors, a long history of pro-social acts can show the trustworthiness of a seller¹⁸. Rational buyers, seeking the most trustworthy partners in the marketplace, might be more likely to choose such pro-social sellers, who are active members in discussion forums within the community, over those who do not make contributions (Fehrler and Przepiorka, 2013; Roberts 1998; Sylwester and Roberts, 2010).

Based on these theoretical arguments, we expect that both strategic market-related signals and non-market related messages (signs) will have a positive effect on sellers’ market outcomes. We expect, however, that sellers’ non-strategic involvement in general discussions will have a stronger effect on buyers’ trust than their market-related messages, since strategic signaling requires additional costs (e.g., aforementioned laboratory testing of purity) in order to be type-separating. In other words, sellers might need to prove that they are good sellers but being kind to community members and helping others might speak for itself.

H1: *The number of strategic, market-related messages in the “Market” section of the forum is positively associated with the number of sales and product price of the sellers.*

18 This argument relies on an assumption that trustworthiness and pro-social preferences are correlated. For a discussion of this association in the context of signs and signals, see Przepiorka and Gambetta, 2014.

H2: *The number of non-market related messages in the “Discussion” section of the forum is positively associated with the number of sales and product price of the sellers.*

H3: *The positive effect of non-market related messages on seller’s market outcomes is larger than that of strategic, market-related messages.*

Market conditions for strategic communication

Signaling theory argues that signals are strategically produced and displayed by an actor to change other actors’ beliefs. Communication with buyers, however, is just one of several types of signals that a seller can produce. As argued previously, an important signal of sellers’ trustworthiness is their market reputation. Market reputation is a credible signal, which is costly to produce – a seller needs to behave trustworthily in multiple market exchanges in order for the reputation score to rise. While costly to produce, this signal is costless to display – once produced, it is displayed for all buyers in the website and positively affects seller’s market outcomes (see Chapter 2; Przepiorka *et al.*, 2017; Hardy and Norgaard, 2016).

We, therefore, expect that strategic market-related communication with buyers – a signal, which requires additional costs to be credible – will have decreasing marginal utility and therefore be produced less often, once a seller establishes a good reputation. In other words, sellers who have already invested in a good reputation, which is costless to display, will be less likely to pay extra costs for signaling in the discussion forum.

There are also several additional implications of this argument. If sellers’ strategic communication with buyers depends on their market reputation, it can be expected that new sellers will be more likely to produce such signals. For market entrants, offering free samples or otherwise communicating with buyers can help with gaining reputation in a competitive market. Reputation cascades are often observed in online markets, where sellers with high reputation gain cumulative advantage over market sellers who are entering the market and have no reputation (Frey and van de Rijt, 2016). Rational buyers are more likely to choose sellers with already high reputation, which further increases concentration of ratings among a small minority of sellers, who are not necessarily the most trustworthy ones. Such concentration has indeed been observed in various cryptomarkets, with the top 1 percent of all marketplace sellers conducting more than 50 percent of all trades (Soska and Christin, 2015).

Another implication is related to noise in reputation systems. Trustworthy sellers might receive bad ratings due to circumstances they are not responsible for (Utz *et al.*, 2009). This aspect is especially relevant in the context of cryptomarkets, since packages with illegal goods might get intercepted during the shipping stage of a

transaction. This might lead buyers to blame sellers for the damage incurred, or to accuse them of not shipping the items at all, because buyers are not always aware of such interceptions. Trustworthy sellers with damaged reputation can no longer display it as a credible signal of trustworthiness and might therefore have to compensate by turning to communication with buyers.

Finally, we expect these conditions to apply only to sellers' market-related signaling. If sellers participate in non-market related discussions for purposes other than attracting new buyers, as we argued in the previous section, the frequency of such signaling should not depend on their market performance. We formulate Hypothesis 7 to test the difference in the effects on strategic and non-strategic signaling frequency. We do not, however, expect this hypothesis to be supported by the data.

Based on the above arguments, we expect that:

- H4:** The frequency of seller's strategic market-related signaling decreases with the number of positive marketplace ratings.*
- H5:** The frequency of seller's strategic market-related signaling increases after receiving a negative marketplace rating.*
- H6:** The frequency of seller's strategic market-related signaling is higher during the first week of marketplace activity than during the remaining active period.*
- H7:** Marketplace ratings and the first week of marketplace activity have a lower effect on non-strategic signaling frequency than on strategic signaling frequency.*

DATA AND METHODS

We analyze data from the cryptomarket ‘Silk Road’. The marketplace opened in February 2011 and was closed in September 2013, following the arrest of one of the marketplace owners. Silk Road was the first large cryptomarket and operated as a monopoly online market for most of its time. The goods traded in the marketplace ranged from illegal drugs to fireworks and software items, although the absolute majority of items and sales were of the former category (Christin, 2013). The website contained listings of items sold by sellers, a design that resembles most licit peer-to-peer online markets. Each listing was categorized, contained a title, description, picture, price, weight of the item and other properties. A buyer could order a good from a seller by depositing the money to the marketplace, which in turn would send the money to the seller upon delivery of the good. Alternatively, a seller could also require the buyer to send the money upfront. After the transaction, a buyer could provide feedback. Each item listing in the marketplace could be sold more than once. Approximately 600 sellers operated in the marketplace at the end of 2012, a number which nearly doubled during the following year. Silk Road also had a discussion forum where marketplace users discussed market and non-market related issues in threaded conversations.

We use two main datasets in our analysis: 1) a marketplace dataset that contains sellers’ item listings and seller ratings awarded by the buyers, and 2) a discussion forum dataset that contains conversations between marketplace users.

The marketplace data contain daily crawls of the marketplace website between February 3 and July 24, 2012 (Christin, 2013). The data contain item names and descriptions, item categories, daily prices, seller identifiers and dated reviews from buyers of each item. Buyer reviews consist of a 5-star rating and a short comment. We use data from all drug categories that contained at least 10 items during the period of data collection. To maintain focus on illegal drugs, and comparability of sellers and goods, we excluded items that contained prescription medicine, steroids and related “performance enhancing substances”. In total, there were 15,790 items in the selected categories, sold by 1,062 sellers.

The discussion forum data we used are publicly available from the “Black market archives” compiled by Gwern Branwen (Branwen *et al.*, 2015). The database contains a copy of the discussion forum website created in October 2013, after the closure of the marketplace. The dataset contains the entire history of conversations, starting at 24th January 2011. The conversations in the discussion forum follow a particular structure. Each user can start a discussion by creating a new thread, which contains a topic reflecting name and user’s message. Any other user can then reply to the message

within the same thread and his message appears below the first one. Each thread was categorized in one of 3 topical categories: “Discussions”, “Market”, or “Support”. Each category is further divided into 16 sub-categories. The entire discussion forum contains 869,290 posts in 84,148 threads by 39,503 users. In total, based on the figures of users’ post counts and number of threads in the discussion forum, the data represent 99.2% of discussion threads and, on average, 78.8% of posts per user. The partial missingness might be caused by incomplete scrapes (Décary-Hétu and Giommoni, 2017), or, in many cases, by deleted posts by the users themselves. We do not have any reasons to expect that incompleteness of the forum scrapes is systematic and could significantly affect our results. We also do not expect cases where posts were deleted by the authors to have a significant impact on the analyses, since these posts were also likely unobserved by other forum users.

We used several sources of information to link sellers’ market profiles to their discussion forum profiles. The original marketplace dataset did not include seller nicknames, which are necessary to link users between datasets. Instead of nicknames, the market dataset included unique seller webpage identifiers¹⁹. To retrieve the nickname of each seller, we would have needed to access their profile pages and link each seller’s market account identifier to that seller’s nickname. Since Silk Road is no longer active, we used seller profile archives, collected by Branwen *et al.* (2015). Additionally, we searched for discussion forum messages that contained listed seller identifiers and linked a seller ID to the seller nickname referred in that forum post if it was mentioned. In total, we could identify 622 sellers (58.6 percent of the 1,062 sellers in the selected categories of drugs sellers) who were active in the marketplace and who collectively sold 11,811 items (74.8 percent of all drug items). Out of the identified sellers, 559 were also active in the discussion forum during or before the observed period of their market activity (89.8 percent of identified sellers; 52.6 percent of all sellers in the market). While unmatched vendors could still be active in the discussion forum, we argue that if a seller used a different nickname in the discussion forum or did not provide a link to his market profile, buyers were also unlikely to match that forum user to a particular market seller. Therefore, we also use market data from sellers whose forum accounts were not found and set their forum activity to 0. As a result, we retrieved a dataset of 1,062 sellers of drugs, 559 of whom were active in the discussion forum.

We extracted two types of information from the forum data. First, we collected all seller posts from the “Market” section of the forum. In total, we collected 17,301

19 For example, if a marketplace is reached via the onion address “ox8za77s21.onion”, each seller would have an individual profile “ox8za77s21.onion/seller_id/”. The data set only included these seller IDs.

forum messages from the “Market” section of 491 marketplace sellers (46.2 percent of all sellers, 78.9 percent of identified sellers). Second, we collected data from the “Discussion” section of the forum. There were 15,025 posts from 327 sellers (30.8 percent of all sellers, 52.6 percent of identified sellers).

In the final step, we constructed two types of datasets that we used in our analyses. In the first dataset, the unit of analysis is an item listing of a seller on a particular week. We analyze whether the number of sales and price for the items were affected by seller’s forum activity in the preceding week. We aggregated each seller’s marketplace outcomes and discussion forum activity to weekly time points, beginning at their market entry²⁰. Seller’s market entry is defined as the date of the first posted item listing.

The second dataset was used to analyze the effect of marketplace reputation on seller’s forum activity. The unit of analysis is seller’s weekly forum activity. The dataset also contains seller’s marketplace ratings aggregated over all items that were sold one week before the forum activity was recorded. We analyze seller’s activity aggregated to weekly time points in the same way as the previous dataset – each case contains seller’s activity in the n th week since seller’s market entry. Since many sellers were active in the discussion forum before this point, we also included weeks before market entry.

Analytical strategy

We use three types of statistical models for panel data to test our hypotheses. To analyze the effect of seller’s discussion forum activity on item sales (M1), we used a hybrid (between-within) effects negative binomial regression model (Allison, 2009), using the *xtnbreg* procedure in Stata (StataCorp, 2015). We used fixed effects to control for time-invariant (un)observed item- and seller-level heterogeneity. Since fixed effects negative binomial models have been argued to insufficiently control for unobserved heterogeneity (Allison and Waterman, 2002), we used the hybrid model as suggested by Allison (2009), which can simultaneously model fixed effects and between-group effects. The model was estimated by creating group-means of independent variables that vary over time – in the case of Model 1, these were the averages for each marketplace item. These were then subtracted from each individual observation. Both the means and the differences-from-the-means were included in the model, and the latter represent the within- or fixed effects, which will be analyzed in our models.

20 We had several arguments for choosing weekly windows. Shorter windows result in a higher proportion of time points with no activity; shipping of goods takes at least several days, which results in a lag between buyers’ actual behavior and the time we observe it in the feedback messages; finally, buyers might not use the website daily. Longer windows would result in fewer cases, which is undesirable given the amount of data.

To estimate the effects of seller's forum activity on item price (M2), we used a fixed effects multilevel linear model using the *xtreg, fe* function. For both models, we used all available data, excluding items with a price of 0 (N = 272 items, 729 observations). The resulting two-level subset of the data contained 65,798 weekly observations of 15,518 items, and time-lagged weekly forum activity of 1,062 sellers who sold these items.

To test the effects of marketplace reputation and time on sellers' forum activity as hypothesized in H4-H7, we used the hybrid effects negative binomial regression model as used in Model 1. Weekly observations (level 1) were nested in seller's (level 2) market and forum activity. Since each seller's forum activity can start before market entry, we also added observations of weeks prior to market entry for each seller if any activity in the forum was observed. In contrast to Models 1 and 2, these models contain the effect of lagged marketplace activity (previous week). The resulting two-level subset of the data contained 13,418 weekly observations of 1,062 sellers.

Dependent variables

We used two different sellers' marketplace outcome measures: *item's price (in USD)* and *item's number of sales* (see Table 5.1 for descriptive statistics). Item's price was calculated using the daily rate for exchanging Bitcoins to U.S. dollars and averaging the price over the window of one week. An item's number of sales was measured by counting the total number of buyer ratings for an item in a given week. This measure has been used to estimate the number of sales in previous studies (e.g., Christin 2013; Soska and Christin 2015), since no direct information on the number of transactions is usually available in cryptomarket webpages. Feedback messages can only be posted after an item is bought, which makes our measure a conservative measure of the number of sales.

Strategic market signaling was operationalized as the number of posts in the "Market" section of the forum in a given week. We aggregate sellers' posts in all threads within this section of the forum. *Non-strategic/non-market signaling* was operationalized as the number of seller's comments in the "Discussion" section of the forum.

Independent variables and controls

The number of Market and Discussion section posts were also used as independent variables in Models 1 and 2, to estimate the effect of signaling on market outcomes. Since we used fixed effects models, these measures capture changes in seller's activity, but not the effect of the aggregate number of forum posts, which could also have an effect on buyers' behavior. To that end, we used cumulative counts captured by dummy variables for 5-, 10-, 30- and 50- *market and discussion section posts*, which indicate whether a seller had accumulated a certain number of forum activity before

the beginning of each week (i.e. a cumulative count of messages). The thresholds were selected after evaluating the distribution of vendors' total number of posts in each subforum.

We used a dummy variable indicating the *first week of seller's marketplace activity* to measure the effect of market entry on seller's forum activity. We used the date when a seller's first item in any category was observed in the market as market entry date. For some sellers, this variable might have all outcomes equal to 0, if the first observed item was in an excluded product category. We used *seller's positive and negative marketplace ratings* to measure seller's marketplace reputation. These variables were measured by summing up all 5-star and non-5-star buyer ratings a seller received before the beginning of the observed week. Cumulative number of ratings is comparable to the reputation score observed by Silk Road buyers in the website. We used buyer ratings from all items and categories. We operationalized *positive ratings* as 5-star ratings and *negative ratings* as 1-4-star ratings. We based this decision on the skewness of the distribution of all feedback ratings provided by the users. Over 96 percent of all buyer reviews were 5-star ratings, which made 1-4-star ratings very rare and indicative of negative aspects of buyers' opinion.

We modeled time effects on seller's market outcomes and signaling behavior in two ways. First, we controlled for the *number of weeks since seller's market entry*. This variable captured the number of weeks a seller had been active in the market at each observation. Since many sellers were active in the discussion forum before market entry, this variable could also have negative values in Models 3 and 4. Second, sellers entered the market at different times and thus two sellers in their second week since market entry, for example, might have faced very different market conditions. To account for time in absolute terms, we controlled for the *calendar month* each individual seller's time point corresponds to. If seller's weekly time points started less than four days before the end of the calendar month, we assigned that time point to the next calendar month.

Finally, to account for weeks of sellers' inactivity in Models 3 and 4, we used a dummy variable that indicated when the seller had *no items in the market*.

Table 5.1. Descriptive statistics of variables used in the analysis.

Item ID * Week (M1-2)	N	Mean	SD	Range
Number of item sales	65,798	1.58	4.71	0-287
Item price (in USD)	65,798	319.53	1390.15	0.03-114,061.30
Number of posts (Discussion section)	65,798	1.85	14.80	0-338
Number of posts (Market section)	65,798	1.59	5.93	0-115
Seller's total posts:				
5-9 market posts	65,798	0.43	-	0/1
10-29 market posts	65,798	0.35	-	0/1
30-49 market posts	65,798	0.19	-	0/1
>= 50 market posts	65,798	0.12	-	0/1
5-9 discussion posts	65,798	0.30	-	0/1
10-29 discussion posts	65,798	0.22	-	0/1
30-49 discussion posts	65,798	0.12	-	0/1
>= 50 discussion posts	65,798	0.09	-	0/1
Seller's 5-star ratings (all items)	65,798	255.88	386.27	0-3380
Seller's 1/4-star ratings (all items)	65,798	14.48	28.55	0-221
Weeks since seller's market entry	65,798	14.55	11.30	1-62
Calendar month (6 dummies)	65,798	-	-	0/1
Seller ID * Week (M3-4)				
Number of posts (Discussion section)	13,418	1.05	8.17	0-338
Post count (Market section)	13,418	1.25	4.96	0-172
Market entry week	13,418	0.08	-	0/1
Seller's 5-star ratings (all items)	13,418	114.34	261.14	0-3380
Seller's 1/4-star ratings (all items)	13,418	0.46	1.59	0-37
Weeks since market entry	13,418	7.51	14.58	-53-62
Calendar month (13 dummies)	13,418	-	-	0/1
No items in the market	13,418	0.20	-	0/1
Total items			789 (487)	
Total sellers			6,204 (3,057)	

RESULTS

Discussion forum activity

Using the full data set ($N = 1,062$ sellers), we find that a seller posts around 0.9 messages in the Market section and around 0.5 messages in the Discussion section of the forum at any given week. The distribution of sellers' total number of forum messages is highly skewed – around 50 percent of sellers active in the discussion forum post less than 1 message per week in the forum, while the most active 5 percent of sellers ($N = 56$) post 7.5 messages on average. One seller was particularly active, averaging 183 messages per week.

The average posting frequency in the two forum sections varies over time (see Figure 5.1). The average market section posting frequency of sellers clearly spikes in the first week after market entry and gradually decreases, whereas Discussion section posts are distributed more evenly over time. This result shows that market-related or strategic posting might be used as a market-entry strategy, which is in line with our expectations for sellers with no reputation.

Figure 5.1. Sellers' forum posting activity by forum section before and after market entrance

Until now, we assumed that discussions in the two sections of the forum follow different types of topics – Market section is related to marketplace activity, seller and product discussions, while the Discussion section is focused on topics not directly related to the market, like security or politics. In Figure 5.2, we display the 20 most frequent keywords in the titles of threads that sellers participated in. We excluded stop-words, used stems of the remaining words and normalized term frequency by the total length of thread names to avoid over-weighting long thread names and sellers, who are active

in many threads. The results show that topics in the Market section (Figure 5.2A) are concentrated on different types of drugs ("weed", "cocain-", "lsd", etc.), marketing ("free", "sampl-", "qualiti-") and other market related topics ("review", "list", "sale", "price"). Discussions section threads (Figure 5.2B) are indeed more concentrated around security-related topics ("ship-", "bitcoin-", "packag-", "post-"). Interestingly, sellers also participate in threads where users ask for help ("need", "help", "pleas-", "question"). Discussions in this section also include topics about sellers, similar to the Market section ("vendor", "seller", "buy"). In general, we can see that the two sections are indeed quite well differentiated in topics along the expected lines.

Figure 5.2A (left) and 5.2B (right). Term frequency of thread names that sellers participated in, by forum section (N = 617 threads).

Marketplace activity

In this section, we only discuss the main descriptive findings of the subsample of sellers in our data. For a more comprehensive description on the entire dataset, see Christin (2012). We analyzed items in 64 drug categories, ranging from marijuana ("weed") to chemical drug substances like methamphetamine. While some categories refer to a particular type of drug, others are more general, like "pills" or even "drugs". We found that not all sellers focus on a specific drug category. While 30.6 percent (N = 325) of all active sellers sell drugs of only a single category, 47.4 percent (N = 504) of sellers sell drugs in 2-4 categories and the remaining 22 percent sell drugs in 5-31 categories. Figure 5.3 shows the distribution of the volume of all item sales (in USD) across drug categories. "Weed" is clearly the most popular drug in terms of number of items and volume of sales, accounting for roughly \$2,000,000 during the observed period of half a year. It is followed by cocaine and MDMA, which sum up to around \$1,000,000-\$1,200,000 in sales each, although contain fewer items.

Figure 5.3. Distribution of total volume of sales (in USD) by drug category. Number of items in parentheses.

Hypotheses testing

In Tables 5.2 and 5.3, we provide the results of regression models for the effects of sellers' forum activity on item sales and price. In Model 1 (see Table 5.2), the effect of seller's forum activity in week $t-1$ on the number of item's sales in week t is estimated. Here we interpret the fixed effects part of the model (see *differences-from-the-means* in the table). The results in Model 1 show that an increase in the number of seller's Discussion section posts ($IRR=1.047$, $p<.01$) is associated with an increase in the incidence of the number of a seller's item sales in the upcoming week. The same positive effect is observed regarding the number of market section posts ($IRR=1.090$, $p<.01$). The effects of absolute number of sellers' forum posts are less clear. We find that sellers' item sales decrease once they reach 5 ($IRR=0.852$, $p<.01$) or 10 ($IRR=0.916$, $p<.05$) market section posts, or 5 ($IRR=0.799$, $p<.01$) or 50 ($IRR=0.732$, $p<.01$) discussion section posts. We find no statistically significant evidence for the other categories of aggregate forum activity. An increase in seller's cumulative number of 5-star ratings increases the incidence of an additional item's sale ($IRR=1.977$; $p<.01$), while an increase in negative ratings reduces it ($IRR=0.820$; $p<.01$). We also find a large negative effect of item price on the number of sales ($IRR=0.509$, $p<.01$). Finally, we observe that items were sold less frequently as seller's lifetime in the marketplace progressed ($IRR=0.976$, $p<.01$) and as the marketplace matured (month 3 vs. month 1 – $IRR=0.906$, $p<.05$; month 7 vs. month 1 – $IRR=0.682$, $p<.01$).

Table 5.2. Hybrid (Between-Within) effects negative binomial regression model for item's number of sales.

	Number of sales M1
<i>Deviances (fixed-effects)</i>	
Discussion post count (t-1) ^{a,b}	1.047** (0.01)
Market post count (t-1) ^{a,b}	1.090** (0.01)
Item price (in USD) ^{a,b}	0.509** (0.02)
Seller's 5-star ratings ^{a,b}	1.977** (0.03)
Seller's 1/4-star ratings ^{a,b}	0.820** (0.01)
Seller's total posts:	
5-9 market posts	0.852** (0.03)
10-29 market posts	0.916* (0.05)
30-49 market posts	1.074 (0.04)
>= 50 market posts	0.931 (0.04)
5-9 discussion posts	0.799** (0.03)
10-29 discussion posts	0.953 (0.04)
30-49 discussion posts	1.011 (0.05)
>= 50 discussion posts	0.732** (0.04)
<i>Means (between-effects)</i>	
Discussion post count (t-1) ^{a,b}	0.973 (0.03)
Market post count (t-1) ^{a,b}	1.070* (0.03)
Item price (in USD) ^{a,b}	0.733** (0.01)
Seller's 5-star ratings ^{a,c}	1.540** (0.01)
Seller's 1/4-star ratings ^{a,c}	0.957** (0.01)
Seller's total posts:	
5-9 market posts	1.382** (0.07)
10-29 market posts	0.849** (0.05)
30-49 market posts	1.157* (0.08)
>= 50 market posts	1.070 (0.07)
5-9 discussion posts	0.896 (0.05)
10-29 discussion posts	0.853* (0.05)
30-49 discussion posts	0.996 (0.09)
>= 50 discussion posts	0.498** (0.05)
Calendar month (6 dummies)	Omitted
# weeks since market entry	0.976** (0.00)
Constant	1.183** (0.08)
N (L2: Item ID)	15,518
N (L1: Week)	65,798

Note: Results are reported in incidence ratios.

a – log-transformed variable.

b – lagged variable (1-week lag).

* - $p < 0.05$; ** - $p < 0.01$ (two-tailed tests).

In Model 2, we estimate the same effects of seller's forum signaling on item's weekly price (see Table 5.3). Results for the two study variables are different from those of Model 1 - the number of seller's posts in the Discussion section has no statistically significant effect on item's price in the following week ($b=0.001$, $p=.26$), while a negative effect is observed for the number of Market section posts ($b=-0.005$, $p<.01$). Similar to Model 1, we do not find clear evidence of the effect of the aggregate seller's forum activity in the market section. On the other hand, the total number of seller's discussion posts has mostly positive effects on seller's item price – reaching a total of 5 ($b=0.015$, $p<.01$), 30 ($b=0.012$, $p<.05$) or 50 ($b=0.033$, $p<.01$) discussion section posts is associated with an increase in item price. The trend of sellers having higher item prices with higher number of total discussion section posts is not linear, however, since we observe a negative effect after reaching 10 posts ($b=-0.011$, $p<.01$). We find that the number of item's sales in preceding weeks has a negative effect on item price ($b=-0.014$, $p<.01$). Similar to Model 1, we find that the number of seller's 5-star rated feedback messages has a positive effect on the market outcome ($b=0.007$, $p<.01$), however, we find no statistically significant effect of negative reputation scores ($b=-0.002$, $p=0.15$). Finally, we find no statistically significant effect of time since seller's market entry.

Table 5.3. Fixed-effects linear regression model for item's price.

	Item's price ^a M2
Discussion post count (t-1) ^{a,b}	0.001 (0.001)
Market post count (t-1) ^{a,b}	-0.005** (0.001)
Item's number of sales ^{a,b}	-0.014** (0.001)
Seller's 5-star ratings ^{a,b}	0.007* (0.001)
Seller's 1/4-star ratings ^{a,b}	-0.002 (0.001)
Seller's total posts:	
5-9 market posts	-0.006 (0.003)
10-29 market posts	0.006 (0.003)
30-49 market posts	0.000 (0.003)
>= 50 market posts	0.004 (0.004)
5-9 discussion posts	0.015** (0.004)
10-29 discussion posts	-0.011* (0.004)
30-49 discussion posts	0.012* (0.005)
>= 50 discussion posts	0.033** (0.004)
# weeks since market entry	-0.001 (0.001)
Calendar month (6 dummies)	Omitted
Constant	4.480** (0.05)
N (L2: Item ID)	15,518
N (L1: Week)	65,798

Note: Results are reported in unstandardized regression coefficients.

a – log-transformed variable.

b – lagged variable (1-week lag).

* - $p < 0.05$; ** - $p < 0.01$ (two-tailed tests).

Models 1 and 2 suggest that sellers' signaling behavior has a positive effect on their market success. Partially in line with hypothesis 2, we find that non-strategic communication in the Discussion section is associated with more sales (M1), but it does not affect price (M2). The absolute number of Discussion section posts also has mixed effects on both market outcomes (M1 and M2). We also find only partial evidence for the hypothesized effects of strategic interaction in Hypothesis 1. Although seller's weekly activity in this section is associated with more item sales in the following week (M1), the effect is negative for item's price (M2). The results are also mixed with regards the absolute number of Discussion section posts on both market outcomes (M1 and 2). We find virtually no evidence for Hypothesis 3, which states that non-strategic signaling of good intentions should result in a larger positive effect on seller's market outcomes compared to strategic signaling in the Market section of the forum. Model 1 shows that a single Market section post increases item's sales more than a single Discussion section post (Wald's test for equality of estimated coefficients – $F(1,50260) = 14.53, p < .01$). Model 2 shows that Discussion posts have no effect on item's price at all. The effects of the absolute number of posts are mixed for both market outcomes.

Table 5.4. Hybrid (Between-Within) negative binomial regression models for market section and discussion section forum post counts.

	Market post count M3	Discussion post count M4
<i>Deviances (fixed-effects)</i>		
Seller's 5-star ratings ^{a,c}	0.890** (0.01)	0.923** (0.02)
Seller's 1/4-star ratings ^{a,b}	0.977 (0.04)	1.021 (0.06)
Market entry week	1.699** (0.11)	0.981 (0.10)
<i>Mean (between-effects)</i>		
Seller's 5-star ratings ^{a,c}	1.182** (0.03)	1.136** (0.04)
Seller's 1/4-star ratings ^{a,b}	1.156 (0.18)	0.562** (0.11)
Market entry week	0.645 (0.20)	0.122** (0.06)
# weeks since market entry	0.975** (0.00)	0.991* (0.00)
Calendar month (13 dummies)	Omitted	Omitted
No items in the market	0.828* (0.06)	0.677** (0.06)
Constant	0.277** (0.05)	0.738** (0.17)
N (L2: Seller ID)	1,062	1,062
N (L1: Weeks)	13,418	13,418

Note: Incidence rate ratios are reported in both models.

a – log-transformed variable.

b – lagged (1 week).

c – cumulative total of all preceding weeks.

* - $p < 0.05$; ** - $p < 0.01$ (two-tailed tests).

Table 5.4 shows the results of the mixed effects regression models for sellers' forum activity. Similar to the analysis of the hybrid model in Table 5.2, we will only interpret the fixed effects part of the model to test the hypotheses. Model 3 shows that in line with hypotheses 4 and 6, sellers make fewer posts with more accumulated positive ratings ($IRR=0.890$, $p<.01$) and are especially active during the first week of market entry ($IRR=1.699$; $p<.01$). We do not find any evidence for hypothesis 5 – sellers do not post more in the Market section after receiving negative feedback ($IRR=0.977$, $p=0.60$). Model 4 shows that the effects are only partially in line with Hypothesis 7 – although sellers are not more active in this section during the first week after market entry ($IRR=0.981$, $p=0.85$), they tend to post less when they accrue a larger number of positive marketplace ratings ($IRR=0.923$, $p<.01$), similar to the case of strategic signaling.

Additional analysis

Although we observed that, contrary to our expectations, sellers with damaged reputation do not increase frequency of strategic signaling behavior, all models implemented so far could not take into account the possibility that negative ratings could lead sellers to leave the market. We estimated a Cox proportional hazard model to analyze whether positive and negative ratings have an effect on sellers' market exit. We marked the last date of seller activity either in the marketplace (any items for sale) or in the forum (posting activity posts in any section of the forum) as the last week of seller's activity. We marked sellers whose last week of activity was the last week of the observation period as censored, since these sellers could have continued their activity after data collection ended.

Table 5.5. Cox proportional hazard model on weeks until the last week of seller's activity.

	Hazard ratio (End of seller's activity) M5
Seller's 5-star ratings ^{a,b}	0.712** (0.02)
Seller's 1/4-star ratings ^{a,b}	1.265** (0.90)
N (L2: Seller ID)	1,062
Time at risk (L1: Weeks since 1st forum or market activity):	10715
Number of failures:	559

a – log-transformed variable.

b – lagged (1 week), cumulative.

* - $p < 0.05$; ** - $p < 0.01$ (two-tailed tests).

Model 5 in Table 5.5 suggests that the hazard ratio to exit Silk Road increases with an increase in negative ratings ($HR=1.26$, $p < .01$), while 5-star ratings decrease the likelihood of an exit ($HR=0.712$, $p < .01$). This increased tendency to exit market after receiving negative ratings could partially explain why we do not observe increased frequency of signaling after receiving negative ratings.

CONCLUSIONS AND DISCUSSION

We analyzed whether communication can be used by sellers as a signal of their trustworthiness, an alternative strategy to reputation building in an environment with full anonymity and no legal assurances. Although reputation systems have been found to facilitate cooperation in observational (Kollock, 1999; Resnick and Zeckhauser 2002; Diekmann *et al.*, 2009; 2014; Przepiorka, 2013) as well as experimental studies (Yamagishi *et al.*, 2009, Bolton *et al.*, 2004), previous findings on trust in cryptomarkets suggest that discussion forums have emerged as an additional facilitator of trust, where buyers and sellers share information about drug safety, privacy and security and trustworthiness of other members (Bancroft and Reid, 2016; Tzanetakis *et al.*, 2016; van Hout and Bingham, 2013; 2014). Such active online communities are not observed in large licit online markets. We used longitudinal data from the first large-scale cryptomarket Silk Road to test whether sellers use discussion forums as a signal of their trustworthiness and whether they do so strategically to substitute for a lack of reputation or to compensate for damaged reputation.

Our findings suggest that, in line with previous experimental studies (Sally, 1995; Balliet, 2010), communication between actors or “cheap talk” can have a positive effect on trust. We find that sellers’ discussion forum activity increases the number of sales of their marketplace items. This result suggests that apart from seller’s market reputation, buyers are also likely to consider seller’s activity in the discussion forum and interpret it as a signal of trustworthiness. Long-term participation in such discussions is possibly too costly for opportunistic sellers oriented towards short-term gain. Alternatively, the content of messages of sellers might help buyers distinguish truthful sellers, which could prevent the opportunistic ones from engaging in communication.

It is important to stress that sellers’ involvement in non-market related discussions yields an increase in their number of sales. This finding shows that sellers can also benefit from discussions that are not directly related to their sold goods but are nevertheless important for the sustainability of the cryptomarket, including knowledge sharing on technical safety and safe use of illicit substances or instructing less experienced members. In other words, drug sellers benefit from contributing to

the cryptomarket community's public goods. A detailed content analysis of sellers' forum messages is beyond the scope of this chapter. Nevertheless, this effect shows that buyers might take into account sellers' behavior as community members and not only as market actors, when deciding which seller to buy drugs from. Cryptomarkets provide a fruitful environment to analyze spillover effects from actors' social embeddedness to trust in market exchanges. This area of inquiry has a long tradition in offline market research (e.g., Coleman, 1988; DiMaggio and Louch, 1998; Granovetter, 1985; 2005), but to the best of our knowledge has so far been neglected in empirical research of online marketplaces, perhaps partly due to an assumption that "thin" online ties would be too weak to produce common norms of good conduct (Diekmann *et al.*, 2014).

It should be noted that market benefits of engaging in discussions with buyers we observed in Silk Road might be endogenous to the time period examined. The allegedly active community and non-market related topics discussed in the forum might be specific to Silk Road, since it was the first cryptomarket, where libertarian ideals were heavily articulated by its founder Dread Pirate Roberts and other moderators (Van Hout and Bingham, 2014; Munksgaard and Demant, 2016). Based on previous findings, the prevalence of political topics declined after the closure of Silk Road (Munksgaard and Demant, 2016). Therefore, while Silk Road provides an opportunity to study cryptomarket users "in isolation", at a time when there was only a single venue for them to interact in, the effects we observe might be platform-specific and not generalize to more recent cryptomarkets. Our results should therefore be replicated using data from multiple cryptomarkets.

We also found that drug sellers' use of discussion forums is partially in line with our theoretical expectations. Sellers' use of market-related messages increases right before and after market entry. Afterwards, the frequency of market-related messages tends to decrease if reputation increases. We hypothesized this to be the case, because sellers' increasing reputation creates market benefits and the marginal utility of posting market-related messages drops. Partially in line with signaling theory, we found that the frequency of discussion section posts is more constant over time, even though it significantly decreases with sellers' market reputation as well. This is in line with our expectation that this section of the forum attracts sellers that are less interested in attracting new buyers, but have other intrinsic, pro-social motives. We can conclude that discussion forums might have several functions – it increases market efficiency via buyer-seller communication and provides a platform for community-building.

A recurring result in our analyses was that a bad market rating does not matter much for signaling behavior – we found that sellers are not more likely to engage in discussion forums to repair the damaged reputation. In an additional analysis we

assessed whether this could possibly be explained by sellers leaving the market. The results showed that, indeed, instead of paying additional costs for reputation damage control, sellers are more likely to become inactive in the marketplace. Such sellers could re-enter the marketplace under a new alias and no reputation, which might be the less costly alternative to signaling or price reductions (Przepiorka *et al.*, 2017). Exit as a strategy is an important concept for future studies that analyze trust in online markets empirically. This is especially relevant in cryptomarkets, where sellers' identity is fully anonymous and duplicate user accounts cannot be prevented by market platforms.

Some results were also contrary to the theoretical expectations. Although communication in the discussion forum increases sellers' item sales, we found no evidence for the hypothesized effects on item price. Contrary to our expectations, we found that sellers who discuss market-related topics tend to decrease the price of their goods, while general discussions have no effects on price. Additional analysis of the content of topics discussed in this section suggests that it might be related to strategic marketing behavior. To attract the interest of potential buyers, sellers use this section of the forum to propose discounts and "freebies" for their items. The use of such strategies has also been identified in previous studies on cryptomarkets (e.g., van Hout and Buskirk, 2014; Ladegaard, 2018), but future studies should use more advanced text mining approaches to rigorously test the effect of such discounted items.

We did not find the expected larger effect of non-market related discussions on buyers' trust. We expected that buyers, keeping in mind the motives of profit-maximizing sellers and the low cost of making fake claims in discussion forums, would consider sellers' market-related communication a weaker signal of trustworthiness than their participation in general discussions, which has no direct market benefit for sellers. We found, however, that sellers' market-related posts have a larger effect on item sales than those of general discussions. One possible explanation could be that sellers use general discussions as strategically as market-related posts. This explanation seems unlikely though, since we also found that, unlike market section posts, frequency of general discussion posts does not spike around market entry and decreases more gradually with increasing market reputation. An alternative explanation in line with theoretical expectations could be that these messages are not as "cheap" as we assumed. It could be the case that sellers, apart from the aforementioned price discounts and "freebies", also use other strategies, like laboratory tests of drug quality or point out users who could vouch for them (Lusthaus, 2012), to increase the strength of the signals.

Finally, throughout our analyses, we found that it is not the cumulative number of forum messages that affects market outcomes, but dynamics of sellers' weekly activities.

Theoretically, we argued that for non-strategic communication, an aggregated number of posts could serve as a sign of pro-social intentions and trustworthiness, and thus allow sellers to sell more and for a higher price. While this partially holds for item price, we found no results for item sales. This effect might be driven by discussion forums' website design – even though the total number of posts is visible for each user under each forum message, older discussions are pushed down to further pages, making participants less visible. Alternatively, it could be that it is the discussion interaction partners of sellers who are more likely to find them in the marketplace, not mere observers. This theoretical claim could be tested more directly by analyzing discussion forums as a communication network between users, rather than posting frequency by market sellers. Unfortunately, the collected data on Silk Road do not allow us to link buyer accounts in the discussion forum and marketplace.

Overall, our results suggest that social embeddedness is an important building block of trust when uncertainty is high, such as in online cryptomarkets. Regardless of reputation systems, buyers and sellers seem to use discussion forums to decrease uncertainty in the market. High uncertainty and risk might explain why such forums emerged and became highly active in cryptomarkets, but not in online licit markets. When actors need additional means to overcome the trust problem, direct communication might emerge spontaneously given that the necessary preconditions, such as online discussion forums, are met. Signaling is an important mechanism to explain how such communication can be used to achieve trust. Ideally, such claims could be tested by comparing environments with and without discussion forums and reputation systems. Such a task is beyond the scope of this chapter. We believe that the emergence of cryptomarkets provides a fruitful and promising environment to examine evolution of cooperative behavior and social institutions empirically, using large-scale non-obtrusive data in future studies.

6

Offline constraints in online drug marketplaces:

An exploratory analysis of a
cryptomarket trade network

ABSTRACT

Cryptomarkets, or illegal anonymizing online platforms that facilitate drug trade, have been analyzed in a rapidly growing body of research. Previous research has found that despite high risks, drug sellers are often willing to ship illegal drugs internationally. There is little to no information, however, about the extent to which uncertainty and risk related to geographic constraints shape buyers' behavior and, in turn, the structure of the global online drug trade network. In this chapter, we analyze the structure of a complete cryptomarket trade network with a focus on the role of geographic clustering of buyers and sellers. We use publicly available crawls of Abraxas, encompassing market transactions between 463 sellers and 3542 buyers of drugs in 2015. We use descriptive social network analysis and Exponential Random Graph Models (ERGMs) to analyze the structure of the trade network. The structure is primarily shaped by geographical boundaries. Buyers are more likely to buy from multiple sellers within a single country, and avoid buying from sellers in different countries, which leads to strong geographic clustering. A small fraction of buyers (10%) account for more than a half of all drug purchases. Online drug trade networks might still be heavily shaped by offline (geographic) constraints, despite their ability to provide access for end-users to large international supply. Cryptomarkets might be more "localized" and less international than thought before. We discuss potential explanations for such geographical clustering and implications of the findings.²¹

21 A version of this chapter is published as: Norbutas, L. (2018). Offline constraints in online drug marketplaces: An exploratory analysis of a cryptomarket trade network. *International Journal of Drug Policy*, 56, 92-100.

INTRODUCTION

Recent years saw an increase in scholarly attention to the growing number of online marketplaces for illicit goods and services called cryptomarkets (Martin, 2014; Barratt and Aldridge, 2016). Cryptomarkets are online trading platforms that bring together individual buyers and sellers. Anonymity of marketplace users is guaranteed by the Tor network and digital currencies used for financial transactions (e.g., Bitcoin; Nakamoto, 2008). These online marketplaces enable buyers and sellers of illicit drugs to interact in relative safety from the law enforcement agents.

Cryptomarkets provide an opportunity for researchers to access large-scale data related to drug trade and use (Barratt and Aldridge, 2016). A rapidly growing body of research has analyzed various aspects of such marketplaces, including buyers' behavior in terms of popular types of drugs and volume of sales (Christin, 2013; Soska and Christin, 2015), prevalence of wholesale trading (Aldridge and Décary-Hétu, 2014; 2016a; Demant *et al.*, 2016), or social mechanisms and technical innovations that ensure buyers' trust in sellers (Tzanetakis *et al.*, 2016; Hardy and Norgaard, 2016; Przepiorka *et al.*, 2017).

An important question with regards to the role of cryptomarkets in global drug trade is whether these marketplaces merely move conventional offline drug trade channels online, or also have the potential to transform localized and fragmented retail trade networks by bringing goods to markets, where their availability had previously been limited (Martin, 2014; Christin 2014, Aldridge and Décary-Hétu, 2016b). While online marketplaces theoretically offer buyers and sellers easy access to international markets, shipping of orders across national borders results in higher risk and longer waiting times. This could potentially limit users' willingness to trade internationally (Décary-Hétu *et al.*, 2016; Broseus *et al.*, 2017).

Previous literature examined geographical patterns of online drug trade using sellers' self-reported origin country and shipping destination data (Broseus *et al.*, 2017; Cunliffe *et al.*, 2017; Décary-Hétu *et al.*, 2016). Based on information from Silk Road, Décary-Hétu *et al.* (2016) found that 69% of analyzed listings, mostly illicit drugs, were open for international orders. Sellers who offered international shipping held 61% of total market revenues. Although it is unclear what share of these revenues came from internationally shipped items, the findings suggest that a significant share of drug sellers were willing to ship internationally. Broseus *et al.* (2017) and Cunliffe *et al.* (2017) found that trade of illegal drugs is primarily domestic in Australia, while a larger proportion of sellers from the United States, Canada, Netherlands, Germany and China offered international shipping.

Analyses of international flows of drugs that are based on geographical information provided by cryptomarket sellers suffer from several significant sources of bias. First, many sellers do not disclose their origin country for security reasons. In previous research such cases were either excluded from the analyses or, due to missing information on origin countries, could not provide information about whether these sellers trade internationally. For example, Décary-Hétu *et al.* (2016) excluded 8% of their collected sample of item listings due to ambiguous sellers' origin locations. Broseus *et al.* (2017) found that about 37% of sellers of illicit drugs in Evolution market listed "Worldwide" as their country of origin. Van Buskirk *et al.* (2016) found that 21% of analyzed drug listings were shipped from undeclared locations in Agora. This issue could have an impact on the reliability of previous results, especially if sellers' willingness to disclose their origin country is associated with willingness to ship internationally.

Secondly, previous research on geographical patterns in cryptomarkets did not incorporate information on the buyers. Information on sellers' origin countries and shipping destinations cannot reveal what fraction of items that have an option for international shipping are bought by foreign-based and not domestic buyers. This could lead to an underestimation of domestic drug trade in cryptomarkets.

We address these issues by analyzing a complete cryptomarket drug trade network, using a social network analysis approach. We construct a network of exchanges between buyers and sellers of illicit drugs and analyze network clustering patterns that might emerge due to geographic constraints. Analysis of a cryptomarket exchange network has several advantages. We can incorporate data on sellers and their items with missing or ambiguous origin countries (e.g., 'Worldwide'), since buyers' and sellers' positions in the global network structure can be a strong signal of their geographic location. Emergent structural patterns of a global buyer-seller exchange network can also be considered a more reliable representation of drug trafficking flows than sellers' willingness to ship internationally, since they are based on completed exchanges rather than sellers' intentions.

Social network analysis has been used to study the structure of offline drug trafficking networks (Kenney, 2007; Natarajan, 2006; Morselli, 2009; Malm and Bichler, 2011; Wood, 2017), online discussion forums of hackers (Holt *et al.*, 2012; Lu *et al.*, 2010) and stolen data markets (Motoyama *et al.*, 2011; Monsma *et al.*, 2013). This approach has also been used to study trust considerations between opioid buyers and sellers in a cryptomarket (Duxbury and Haynie 2018a; 2018b). The results show that the opioids' exchange network is highly clustered, but not geographically – buyers tend to exchange with few well-reputed sellers. The lack of any geographic structure in this network

is counter-intuitive, given that a significant share of sellers in many cryptomarkets only ship domestically (Décary-Hétu *et al.*, 2017; Broseus *et al.*, 2017). This finding could be heavily influenced by the relatively small subset of the total cryptomarket network analyzed, especially given that the absolute majority of analyzed sellers were from a single country.

Here we use a complete buyer-seller trade network data set from a cryptomarket Abraxas (Branwen *et al.*, 2015). To our knowledge, apart from the anonymous cryptomarket analyzed by Duxbury and Haynie (2018a), this is the only marketplace where buyer identifiers are available for each transaction. We construct a full buyer-seller trade network with information on almost 11,000 trades of drugs between 463 sellers and 3,542 buyers, over a period of 7 months in 2014-2015. These unique data allow us to explore the structure of online drug trade in detail and shed light on possible mechanisms that underlie formation of such networks.

STRUCTURE OF OFFLINE AND ONLINE RETAIL DRUG TRADE NETWORKS

To operate efficiently, markets must minimize the amount of uncertainty for its actors, to make assessment of costs and benefits of a potential exchange possible (Beckert and Wehinger, 2013). Contracts in illegal markets are not secured by law, which increases potential risks for market actors and makes them turn to alternative strategies to minimize uncertainty and potential losses (Reuter, 1983).

The level of uncertainty and the resulting behavior of buyers and sellers might differ depending on whether illegal market exchanges take place online or offline (Brynjolfsson and Smith, 2000; Cambini *et al.*, 2011). Buyers and sellers in offline retail drug trade networks face uncertainty with regards to true intentions of their exchange partners. Face-to-face contacts lead to increased risk of violence and potential exposure to law enforcement for both buyers and sellers (Jacques and Wright, 2011; Bouchard and Ouellet, 2011). Additionally, buyers face uncertainty with regards to quality and purity of purchased drugs, since drug markets are “markets for lemons”, characterized by substantial information asymmetry between buyers and sellers with regards to true quality of the goods (Akerlof, 1970; Reuter and Caulkins, 2004). Information about trustworthiness of sellers and quality of their goods is scarce, which makes it costly for buyers to look for market alternatives (Galenianos *et al.*, 2012).

The risk of violence and exposure to law enforcement, product quality uncertainty and a lack of information about trustworthiness often lead actors in offline retail drug markets to form “closed”, “overembedded” or highly clustered trade networks,

where they form small, fragmented groups, consisting of long-lasting dyads of repeated interactions (May and Hough, 2004; Uzzi, 1997). Drug sellers have been found to screen potential customers for trustworthiness and incentivize long-term clients by offering credit or discounts (Chalmers and Bradford, 2013; Jacques *et al.*, 2014). The geographic area of retail drug sellers' activity might be limited deliberately to prevent additional exposure to law enforcement (Reuter, 1983). Since illegal drugs are consumer goods, buyers, learning from their successful transactions with a seller in the past and facing high search costs for alternatives, have an incentive to maintain existing cooperation (Buskens and Raub, 2002).

Online drug markets, just like online markets for legal goods, might reduce many of these uncertainties and lead to more dynamic, open and efficient retail drug trade networks (Brynjolfsson *et al.*, 2000; Cambini *et al.*, 2011). Cryptomarkets increase information availability for buyers – complete lists of items and sellers on the market can reduce search costs and make it easier to choose the best market alternative (Cambini *et al.*, 2011). Buyers and sellers gain easy access to international markets, where drugs are sold, which are not available locally (Van Buskirk *et al.*, 2016). Due to absence of face-to-face contact and increased anonymity, sellers can be more expansive – exposure to more buyers no longer increases risk of being arrested (Reuter, 1983; Morselli *et al.*, 2007). Finally, cryptomarket buyers can assess sellers' trustworthiness and product quality via reputation systems, which publicly disseminate buyers' feedback based on their past transactions with each seller (Przepiorka *et al.*, 2017; Hardy and Norgaard, 2016).

An important source of risk in online drug markets that might diminish their ability to transform localized and dyadically embedded offline drug trade networks, is the shipping stage of online exchanges (Aldridge and Askew, 2017). International shipping of packages leads to increased risk of potential interceptions by the law enforcement (Décary-Héту *et al.*, 2016). Branwen (2017) found that a substantial fraction of arrests of cryptomarket buyers and sellers were related to international orders. Cryptomarket users also identify shipping stage as the main source of risk of being arrested (Aldridge and Askew, 2017). Having this risk in mind, some sellers choose to sell their goods only domestically (Décary-Héту *et al.*, 2016).

Buyers must also consider shipping time when choosing a seller as an additional cost. All else equal, an international seller, especially from a geographically distant location, might be a less desirable option than a domestic one. Together these aspects might lead to increased geographical clustering of buyers and sellers – a formation of buyer-seller groups limited by national or regional borders – and limit cryptomarkets' ability to globalize retail drug trade.

Aims

The aim of this chapter is to analyze the structure of an exchange network between buyers and sellers of illicit drugs in a cryptomarket Abraxas, with a focus on geographic constraints. Firstly, background information and descriptive statistics are provided regarding the number of buyers, sellers and transactions in the marketplace over time. Secondly, geographic clustering patterns between buyers and sellers in the marketplace are analyzed by using exponential random graph models (ERGM).

METHOD

We use data from Abraxas, a cryptomarket that was active from December, 2014 to November, 2015. The data set collected by Branwen *et al.* (2015) contains data from the period between December, 2014 and July, 2015, with an average of 1 crawl every 2-3 days. The first data collection point is dated several days after the start of the market, with only several active sellers and no active buyers. This allows us to observe the growth of marketplace activity from its very beginning.

The data contain copies of item listings, seller profiles and customer profiles. A customer profile becomes visible only after a customer leaves a feedback message on an item page after an exchange. We can therefore only observe active buyers after their first purchase. Item pages contain detailed information, including seller's nickname, price, description and feedback of previous buyers. Each feedback message contains a date, a 0- to 5-star rating and the original price for which the item was bought.

The data set collected by Branwen *et al.* (2015) contains information on multiple cryptomarkets and is known to suffer from incompleteness (Décary-Héту and Giommoni, 2016). Daily copies of marketplaces might contain information on only a fraction of items and user profiles. To get a better assessment of this problem in our case, we compared the number of crawled item pages in the data to the actual number of items displayed in the home page of Abraxas at each date. The average percentage of collected items across all crawls is 92.4%, ranging from 26% to 100% for each crawl. While the average coverage of the data is rather high, it might still pose a significant problem for the reliability of our analysis. To minimize the impact of this issue, we aggregated information across all daily crawls of item pages and profiles ($N=91^{22}$), maintaining only the most recent version of every page. During the observed period of 7 months, the aggregated data contain 11,814 item pages, 463 seller and 3,542 buyer accounts, and a total of 10,898 transactions.

Each collected feedback message needs to be attributed to a particular buyer to construct a network data set of exchanges between individual buyers and sellers. While this poses a problem in many cryptomarket data sets due to partially or fully hidden buyer nicknames, Abraxas contained unique buyer profile identifiers for each feedback message, which was located in the HTML code of item pages. We used these buyer identifiers to aggregate feedback messages left by each buyer account. While we were able to identify purchases of individual buyer accounts, the data did not include buyers' country of residence. Although we cannot observe buyers' geographic location

22 We excluded 3 crawls (2015-04-07; 06-04; 07-01), since contained very incomplete information on only several items.

directly, inferences about geographic clustering in the marketplace can be drawn based on buyers' selection of sellers located in particular countries. We will discuss this approach in the following section. It is also important to note that while we can attribute feedback messages to individual buyer accounts, some buyers could have used multiple accounts for different purposes. For the sake of clarity, we will use the terms "buyer account" and "buyer" interchangeably.

To exclude items that are irrelevant for this chapter (e.g., fake documents or eBooks), we use a subset of the aggregated data set, which contains buyer profiles²³ and transactions of items in the "Drugs" category. This category contains data on 390 sellers (84.23%), out of which 282 sellers made at least 1 sale, 3,192 buyers (90.11%) and 10,234 transactions (93.90%). The category contains items that are further divided into 11 subcategories: benzodiazepines, cannabis, dissociatives, ecstasy, opioids, prescription drugs, psychedelics, RCs, steroids, stimulants and mixed drugs. We hand-coded weight of every item with at least 1 sale, based on the name and description. There were 83 items²⁴ (purchased 342 times) that had no information on weight.

We use this information to construct the network data set for our analysis. The network contains a set of nodes that represent individual profiles in Abraxas, and ties between nodes that represent market transactions. We constructed a bipartite network, which represents two types of nodes: buyers and sellers (Newman, 2010).

23 Customer accounts contain aggregate information on the number of purchases, refunds, amount of money spent in Bitcoin. We did not include these data in our analysis, since we could not distinguish which part of this information refers to orders of illegal drugs.

24 We use "items" and "listings" interchangeably.

EXPONENTIAL RANDOM GRAPH MODELS

To assess geographic clustering in the network, we use Exponential Random Graph Models (ERGMs) for bipartite networks (Robins *et al.*, 2007a; 2007b). These models are designed for network data and take network connections as the dependent variable. ERGMs take into account structural interdependence between network actors, which is not possible in ordinary logistic regression models. ERGMs allow to model the effects of exogenous actor-level attributes (e.g., seller's geographic location) and endogenous structural factors (e.g., buyer's position in the network) on tie formation. The resulting model estimates can be interpreted as a comparison of likelihood of tie formation to random chance, given a certain property of a network node or a dyad. For example, a zero effect of seller's reputation on tie formation would show that it does not change the likelihood of a seller being selected by a buyer from random chance, while a positive effect would show that highly reputed sellers are more likely to be selected. The likelihood of occurrence of certain structural features in the observed network, such as inter-connected cliques, can also be modelled. We used the *statnet* package in R to implement the models (Handcock *et al.*, 2008).

To analyze geographic clustering, we model the occurrence of *geographically homogenous and heterogeneous buyer-seller 2-stars* in the network (see Figure 6.1). Geographic location of sellers is constructed based on shipping destinations provided in their profiles (see sub-section *Network structure and geographic clustering* for more methodological details). A 2-star is a structural pattern in the network that represents a buyer with connections to two sellers. A buyer might have multiple 2-stars if she is connected to more than 2 sellers. These sellers might be from the same or different countries, resulting in the two types of 2-stars. Unfortunately, given the data availability, we cannot directly observe the geographical location of buyers. However, if strong geographical clustering is present in the cryptomarket, we would observe positive estimates of buyers making purchases from multiple sellers in the same country (homogenous 2-stars), and negative estimates of buyers purchasing from multiple sellers from different countries (heterogeneous 2-stars).

There might be several explanations for the occurrence of homogenous 2-stars. We argue that the most likely explanation is buyer's residence in the same country as the sellers (domestic transactions). There might also be cases where a buyer chooses multiple sellers from the same foreign country, for example, in cases where a particular type of drug is mostly available in a single foreign country. This would result in homogenous 2-stars that are in fact international exchanges. While we cannot distinguish between these two cases with our data, we argue that the latter scenario should be much less prevalent, given that concentration of sellers and items of specific

types of drugs in particular countries is generally low in cryptomarkets (Broseus *et al.*, 2017; van Buskirk *et al.*, 2016).

Figure 6.1. An example of buyer-seller 2-star structures used in the ERG models. Circles represent buyers and squares represent sellers.

DESCRIPTIVE RESULTS

The number of buyers and sellers grew steadily over time (see Figure 6.2A). Although Abraxas started operating in December, 2014, the first observed feedback message was posted on 14th January, 2015. The most rapid increase in the total number of users and items began in March, 2015. This increase might be related to sellers' migration from a major cryptomarket Evolution following an exit scam, which took place around 14th March, 2015.

Figure 6.2. A. Number of buyers, sellers and drug items over time. B. Cumulative distribution of unweighted degree (number of individual contacts) by market user type.

In total the network of drug exchanges during the entire period of data collection contains 10,234 weighted ties, or market transactions, between 282 sellers (72.31%) and 3,192 buyers. Tie weight represents the number of repeated transactions in the

same buyer-seller dyads. Once we exclude repeated exchanges, a total of 5,644 ties are observed, which show that almost half of all interactions are repeated between the same users. 108 sellers (27.69%) who had posted drug items in the market had no sales. The full network consists of 15 connected components with 3,474 (98.9%) users in the largest component. The remaining connected components consist of 1 buyer and 1 seller on average. This result shows that buyers tend to purchase from various sellers over time, which leads to formation of a large group of interconnected users with very few isolated buyer-seller cliques. We will further focus on this largest component in our analysis.

Figure 6.2B shows the cumulative distribution of unweighted degree among buyers ($N = 3,192$) and sellers ($N = 282$). Unweighted degree refers to the number of user's ties, excluding repeated exchanges with any seller. For buyers this measure reflects the number of sellers she has bought from, and vice versa for sellers. The figure shows that 60% of buyers only interacted with a single seller, an additional 21.4% of buyers bought from 2 different sellers. Percentage of buyers with higher degree decreases rapidly after this point, with a maximum value of 22 sellers. This shows that most buyers only purchase from a single seller and it is a relatively small group of buyers whose ties maintain the largest network component connected.

The same distribution for cryptomarket sellers is much less skewed – 50% of all sellers exchanged with 8 or fewer buyers. Sellers' degree distribution has a long tail and the highest degree of 297 (not shown in Figure 6.2B), which shows that there is a small outlier group of highly popular sellers. These numbers reinforce findings of Soska and Christin (2015), who showed that only a small fraction of all sellers generate significant revenue.

Marketplace characteristics

Table 6.1 shows transaction statistics by drug category. Drug items have been found to get misclassified by cryptomarket sellers and the categories provided in the website often contain multiple types of drugs (Aldridge and Décary-Héту, 2016a). Drug items were re-classified to sub-categories (column 2), using regular expressions based on item names and the categorization provided in Abraxas (column 1). To reduce the size of the table, drug items in smaller sub-categories were merged.

Based on the total volume of sales, Abraxas was a relatively small cryptomarket compared to other cryptomarkets operating at the time (e.g., Evolution, Agora or Nucleus). Evolution, for example, totaled for around \$350,000 in daily volume of sales based on the last known estimate from February, 2015 (Soska and Christin, 2015). In comparison, Abraxas on average made \$15,200 per day in sales of illegal drugs during

the most active month in June, 2015. The volume of sales had been increasing steadily up to this month, however, and there are reasons to believe that Abraxas became one of the largest cryptomarkets before closing, since two of the largest competing cryptomarkets – Evolution and Agora, had both been closed before this time (Branwen, 2017).

In terms of the most popular drugs, Abraxas is relatively similar to other cryptomarkets, such as Silk Road 1 (Aldridge and Décary-Hétu, 2016a; Christin, 2013) or Agora (van Buskirk *et al.*, 2016). The most popular categories in terms of number of items on sale are cannabis (N = 2,578), stimulants (N = 1,532) and ecstasy drugs (N = 1,131). The same pattern holds if we consider the number of unique buyers in each category. If we consider the value of transactions, opioids closely follow cannabis products with an estimated transaction volume of \$287.854, with heroin accounting for 74.5% of this figure. While heroin has relatively few buyers compared to other major drugs (N = 77), the number of transactions per buyer in this category is among the highest (6.24 purchases per buyer). This suggests that a small number of opioid buyers make frequent purchases and generate a relatively large volume of trade.

Table 6.1. Market item and transaction statistics by drug category in Abraxas.

Category	Sub-category (recoded)	Number of items	Number of sellers	Number of buyers	Number of transactions	Volume of transactions (USD)	Avg. weight of purchased items (g)*
Cannabis	Marijuana	1,591	126	435	3,230	327,547	11.16
	Cannabis products ¹	530	57	79	257	18,884	3.71
	Hashish	457	49	123	722	43,122	6.86
Opioids	Misc. prescription opioids ²	278	51	62	306	25,787	5.73
	Heroin	247	35	77	481	214,400	1.45
	Oxycodone	105	25	30	215	37,046	0.32
	Buprenorphine	33	9	14	74	10,621	0.06
Stimulants	Cocaine	626	87	151	1,015	178,330	1.77
	Amphetamine	374	56	107	699	48,777	16.81
	Misc. prescription stimulants ³	318	48	38	101	7,822	1.21
	Methamphetamine	214	39	70	354	45,589	2.07
Ecstasy	Ecstasy pills	604	61	141	627	73,694	8.54
	MDMA	467	72	125	589	90,762	6.64
	Mephedrone	60	14	18	83	14,069	10.39
Psychedelics	LSD	235	34	71	448	22,321	3.00
	Misc. psychedelics ⁴	223	29	52	199	10,933	0.65
	Mushrooms	69	22	27	71	3,453	8.22
Benzodiazep. ⁵		509	53	97	483	21,386	0.17
Prescription	Misc. other prescription ⁶	422	14	35	67	2,291	1.40
	Misc. relaxants ⁷	139	43	11	27	2,410	24.51

Table 6.1. (Continued)

Category	Sub-category (recoded)	Number of items	Number of sellers	Number of buyers	Number of transactions	Volume of transactions (USD)	Avg. weight of purchased items (g)*
Dissociatives	Ketamine	66	14	18	93	9,737	2.20
	Misc. dissociatives ⁸	57	12	11	42	2,174	13.98
Steroids		260	13	11	26	1,253	0.77
RCs ⁹		69	13	7	23	822	1.41
Packages of mixed drugs		8	5	2	2	179	1.12
Total		7,961	390	3,192	10,234	1,213,457	6.70**

* - Calculated only for items with sales and available weight information, N = 2079

** - Weighted average (price weighted by number of transactions in each category; item weight weighted by number of items in each category)

1 - contains drug infused candy and chocolate, concentrates; 2 - fentanyl, hydrocodone, tramadol, codeine, etc.; 3 - Adderall, dextroamphetamine, Ritalin, etc.; 4 - synthetic psychedelics (25D-NBOMe, 2C-B, etc.), dimethyltryptamine; 5 - Xanax, Valium, Diazepam, Etizolam, etc.; 6 - Viagra, Cialis, Prozac, etc.; 7 - Etizolam, Zolpidem, etc.; 8 - GHB, methoxetamine; 9 - A-PVP, ethylphenidate, Modafinil

Purchase volume distribution

The distribution of the total volume of purchases is highly skewed among buyers (Figure 6.3). The total value of purchases per buyer ranges from \$0.23 to \$10888.69. About 50% of buyers spent less than \$150 and made only a single purchase over the period of data collection. Around 5% of buyers spent more than \$1,200 on an average of 10 purchases. The total value of purchases (in USD) made by the top 10% accounts for 50% of the entire market turnover of drug purchases during the observed period. The distribution of the relative number and volume of purchases across drug categories are similar for the top 10% and bottom 90% buyers. The top 10% of buyers on average buy larger quantities of most drugs: cannabis (18.4g vs. 6.9g), ecstasy (16.7g vs. 4.6g) and opioids (2.8g vs. 1.0g) being the largest differences between the groups. This result shows that market activity is as skewed among buyers, as it is among sellers (Soska and Christin, 2015) – a small group of users account for most transactions. A fraction of these transactions are purchases of large quantities of drugs.

Network structure and geographic clustering

Figures 6.4A and 6.4B display the structure of Abraxas trade network visually – the nodes represent buyers and sellers and network ties represent market exchanges. We used “ForceAtlas 2” algorithm in Gephi (Jacomy, 2009), which aims to represent connected nodes closer to each other, while pushing unconnected nodes away simultaneously. The resulting layout shows that the trade network has several large clusters.

In Figure 6.4B, sellers are colored by their stated geographic origin. Sellers’ geographic location is coded based on their provided “shipping from” locations in item pages. If more than one value was provided (e.g., “Italy” and “EU”), we used the value of the “lowest” geographical level value (e.g., country instead of region). To get a better picture of geographical trends in our analyses, we reduced the number of categories by merging countries with few sellers into larger categories (see Table 6.2).

The resulting network structure shows that buyer-seller network is highly fragmented across geographical borders. Sellers from the same countries are depicted closer to each other, because there are many buyers who make orders from each one of them, and fewer or no orders from sellers in other countries. As mentioned previously, buyers might prefer sellers from one specific country for several reasons (see also the Discussion section). The visualization also does not provide the extent to which this preference applies after controlling for other key factors (e.g., reputation, types of drugs). We will therefore analyze geographical clustering in more detail.

Figure 6.3. Distribution of number and volume of purchases among drug buyers in Abraxas.

Figure 6.4. A. (left): Network of market trades between drug buyers (blue) and sellers (yellow). Node size reflects the total number of seller's sales. **B. (right):** The same network of drug buyers and sellers; sellers colored by geographical location ('Ships from').

Table 6.2. Recoding scheme of Abraxas' sellers' locations.

Original value	Number of sellers	Recoded value	Number of sellers
Australia	33	Australia	33
Canada	11	Canada	11
Netherlands	27	Netherlands	27
Germany	33	Germany	33
UK	33	UK	33
USA	72	USA	72
Belgium	3		
Bulgaria	1		
Czech Republic	1		
Denmark	2		
Europe	26		
France	3		
Hungary	1	Europe	52
Italy	2		
Norway	1		
Poland	1		
Spain	7		
Sweden	3		
Switzerland	1		
China	1		
Columbia	1		
Mexico	1	Other/N.A.	21
South Africa	1		
Not Available	17		

ERGM RESULTS FOR GEOGRAPHIC CLUSTERING PATTERNS

In order to apply bipartite ERG models, we excluded repeated ties between the same buyers and sellers ($N = 5,644$). We used the same coding of sellers' countries of origin provided in Table 6.2. We do not explicitly model the structural effects for sellers in the "Other/N.A." category, in order to decrease the number of parameters in the model.²⁵ In total, the model includes 28 possible combinations of buyer-seller 2-stars.

Table 6.3. Descriptive statistics of variables used in the ERG model.

Variable name	N	Mean (std. dev)	Min/Max
<i>Seller origin</i>			
USA	282	0.255 (0.43)	0/1
Europe	282	0.184 (0.38)	0/1
Australia	282	0.117 (0.32)	0/1
United Kingdom	282	0.117 (0.32)	0/1
Germany	282	0.117 (0.32)	0/1
Canada	282	0.039 (0.19)	0/1
Netherlands	282	0.095 (0.29)	0/1
Other non-Europe/NA	282	0.074 (0.26)	0/1
Seller's reputation	282	4.744 (0.73)	0-5
<i>Seller's number of items</i>			
Weed	282	0.393 (1.81)	0-17
Ecstasy	282	0.109 (0.59)	0-6
Opioids	282	1.124 (3.01)	0-26
Psychedelics	282	0.687 (2.06)	0-13
Stimulants	282	0.375 (1.62)	0-18
Benzodiazepines	282	0.567 (1.66)	0-13
Number of sellers	3,192		
Number of buyers	282		
Number of edges (unweighted/undirected)	5,644		

²⁵ Please note that while we exclude 2-star parameters with sellers in the "Other/N.A." category, network connections between these sellers and their buyers are still included in the data.

We include several control variables in our ERG model. *Edge* variable is the baseline likelihood of tie formation, which is often included in ERG models and can be interpreted as the intercept term, or a baseline likelihood of a tie occurring in a network. We control for the general tendency of buyers to form 2-stars and the *number of buyers with multiple (>2) purchases*. These structural terms are used to improve model fit.

We include the main effects of *seller's location* to control for the likelihood of buyers to form a tie with a seller from a particular country (see Table 6.3). *Seller's reputation* has been found to affect buyer's trust in previous research (Przepiorka *et al.*, 2017; Duxbury and Haynie, 2018a). We averaged seller's ratings over all feedback messages, including non-drug items that have been excluded from our data. This variable has a theoretical range of 0 to 5, based on the 5-star feedback system. Finally, to account for the effect of the kind of drugs sold on tie formation, we include a variable for the number of seller's items in the 6 largest drug categories: *marijuana, ecstasy, opioids, psychedelics, stimulants and benzodiazepines*.

Table 6.4. ERG model estimates – likelihood of geographically homogenous (diagonal) and heterogenous buyers 2-stars. The matrix represents all possible combinations of buyer-seller 2-stars. Geographically homogenous 2-stars (both sellers from the same country) are presented on the diagonal of the matrix.

Seller 2 Seller 1	Australia	Canada	Europe	Germany	Netherlands	UK	USA
Australia	0.288*** (0.05)						
Canada	-0.750 (0.46)	1.084*** (0.07)					
Europe	-2.400*** (0.39)	0.123 (0.08)	0.195*** (0.06)				
Germany	-4.491*** (1.01)	-0.631** (0.21)	-0.250*** (0.06)	0.103† (0.05)			
Netherlands	-3.494*** (0.95)	0.029 (0.13)	-0.009 (0.06)	-0.286*** (0.06)	0.378*** (0.04)		
UK	-2.038*** (0.29)	-0.169 (0.18)	-0.328*** (0.06)	-0.925*** (0.08*)	-0.179* (0.07)	0.311*** (0.04)	
USA	-2.686*** (0.36)	-0.299 (0.18)	-0.868*** (0.09)	-1.441*** (0.11)	-1.432*** (0.16)	-1.686*** (0.16)	0.161*** (0.05)

Table 6.4. (Continued) ERG model estimates – effects of the control variables on the likelihood of ties.

Variable name	Coefficient	Std. Err.
Edges	-4.984***	0.175
Buyer 2-stars	-0.097*	0.049
Buyers >1 purchases	-1.946***	0.077
<i>Seller origin</i>		
USA	(ref.)	
Europe	-0.332***	0.061
Australia	0.404***	0.059
United Kingdom	0.277***	0.052
Germany	0.583***	0.054
Canada	-1.312***	0.185
Netherlands	-0.394***	0.070
Other non-Europe/NA	-1.347***	0.135
Seller's reputation	0.231***	0.033
<i>Seller's number of items</i>		
Weed	-0.034***	0.007
Ecstasy	0.009	0.017
Opioids	0.085***	0.002
Psychedelics	0.076***	0.005
Stimulants	0.076***	0.008
Benzodiazepines	0.102***	0.005
AIC/BIC	61816/62343	

The model results for the occurrence of buyer-seller 2-stars are displayed in a matrix in the first part of Table 6.4. The results on the diagonal cells are the estimates of geographically homogenous 2-stars, where a buyer is connected to 2 sellers from the same country. The results show that geographically homogenous 2-stars are more likely to appear than would be expected by chance. This applies to all countries, except Germany, where the result is statistically insignificant (log-odds = 0.103, $p = 0.07$). In contrast, the estimates for geographically heterogenous 2-stars below diagonal are all negative and statistically significant for most country combinations. These results show that buyers in Abraxas are unlikely to order from sellers in multiple countries and are especially likely to order from multiple sellers within the same country. These two effects, working together, give rise to the clustering observed in Figure 6.4B.

The negative estimates of geographically heterogenous 2-stars below the diagonal are especially highly negative for 2-stars that contain sellers from Australia and USA, while

estimates are closer to zero for 2-stars with sellers from different European countries. This result suggests that the largest amount of geographical clustering is observed between continents, while simultaneous purchases from several European sellers, although unlikely, occur more often. Most estimates are statistically insignificant for 2-stars that contain Canadian sellers. This result might be partially explained by the small number of Canadian sellers in the marketplace ($N = 11$).

The estimates of the control variables in the model show that, generally, the likelihood of buyer-seller 2-star formation in the network, and the number of buyers with more than a single purchase are lower than could be expected by chance. This is in line with the skewed degree distribution of buyers in Figure 6.1B, which shows that many buyers only exchange with a single seller. The results also show that, all else equal, sellers from Australia, the UK and Germany are more likely to form exchange relations than their competitors in the United States, while sellers from Canada, the Netherlands and other analyzed European and uncategorized countries are less likely to attract buyers²⁶. Finally, in line with previous research, we observe a positive effect of sellers' reputation on the number of exchange relations.

²⁶ Please note that this result does not necessarily reflect the general distribution of purchases across sellers in these countries, since the model takes structural effects, reputation and other covariates into account. Sellers from the United States on average have more sales and buyers per person than sellers in Australia, UK and Germany

CONCLUSIONS AND DISCUSSION

Cryptomarkets provide unprecedented access for researchers to data not only on macro-level structure of large-scale drug trade networks, but also on individual buyer decisions and buying patterns. In this chapter, we made the first attempt to shed light on the structure of a complete online drug trade network and the shaping factors.

Analysis of the Abraxas trade network illuminates several important structural characteristics. First and foremost, we find that the network is largely shaped by geographical boundaries. Buyers tend to make orders from multiple drug sellers from a single country and avoid ordering from multiple countries. This effect is especially strong for continental boundaries – buyers are more likely to simultaneously order drugs from sellers from several European countries, than from sellers in different continents. This structural aspect of cryptomarket networks has not been observed in previous studies that analyzed subsets of a cryptomarket network (Duxbury and Haynie, 2018a; 2018b).

There might be several explanations for this geographic clustering. Buyers might be more willing to order domestically to avoid increased risks of package interception, possibility of getting arrested and long shipping times. This might also be amplified by sellers' risk aversion and unwillingness to ship internationally (Décary-Héту *et al.*, 2016). Another explanation could be buyers' tendency to buy specific types of drugs from particular countries, regardless of their own geographic location (e.g., due to drug availability being limited to few countries). We argued that this explanation might not be the primary one, since supply of all types of drugs is relatively well distributed across different countries in cryptomarkets (Broseus *et al.*, 2017; van Buskirk *et al.*, 2016). Unfortunately, we were not able to test these explanations directly, since buyers' geographic locations were not available in the cryptomarket website, and this aspect remains an important venue for future research.

These results show that cryptomarkets are heavily affected by offline factors and geographic boundaries. Their ability to internationalize retail drug trade could therefore be more limited than shown by sellers' willingness to ship internationally in previous studies (Décary-Héту *et al.*, 2016; Broseus *et al.*, 2017). Even though cryptomarkets technically provide its users an easy access to information and worldwide markets, rational cost and benefit considerations of market actors might push them to exchange in "local" niches.

Additionally, the network analysis suggests that trade volume distribution is as skewed for buyers, as it has previously been found among sellers (Christin, 2013; Soska and Christin, 2015). We find that around 10% of buyers accounted for a half of

marketplace's entire trading volume, while 50% of buyers never spent more than \$150 and purchased only once. If such pattern is consistent across larger cryptomarkets, the growth and prospects of cryptomarkets might be overestimated with only a small fraction of buyers using such markets on a constant basis. Décary-Héту and Quessy-Doré (2017) found, in contrast, that 91% of buyers made more than a single purchase. Although the overall distribution of purchases across buyers was not analyzed, it could be the case that results of this study are limited due to a short period of time used in the analyses. Alternatively, the result of Décary-Héту and Quessy-Doré (2017) could be overestimated. They matched buyer accounts using partially anonymized nicknames, which could have led to a large underestimation of distinct buyer accounts (i.e. attribution of purchases from different buyers to the same case in the analysis). It should also be noticed that our data are based on buyer accounts and not individual buyers. If buyers tend to use multiple accounts (e.g., for security reasons), the true concentration of purchases could be even larger.

Limitations and policy implications

There are several limitations of this study. First, the data do not include buyers' geographic location, which prevents us from directly testing the effect of geographic homophily between buyers and sellers and alternative mechanisms that lead to it. The data set is also too small to analyze drug-type specific geographic clustering patterns.

Secondly, Abraxas is a relatively small market and the extent to which our findings can be generalized to other cryptomarkets should be further evaluated. While virtually all cryptomarkets anonymize buyer nicknames in feedback messages, which makes our findings hard to replicate, there could be opportunities in new marketplaces. We encourage researchers to put more emphasis on individual-level buyer and seller interactions. Such large-scale granular data can be very valuable to answer important questions, such as what drives buyers' trust in sellers, what kind of buyers stay in cryptomarkets for the long term, how individual drug use patterns change over time or why do some actors end up being so important.

The findings of this chapter contribute to the debate on the international nature of cryptomarkets, previously raised by Décary-Héту *et al.* (2016). Based on the structure of trade network in Abraxas, it might be more fruitful to analyze cryptomarkets as conglomerations of regional sub-markets rather than as uniform international market entities. While the threat of law enforcement undeniably plays a significant role in increasing the risks of international shipping, relatively high clustering of European sellers and low frequency of inter-continental trade by the same buyers might suggest that other factors, such as considerations of shipping speed, could play a sufficient role in "localizing" cryptomarket exchanges. Our findings suggest that for monitoring and

enforcement coordination purposes, data on buyers' behavior is crucial to capture the scope and potential growth of cryptomarkets as an international phenomenon. Finally, additional research is needed to better understand the conditions under which buyers are likely to order internationally.

Appendices

APPENDIX 1 - Supplementary material for Chapter 2

Additional analyses

Recall that the results reported in the main study are based on regression estimations which account for seller fixed effects (FE) and therefore discard the between-seller variability in the data. Although this approach is reasonable in the light of our data structure (see Data and Methods in Chapter 2), it will likely produce conservative estimates of the reputation effects. Before selecting a seller to buy from, buyers are likely to compare different sellers with each other, in which case between-seller variability comes into play. The OLS regression models we report in Table A1.1 partly capture this between-seller variability. First note that these model estimations qualitatively produce the same results as the regression models with seller FE reported in Table 2.2. Moreover, the coefficient estimates of the log number of 5-star ratings and non-5-star ratings are larger in absolute terms. Although we cannot rule out that the larger magnitude of these effects is due to omitted variable bias, these results are at least consistent with the idea that part of the reputation effect is absorbed when buyers choose their sellers. Figure A1.1 compares the reputation effects estimated using seller fixed effects with the reputation effects estimated by means of OLS regressions.

Recall, moreover, that our main analyses are based on items which received at least one feedback message indicating that they were sold at least once. Table A1.2 shows the estimates of logistic regressions based on the entire sample, which also includes items which had not received a feedback message (also see Data and Methods in Chapter 2). The binary dependent variable in both models in Table A1.2 is one if an item was sold at least once (i.e. received at least one feedback message) and is zero otherwise. The covariates used in these models are the same as the covariates used in the models of sales per day (see Table A1.1) with one additional variable, namely the log-transformed duration in days an item was seen online. Models M5 and M6 are estimated without and with seller fixed effects, respectively. Note that the estimation of the FE logit (model M6) is entirely based on within-seller variation in outcome and explanatory variables. We therefore lose 229 sellers (and 828 items), who offered items all of which had either one registered sale or none. In both models the coefficient estimates point in the expected directions. Higher item prices decrease the probability of sale, larger quantities, *ceteris paribus*, increase the probability of sale, etc. Most importantly, a seller's number of 5-star ratings increases and his or her number of non-5-star ratings decreases the probability of sale. Although the coefficient estimates of 5-star and non-5-star ratings are about three times smaller if seller FE are accounted for (model M6), they remain significant albeit only at the 10%-level for non-5-star ratings ($p = 0.090$). These results corroborate our findings based on items for which

at least one transaction was recorded. Again, we prefer not to include unsold items in our main analysis because we cannot be sure that the sellers posting these items had the intention to sell them as specified.

Figure A1.1. The figure shows the effect of a seller's rating history on item prices (A) and selling speed (B) based on model estimations with (same as Figure 2.1) and without seller fixed effects (shaded bars).

Table A1.1. OLS regression models of item price per g and sales per day.

	Log(item price per g in USD) M3	Log(# item sales per day) M4
Const.	3.000*** (0.032)	0.460 (0.269)
<i>Item variables</i>		
Log(item price per g in USD)		-0.644*** (0.086)
Log(weight in g)	-0.219*** (0.010)	-0.449*** (0.068)
Low price	(ref.)	(ref.)
Medium price	1.465*** (0.043)	0.913*** (0.161)
High price	2.151*** (0.053)	1.389*** (0.219)
Poor quality (weed & hash)	-0.884*** (0.069)	-0.074 (0.189)
Last two days	0.055* (0.026)	0.031 (0.106)
<i>Seller variables</i>		
Log(# 5-star ratings + 1)	0.037*** (0.009)	0.179*** (0.035)
Log(# non-5-star ratings + 1)	-0.055** (0.019)	-0.245*** (0.073)
Log(# item sales)	-0.017* (0.007)	
<i>Seller ships to</i>		
unknown	0.005 (0.064)	-0.322 (0.167)
domestic only	(ref.)	(ref.)
foreign	-0.081** (0.031)	0.032 (0.092)
N_1	3153	3153
N_2	445	445
adj. R^2	0.88	0.21

Note: The table lists coefficient estimates and cluster-robust standard errors (***) $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, for two-sided tests) of OLS regression models. The target variable in model M3 is the log-transformed item price per g in USD. The target variable in model M4 is the log-transformed number of item sales per day. N_1 denotes the number of cases (items) and N_2 denotes the number of clusters (sellers). Fig. A1 are based on these model estimations.

Table A1.2. Logistic regression models of probability of sale.

	Sold at least once (0/1)	
	M5	M6
Const.	1.509*** (0.428)	
<i>Item variables</i>		
Log(item price per g in USD)	-1.299*** (0.135)	-2.189*** (0.165)
Log(weight in g)	-0.797*** (0.060)	-1.078*** (0.053)
Low price	(ref.)	(ref.)
Medium price	1.246*** (0.261)	2.909*** (0.345)
High price	2.055*** (0.358)	3.931*** (0.482)
Poor quality (weed & hash)	0.145 (0.257)	-0.198 (0.428)
Last two days	-0.056 (0.198)	0.541** (0.198)
<i>Seller variables</i>		
Log(# 5-star ratings + 1)	0.334*** (0.077)	0.142* (0.056)
Log(# non-5-star ratings + 1)	-0.352** (0.129)	-0.196 (0.114)
Log(time online in days)	1.321*** (0.053)	1.647*** (0.059)
<i>Seller ships to</i>		
unknown	-0.385 (0.263)	0.024 (0.429)
domestic only	(ref.)	(ref.)
foreign	-0.135 (0.163)	0.277 (0.249)
N_1	5675	4847
N_2	550	321
pseudo R^2	0.44	0.51

Notes: The table lists coefficient estimates and standard errors (***) $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, for two-sided tests) of logistic regression models. The binary target variable in both models is one if an item was sold at least once (i.e. received at least one feedback message) and is zero otherwise. N_1 denotes the number of cases (items) and N_2 denotes the number of clusters (sellers). Model M5 is estimated with robust standard errors adjusted for seller clustering. Model M6 is estimated with seller fixed effects.

APPENDIX 2A - Full results of logistic regression models for Hypothesis 1, Chapter 4.

Table A2.1. Logistic regression model of seller properties on odds of migrating to a new market with the same identity

	M1 (Sales)	M2 (M2 + controls)	M3 (M2 + reputation)
	Odds ratio (SE)	Odds ratio (SE)	Odds ratio (SE)
Number of sales	1.005*** (0.000)	1.004*** (0.000)	1.004*** (0.000)
Average reputation			1.689*** (0.163)
Cryptomarket (= Abraxas)	1.961*** (0.220)	1.642*** (0.210)	1.786*** (0.272)
Total # of listings		1.012* (0.006)	1.014* (0.006)
% of listings in Q2 price		1.352 (0.279)	1.383 (0.301)
% of listings in Q3 price		0.959 (0.186)	0.993 (0.205)
% of listings in Q4 price		0.877 (0.152)	0.964 (0.175)
<i>Number of items in:</i>			
Cannabis		0.989 (0.007)	0.985 (0.007)
Stimulant		0.984 (0.012)	0.982 (0.012)
Ecstasy		1.008 (0.012)	1.004 (0.012)
Opioid		1.001 (0.016)	0.996 (0.017)
Psychedelic		1.002 (0.014)	0.996 (0.014)
Benzo		1.014 (0.018)	1.008 (0.019)
Prescription		0.980* (0.009)	0.977* (0.010)
Dissociative		0.972 (0.040)	0.978 (0.042)
<i>Ships to:</i>			
Worldwide		1.152 (0.117)	1.167 (0.124)
U.S. only		1.217 (0.131)	1.232 (0.138)
Europe only		1.099 (0.164)	1.063 (0.165)
U.K. only		1.011 (0.200)	0.951 (0.194)
Australia only		1.568** (0.250)	1.404* (0.234)
Constant	0.662 (0.038)	0.550 (0.068)	0.042 (0.027)
N(sellers)	2,392	2,392	2,265
Pseudo R ²	0.068	0.077	0.095

* - $p < .05$; ** - $p < .01$; *** - $p < .001$. Odds ratios are reported with standard errors in parentheses.

APPENDIX 2B - Full results of multi-level random intercept negative binomial regression models for Hypotheses 2 and 3, Chapter 4.

Table A2.2. Multi-level random intercept negative binomial regression model of seller pre-AlphaBay history of sales and AlphaBay activity on weekly number of sales

	M4 (pre-Alpha sales + controls)	M5 (pre-Alpha rep. + controls)	M6 (M4 + interaction)	M7 (M5 + interaction)
Number of sales (Abraxas+Agora)	1.001*** (0.00)		1.002*** (0.00)	
Average reputation (Abraxas+Agora)		1.138*** (0.02)		1.123** (0.04)
# Markets before Alphabay	0.989 (0.02)	0.962 (0.02)	0.999 (0.02)	0.957 (0.03)
Number of sales (Abr.+Ago.) * # Market bef. Alphabay			0.999 (0.00)	
# Average rep. (Abr.+Ago.) * # Market bef. Alphabay				1.004 (0.01)
# Average reputation (Alphabay, cumulative)	1.043*** (0.01)	1.043*** (0.01)	1.043*** (0.01)	1.043*** (0.01)
No sales before Alphabay		1.625*** (0.23)		1.631*** (0.23)
No accounts before Alphabay	0.809*** (0.05)	0.514*** (0.08)	0.828*** (0.05)	0.507*** (0.08)
Weeks since market entry	0.994*** (0.00)	0.994*** (0.00)	0.994*** (0.00)	0.994*** (0.00)
Months since market opened	1.005*** (0.00)	1.005*** (0.00)	1.005*** (0.00)	1.005*** (0.00)
<i>Number of items in:</i>	<i>8 categories – results omitted from the table</i>			
<i>Ships to:</i>	<i>5 categories - results omitted from the table</i>			
% of listings in Q2 price	0.906 (0.08)	0.901 (0.08)	0.903 (0.08)	0.901 (0.08)
% of listings in Q3 price	0.855 (0.07)	0.847 (0.07)	0.855 (0.07)	0.848 (0.07)
% of listings in Q4 price	0.605*** (0.04)	0.600*** (0.04)	0.605*** (0.04)	0.600*** (0.04)
Constant	1.963 (0.19)	1.909 (0.18)	1.914 (0.19)	1.928 (0.19)
N(sellers)	7,593	7,593	7,593	7,593
N(seller*week)	341,223	341,223	341,223	341,223
Variance (intercept)	2.279 (0.04)	2.281 (0.04)	2.278 (0.04)	2.281 (0.04)

* - $p < .05$; ** - $p < .01$; *** - $p < .001$. IRR values reported. Standard errors in parentheses.
Seller*week cases clustered in seller ids.

APPENDIX 2C - Full results of multi-level random intercept multinomial logistic regression models for Hypothesis 4, Chapter 4.

Table A2.3. Multi-level random intercept multinomial logistic regression model of buyer migration history on migration-based seller selection

	M8 (migration background only)		M9 (M1 + controls)	
	Select Agora migrant seller	Select Abraxas migrant seller	Select Agora migrant seller	Select Abraxas migrant seller
Buyer entered after Agora	1.229 (0.14)	1.568*** (0.11)	0.862 (0.14)	1.297** (0.10)
Buyer entered after Abraxas	1.685*** (0.10)	2.028*** (0.08)	1.269* (0.10)	1.600*** (0.02)
Months since market opened			0.972*** (0.00)	0.976*** (0.00)
<i>Selected item in:</i>	<i>8 drug categories – results omitted from the table</i>			
<i>Ships to:</i>	<i>5 categories - results omitted from the table</i>			
Selected listing in Q2 price			0.898 (0.07)	1.044 (0.04)
Selected listing in Q3 price			1.060 (0.08)	0.944 (0.04)
Selected listing in Q4 price			1.035 (0.11)	0.841** (0.06)
Constant	0.001 (0.04)	0.004 (0.04)	0.0002 (0.24)	0.003 (0.09)
N(buyers)	16,941	16,941	16,941	16,941
N(buyers*feedbacks)	237,636	237,636	237,636	237,636
Variance (intercept)	3.847 (0.14)		2.944 (0.11)	

* - $p < .05$; ** - $p < .01$; *** - $p < .001$. RRR values reported. Standard errors in parentheses.
Buyer*feedback cases clustered in buyer ids.

APPENDIX 3 - Additional analysis of transferred reputation effects over time, Chapter 4.

To gain more insight into how the history of sales affects market outcomes over time, we ran Model 3 (Table 4.4) with an interaction effect between seller's pre-AlphaBay sales and a non-linear effect of time (number of weeks since seller's market entry). This analysis shows the sales trajectories of sellers in AlphaBay over time, depending on how many sales they already had before joining. The results are depicted in Figure A3. The figure shows that sellers who had no sales before entering the market initially receive fewer sales and catch up slightly over time. Sellers who already have an established history of sales increase their current sales more rapidly. For sellers with the most pre-AlphaBay sales, this effect seems to diminish over time.

Figure A3.1. Predicted seller's weekly sales over time by number of sales before entering AlphaBay (C.I. represented with dashed lines).

Samenvatting

(Summary in Dutch)

INLEIDING

Illegale online markten, of cryptomarkten, zijn websites die worden gehost op het “verborgen” deel van het internet. Ze kunnen niet worden gevonden met reguliere zoekmachines zoals Google, Bing of Yandex, en zijn alleen toegankelijk met de gespecialiseerde internetbrowser TOR (Barratt en Aldridge, 2016). Deze browser is speciaal gemaakt om zijn gebruikers volledig te anonimiseren. Hij verhult hun offline locatie door het netwerkverkeer via een reeks tussenliggende computerknooppunten over de hele wereld te leiden. Websites die op dit netwerk worden gehost, profiteren van dezelfde mate van anonimiteit; fysieke servers waar deze websites worden gehost, zijn net zo moeilijk te vinden.

Cryptomarkten worden vooral opgezet als ruimten voor individuele kopers en verkopers van verboden middelen (Martin, 2014; Barratt en Aldridge, 2016). Dankzij de volledige anonimiteit van het netwerk kunnen de gebruikers relatief veilig goederen en diensten uitwisselen, buiten het bereik van politie en justitie. Websites op cryptomarkten lijken doorgaans sterk op gewone online winkels als eBay of Amazon. Verkopers maken een lijst van de producten die ze willen verkopen, met foto's en extra informatie, zoals het gewicht en de prijs. Kopers kiezen het gewenste product en nemen contact op met de verkoper. Voor de financiële afwikkeling van de transactie worden cryptovaluta's zoals Bitcoins of Monero gebruikt. Ook die verhullen de identiteit van verzender en ontvanger (Christin 2013, Nakamoto, 2008). De laatste fase van de transactie is de fysieke aflevering van de bestelde drugs aan de koper. Dit gebeurt meestal met behulp van een soort gecamoufleerd pakket (bijvoorbeeld een vacuolop) dat met de reguliere postbezorgingssystemen of koeriersdiensten wordt verzonden.

Volledige anonimiteit is de belangrijkste reden waarom cryptomarkten kunnen opereren zonder permanent te worden platgelegd door nationale instanties, maar ze zorgt ook voor onzekerheid en verschillende risico's voor cryptomarktgebruikers. Kopers kunnen er niet zeker van zijn of de drug die ze hebben besteld van dezelfde kwaliteit is als waarmee de verkoper adverteert. De onzekerheid over de productkwaliteit is met name belangrijk gezien de potentiële nadelen van sommige middelen, waaronder het risico op een overdosis. In sommige gevallen hebben kopers ook geen zekerheid dat de verkoper de producten na betaling ook echt verzendt. Anonieme verkopers hebben immers een financiële prikkel om een klant te misleiden, vooral omdat de overeenkomsten niet wettelijk zijn beschermd. Zowel kopers als verkopers kunnen pogingen tot chantage doen, dreigen de identiteit van de andere partij bekend te maken of onjuiste informatie over een product verspreiden (Moeller et al., 2017).

Ondanks de verschillende risico's is de populariteit van cryptomarkten de laatste acht jaar enorm gestegen. De eerste cryptomarkt, Silk Road, werd begin 2011 opgericht. In 2013 was de marktplaats al goed voor naar schatting \$300,000 aan drugsverkopten per dag (Soska en Christin, 2015). Nadat Silk Road was opgerold en de oprichter eind 2013 was gearresteerd, namen diverse nieuwe cryptomarkten het stokje over. Soska en Christin (2015) ontdekten dat er in 2014 al ten minste vijf platforms waren waarop dagelijks dezelfde hoeveelheid of meer werd verkocht, terwijl tussen 2013 en 2015 meer dan zestig cryptomarkten werden geopend (Branwen, 2019). Het aantal unieke identiteiten van verkopers is gegroeid van ongeveer 600 in de tijd van Silk Road naar bijna 10.000 eind 2014. Uit de Global Drug Survey van 2017 bleek dat ongeveer 9% van de druggebruikers die in 2016 aan de drugsenquête deelnamen, zei wel eens drugs te hebben gekocht op het darkweb, terwijl 7% toegaf dat in het voorgaande jaar nog te hebben gedaan (Winstock et al., 2017).

Cryptomarkten vormen een raadselachtig geheel dat de drijfveer vormt voor dit onderzoek – hoe kunnen we de snelle groei en populariteit van cryptomarkten verklaren, gezien alle onzekerheden en risico's die deze omgeving met zich meebrengt? Hoe gaan gebruikers van deze marktplaatsen om met de vertrouwensproblematiek en wat kunnen we daarvan leren? Met deze dissertatie willen we dan ook inzicht krijgen in hoe kopers en verkopers op cryptomarkten elkaar kunnen vertrouwen in een omgeving waarin elke gebruiker anoniem is, een prikkel heeft om andere gebruikers te misleiden en waarin geen juridisch vangnet bestaat om op terug te vallen wanneer overeenkomsten worden geschonden. De specifiekere onderzoeksvraag van deze dissertatie is: wat zijn de mechanismen die de samenwerking en het vertrouwen tussen kopers en verkopers op cryptomarkten vergroten?

Het specifieke doel van deze dissertatie is tweeledig. Ten eerste gebruiken we cryptomarkten als proeftuin voor sociaalwetenschappelijke theorieën die uitgaan van bepaalde omstandigheden waaronder anonieme spelers meer geneigd zijn elkaar te vertrouwen, en van mechanismen die samenwerking in onzekere situaties vergroten. Cryptomarkten zijn het ideale platform om sociaalwetenschappelijke theorieën over interpersoonlijke samenwerking te testen, omdat ze een zeer riskante omgeving zonder centrale coördinatie vormen en illegaal zijn. Onderzoekers naar cryptomarkten zijn in de unieke gelegenheid om een grote hoeveelheid discrete gedragsgegevens te verkrijgen van individuen die in zeer onzekere omstandigheden als vanzelfsprekend transacties met elkaar aangaan. We zijn in staat te observeren welke sociale mechanismen en regels ontstaan die de samenwerking ondersteunen en in de plaats komen van de gecentraliseerde juridische bescherming van overeenkomsten.

Ons tweede doel is cryptomarkten als fenomeen op zich te doorgronden. Al is het testen van theorieën een essentieel onderdeel van wetenschappelijk onderzoek, sommige hoofdstukken in deze dissertatie gaan ook over problemen die specifiek te maken hebben met het vertrouwen tussen gebruikers van cryptomarkten. Het aantal onderzoeken naar de verschillende aspecten van cryptomarkten is de afgelopen vijf jaar enorm gegroeid. De huidige kennis over hoe vertrouwen in deze omgeving ontstaat, ontbeert een sterkere theoretische onderbouwing, wat een reden kan zijn om systematischer nieuwe vragen te stellen.

We realiseren de doelstellingen van dit onderzoek door middel van een analyse van de digitale voetafdrukken van cryptomarktkopers en -verkopers (Décary-Hétu en Aldridge, 2015) die door andere onderzoekers (Christin, 2013; Branwen, 2019) zijn gebundeld in grote verzamelingen kopieën van cryptomarktwbsites, maar ook digitale afdrukken die specifiek voor dit onderzoek zijn verzameld. Cryptomarktwbsites bevatten sporen van gebruikersactiviteit, zoals productinformatie, feedback met datumvermelding van kopers voor verkopers, gesprekken op discussieforums en andere informatie. Met deze gegevens kunnen de acties van gebruikers door de tijd heen op grote schaal worden gereconstrueerd en kunnen de concepten die nodig zijn voor dit onderzoek worden geoperationaliseerd, bijvoorbeeld wie wanneer van wie heeft gekocht, wat de reputatie van elke verkoper op willekeurige momenten was of hoe waarschijnlijk het is dat een koper zich tot een verkoper wendt nadat die misbruik van zijn vertrouwen heeft gemaakt.

De effectiviteit van reputatie

In hoofdstuk 2 wordt reputatie, ofwel het vermogen van individuen om informatie te delen over de betrouwbaarheid van verkopers, geanalyseerd. Eerdere onderzoeken lijken erop te wijzen dat reputatiesystemen op grote online marktplaatsen een succesvolle vervanging zijn voor het gebrek aan sociale relaties tussen gebruikers en dat ze voldoende prikkels geven voor coöperatief gedrag (Diekmann et al., 2014). Kopers zijn geneigd te kiezen voor verkopers met een goede reputatie en akkoord te gaan met hogere prijzen, die verkopers compenseren voor goed gedrag en hen aanmoedigen om in de toekomst coöperatief te blijven.

We onderzoeken welke invloed de reputatie van verkopers heeft op het vertrouwen van kopers op Silk Road, een illegale online drugsmarkt op het darkweb. We zien dat reputatie het gedrag van zowel kopers als verkopers beïnvloedt. Verkopers passen hun prijzen aan overeenkomstig hun reputatie. Ze verhogen de prijzen van hun producten naarmate hun reputatie verbetert, wat de kosten voor het opbouwen van een goede reputatie compenseert. Verkopers met een slechtere reputatie verlagen hun prijzen, wat kopers compenseert voor het risico dat ze lopen door bij een verkoper met een

slechte reputatie te kopen. Verkopers met een goede reputatie verkopen ook meer producten in dezelfde tijd, wat aantoont dat kopers geneigd zijn hun keuze te baseren op de reputatie van de verkoper en onbetrouwbare verkopers zo misschien geleidelijk uit de markt drukken.

We constateren dat reputatiesystemen voor de spelers echte economische prikkels tot samenwerking creëren, zelfs als een centrale instantie of sociale inbedding ontbreekt. Reputatiesystemen zijn daarom een belangrijke organisatorische waarborg die online handelaren beschermt tegen opportunistisch gedrag van hun collega's.

Herhaalde transacties en sterke dyadische banden

Producten die op cryptomarkten worden verkocht zijn meestal genotmiddelen, en transacties tussen dezelfde koper en verkoper kunnen worden herhaald. Hierdoor ontstaat een geschiedenis van transacties tussen tweetallen van koper en verkoper. Dat betekent dat naast de reputatie van de verkoper die door andere kopers is gemeld, een koper ook informatie heeft op basis van zijn eigen transactieverleden die kan worden gebruikt om de betrouwbaarheid van de verkoper in de toekomst te beoordelen.

De gegevens over een verkoper uit deze twee bronnen kunnen elkaar aanvullen of tegenspreken. In hoofdstuk 3 analyseren we hoe kopers besluiten wie ze vertrouwen, rekening houdend met individuele dyadische transactieverledens met elke verkoper en met de algemene reputatie van elke verkoper op de markt. Theoretisch gezien willen we aan de hand van een gelijktijdige analyse van de ervaringen op kopersniveau begrijpen hoe een-op-een- en netwerkervaringen de kopers beïnvloeden bij hun beslissingen.

We zien dat kopers geneigd zijn te kiezen voor verkopers die ze in het verleden al eerder hebben vertrouwd, ondanks het feit dat er op de markt goedkopere of hoger aangeschreven verkopers zijn. Dit zorgt voor een sterke dyadische inbedding in de markt, waar kopers veelal van één of enkele verkopers kopen.

De algemene reputatie van verkopers heeft een aanzienlijke invloed op de beslissing van kopers, wat vooral het geval is bij de eerste transactie nadat de koper de markt is opgegaan als hij nog met geen enkele verkoper een individueel transactieverleden heeft opgebouwd. Na de eerste uitwisseling neemt de invloed van de reputatie op netwerkniveau echter af en wordt de individuele ervaring met betrouwbaarheid de belangrijkste drijfveer voor toekomstige beslissingen.

We constateren dat reputatie op cryptomarkten primair op dyadisch niveau werkt, al beïnvloedt de algemene reputatie van een verkoper de koper ook bij zijn beslissingen. Een sterke dyadische inbedding tussen kopers en verkopers is een belangrijk

mechanisme dat helpt bij het behouden van vertrouwen en dat een sterkere invloed heeft dan de inbedding in het netwerk.

Reputatie volgt verkopers van markt naar markt

Van cryptomarkten is bekend dat ze geregeld worden platgelegd door acties van politie en justitie, hacks of cryptofraude door marktplaatsbeheerders, die van tijd tot tijd verdwijnen met het geld van de gebruikers. Het cryptomarkt-ecosysteem is niettemin veerkrachtig; gewoonlijk nemen meerdere nieuwe cryptomarkten de plaats in van een oude die is opgerold. De anonieme marktspelers wisselen dan ook voortdurend van omgeving.

In hoofdstuk 4 analyseren we hoe kopers en verkopers, die constant van marktomgeving wisselen, hun vertrouwen behouden in een volledig anonieme omgeving waarin online identiteiten moeilijk na te trekken zijn, en informatie over de eerdere reputatie van elke verkoper zeldzaam en onvolledig kan zijn.

De bevindingen in dit hoofdstuk laten zien dat verkopers met een goede reputatie en hoge verkoopcijfers eerder geneigd zijn met dezelfde online identiteit van cryptomarktplaats te veranderen dan verkopers met een minder goede reputatie en lagere verkoopcijfers. Verkoopgeschiedenis en een goede reputatie in eerdere omgevingen leiden tot betere marktresultaten voor migrerende verkopers die hun online identiteit behouden vergeleken met verkopers die met een nieuwe identiteit en zonder voorgeschiedenis op de markt komen. Ook ontdekten we dat het effect van een overdraagbare reputatie op de marktverkoop van verkopers in nieuwe omgevingen vergelijkbaar is met het effect van de reputatie die verkopers op de nieuwe markt opbouwen.

We constateren dat als de reputatie van een verkoper eenmaal gevestigd is, het niet uitmaakt of hij zich beperkt tot één cryptomarkt. De resultaten wijzen er ook op dat de overdraagbaarheid van reputaties kan bijdragen aan een snel herstel van de online drugshandel nadat een markt is stilgelegd. Dit beperkt in aanleg de effectiviteit van het optreden van politie en justitie tegen specifieke marktplaatsen.

Communicatie in discussieforums en vertrouwen

Eerdere resultaten laten zien dat reputatie een sterk signaal van de betrouwbaarheid van een verkoper is, aangezien aan het voorwenden van een goede reputatie door frauduleuze verkopers een stevig prijskaartje hangt. Andere signalen, zoals de verbale communicatie van verkopers met kopers, waarbij ze hen proberen te overtuigen van hun goede bedoelingen en de kwaliteit van hun producten, zijn gemakkelijker voor te wenden aangezien dergelijke signalen ook door frauduleuze verkopers

gemakkelijker kunnen worden afgegeven. Kopers kunnen het waarheidsgehalte van de mededelingen van verkopers op geen enkele manier controleren. Theoretisch gezien zou rechtstreekse communicatie dan ook niet effectief zijn om het vertrouwen van kopers te vergroten en samenwerking te garanderen.

Deze conclusies sluiten niet aan bij experimenten en empirische bevindingen uit waarnemingsstudies, die laten zien dat in situaties met sociale dilemma's "goedkope praatjes" wel een positieve invloed hebben op de samenwerking tussen spelers. In hoofdstuk 5 analyseren we onder welke omstandigheden verkopers rechtstreeks het gesprek met kopers aangaan op cryptomarktdiscussieforums, en in welke mate de activiteiten van verkopers op discussieforums hun marktverkopten verhogen.

De resultaten van deze analyse tonen aan dat de activiteiten van verkopers op discussieforums hun verkopen aanzienlijk vergroten. Dit geldt interessant genoeg ook voor de deelname van verkopers aan algemene (niet-marktgerelateerde) discussies. We stellen dat communitygesprekken sociale relaties tot stand brengen en marktvoordelen opleveren voor verkopers die in die community actief zijn. We wijzen erop dat communicatie en sociale banden belangrijke bouwstenen zijn bij het opbouwen van vertrouwen tussen gebruikers in een risicovolle marktomgeving.

Geografische structuur van online drugshandelnetwerken

In het laatste hoofdstuk zetten we de stap naar het macroniveau en analyseren we de structuur van een compleet transactienetwerk van kopers en verkopers op een cryptomarkt. Over cryptomarkten is steeds gesproken als wereldwijde platforms voor drugsverkopten, die een ware revolutie teweeg zouden kunnen brengen voor offline drugshandelnetwerken, die sterk gelokaliseerd en geclusterd zijn. Drugsverkopers op cryptomarkten kunnen internationale verzending van producten aanbieden, maar informatie over waarvandaan ze worden verzonden, wordt doorgaans niet gegeven. Op basis van de lijst van bestemmingen van de verkopers is in meerdere onderzoeken geconcludeerd dat een aanzienlijk deel van de drugs internationaal wordt verkocht. Deze conclusies zouden onjuist kunnen zijn als producten die internationaal verzonden kunnen worden, alleen door binnenlandse kopers worden besteld.

We willen het probleem van een beperkte hoeveelheid geografische gegevens op kopersniveau oplossen aan de hand van een analyse van de structuur van een transactienetwerk op de cryptomarkt, die indirect geografische patronen aan het licht zou kunnen brengen zonder kennis van de locatie van de kopers.

Onze bevindingen laten nog een vorm van sterke inbedding zien tussen marktspelers op cryptomarkten: een sterke clustering van kopers en verkopers in de zin van geografische locaties, namelijk op continentaal en landelijk niveau. We zien dat kopers

meer geneigd zijn te kopen van meerdere verkopers binnen één land en het kopen van verkopers in verschillende landen uit de weg gaan, wat duidt op een sterke voorkeur voor binnenlandse bestellingen.

We constateren dat onzekerheid en het risico dat politie en justitie internationale verzendingen en levertijdstoppen op het spoor komen, cryptomarkten in hechte, geografische clusters versnipperen. Daarom zou de onzekerheid die voortvloeit uit de illegale aard van de producten er wel eens voor kunnen zorgen dat cryptomarkten de offline drugshandel veel minder sterk kunnen internationaliseren dan tot nu toe werd gedacht.

ALGEMENE CONCLUSIES

Een eerste thema dat ten grondslag ligt aan de meeste bevindingen in deze dissertatie is het feit dat reputatiesystemen prikkels kunnen creëren voor samenwerking tussen cryptomarktgebruikers. We hebben in alle hoofdstukken gezien dat verkopers met een goede reputatie worden beloond met een hogere verkoop, terwijl verkopers met een beschadigde reputatie worden afgestraft door lagere verkopen en kopers vaak met lagere prijzen moeten compenseren voor het grotere risico.

Het gebrek aan wetshandhaving op cryptomarkten verlaagt de kosten van opportunistisch gedrag van verkopers en kan meer spelers met twijfelachtige bedoelingen aantrekken. Deze dissertatie levert, op basis van de ervaringen met meerdere cryptomarkten, het overtuigende bewijs dat reputatie in sterke mate bepalend is voor het vertrouwen en de samenwerking tussen een groot aantal volledig anonieme gebruikers zonder juridische of morele waarborgen.

De tweede bevinding die steeds naar voren komt, is dat vertrouwen en samenwerking tussen cryptomarktgebruikers worden gecreëerd en in stand gehouden via sterke dyadische banden. Uit de bevindingen in hoofdstuk 3 blijkt dat de algemene reputatie van verkopers vooral belangrijk is voor kopers als zij na hun entree op de markt hun eerste aankoop doen. Vervolgens vertonen kopers een sterke neiging om de interactie met dezelfde verkoper te herhalen, vooropgesteld dat de verkoper het vertrouwen niet beschaamt. Als een verkoper dus de beloofde producten verzendt, zal de koper waarschijnlijk klant bij hem blijven, ook al komen er goedkopere leveranciers op de markt. Als er tussen een tweetal een vertrouwensrelatie is opgebouwd, heeft negatieve feedback van andere kopers over de verkoper nauwelijks invloed op de neiging van de koper om de verkoper in de toekomst weer te vertrouwen.

In deze zin lijken cryptomarkten op offline drugsnetwerken, die vaak een “gesloten”, “zeer sterk ingebedde” structuur hebben die bestaat uit langdurige dyades met herhaalde interacties tussen drugsverkopers en -kopers (May en Hough, 2004; Beckert en Wehinger, 2013). Hoge kosten om op zoek te gaan naar andere (ver)kopers, het risico op geweld en confrontaties met de politie en onzekerheid over de productkwaliteit worden genoemd als redenen voor dit effect op de straatmarkt. Hoewel het in zekere mate aannemelijk is dat veel van deze onzekerheden kunnen worden weggenomen door de reputatiesystemen en het gebrek aan persoonlijk contact op cryptomarkten, laten onze resultaten zien dat de online uitwisselingsstructuur niet lijkt op een open markt waar kopers voortdurend op zoek zijn naar de goedkoopste verkoper of de verkoper met de beste reputatie.

Het voortdurende risico om met politie en justitie in aanraking te komen veroorzaakt een belangrijk spanningsveld tussen enerzijds de wil van een verkoper om zijn reputatie in stand te houden en anderzijds zijn wil om anoniem te blijven. Het regelmatig oprollen van cryptomarkten creëert een omgeving waarin anonieme spelers worden gedwongen zich voortdurend van de ene naar de andere markt te verplaatsen. Een reputatie kan niet van markt naar markt worden overgedragen, tenzij verkopers hun online identiteit verifiëren met behulp van encryptietechnieken (zie hoofdstuk 4; Broseus et al., 2016; Bancroft en Reid, 2016). Aan de andere kant vergroot een niet-veranderende online identiteit het risico dat in de loop der tijd kleine stukjes gevoelige informatie lekken, wat de anonimiteit van de verkoper in gevaar zou kunnen brengen.

Onze bevindingen laten zien dat verkopers met een opgebouwde verkoopgeschiedenis en een goede reputatie meer geneigd zijn om hun identiteit te behouden als ze zich naar nieuwe markten verplaatsen. Migrerende kopers geven doorgaans de voorkeur aan deze verkopers boven nieuwkomers. Deze bevindingen hebben twee belangrijke implicaties. Ten eerste maakt de mogelijkheid van gebruikers om hun online identiteit te verifiëren de migratie van reputatie tussen omgevingen mogelijk. Reputatie is niet langer gebonden aan één bepaalde omgeving, wat de “schaduw van de toekomst” nog verder vooruitwerpt, en verkopers nog meer stimuleert om samen te werken en kopers om op samenwerking gericht gedrag van verkopers te belonen. Dat een reputatie kan worden meegenomen, beperkt mogelijk ook het effect van het optreden van politie en justitie tegen één enkele cryptomarkt. Als gebruikers belangrijke informatie over een reputatie kunnen overbrengen naar andere omgevingen, kunnen ze op de nieuwe cryptomarkten doorgaan met hun transacties zonder dat de onzekerheid toeneemt.

Ten tweede betekent dit dat het versterkende effect van reputatiemigratie (Frey en Van de Rijt, 2016) een belangrijke uitdaging kan worden voor de spelers op cryptomarkten. Aangezien kopers liever zaken doen met verkopers met een goede reputatie, zouden de meeste verkopen zich kunnen concentreren in de handen van een paar succesvolle verkopers, wat de drempel voor betrouwbare nieuwkomers steeds hoger zou maken. Dit effect zal waarschijnlijk worden versterkt op cryptomarkten als enkel de meer succesvolle verkopers van markt naar markt gaan.

In de hoofdstukken 5 en 6 is gewezen op het belang van twee andere vormen van inbedding voor het vertrouwen in cryptomarkten. We zagen dat sociale inbedding een belangrijk aspect zou kunnen zijn bij het verstevigen van de samenwerking tussen kopers en verkopers. Hoewel wordt aangenomen dat spelers op online markten doorgaans niet sociaal zijn ingebed (Diekmann et al., 2014), wat een nog overtuigender aanname lijkt als het gaat om volledig anonieme cryptomarkten, is dit mogelijk niet

waar. Er zijn inmiddels meerdere onderzoeken die aantonen dat kopers en verkopers zich actief mengen in allerlei discussies, hulp en informatie zoeken over druggebruik, nieuwe leden helpen of politieke idealen bespreken (Martin, 2014; Munksgaard en Demant, 2016; Aldridge en Askew, 2017; Bancroft en Reid, 2017). We vullen deze bevindingen aan door te laten zien dat de deelname van verkopers aan dergelijke discussies een overloopeffect kan creëren, waardoor kopers meer bereid zijn actieve communityleden op de cryptomarkt te vertrouwen.

Een andere bevinding die uit een aantal hoofdstukken van deze dissertatie duidelijk naar voren komt, is de asymmetrische invloed van negatieve beoordelingen. In hoofdstuk 2 hebben we vastgesteld dat transacties waarover kopers ontevreden zijn en negatief oordelen, een groter absoluut effect hebben op de marktresultaten van de verkopers. Hoofdstuk 3 liet zien dat kopers in plaats van maatregelen te treffen, meer geneigd zijn om de cryptomarkt na dergelijke ervaringen te verlaten en een andere markt te zoeken. We hebben aangevoerd dat kopers, nadat hun vertrouwen is geschaad, op zoek kunnen gaan naar alternatieven buiten de cryptomarkten. Hoofdstuk 5 liet zien dat verkopers ook meer geneigd zijn om de geanalyseerde cryptomarkt na negatieve beoordelingen te verlaten dan zich bezig te houden met schadebeperking en communicatie met hun kopers. Het is mogelijk dat verkopers met een nieuwe alias terugkeren op de markt, met name als de reputatiegeschiedenis kort is en er weinig te verliezen valt. Samen laten deze bevindingen zien dat misbruik van vertrouwen, of dat nu kwade opzet van de verkoper is of het gevolg van een gebrek aan deskundigheid of van gebeurtenissen waar de verkoper niets aan kan doen, zoals onderschepte pakketten, een nadelig effect kan hebben op toekomstige samenwerking.

Tot slot hebben we in hoofdstuk 6 laten zien dat de risico's en onzekerheden waarmee cryptomarktgebruikers te maken krijgen, op hun beurt kunnen leiden tot structurele resultaten op macroniveau. We hebben vastgesteld dat transacties tussen kopers en verkopers niet alleen zijn ingebed in de zin van koper-verkoperrelaties, maar dat ze ook sterke patronen van geografische inbedding vertonen. Hoewel cryptomarkten theoretisch gezien de offline drugshandel zouden kunnen globaliseren door kopers en verkopers snel toegang tot wereldwijde markten te verschaffen, zien we dat de netwerkstructuur geografisch wordt bepaald. In combinatie met de bevindingen uit hoofdstuk 3 kunnen we concluderen dat cryptomarktnetwerken zeer versnipperd zijn, net als de "gesloten" offline drugshandelnetwerken die in eerdere onderzoeken zijn geanalyseerd.

References

REFERENCES

- Abraham, M., Grimm, V., Neeß, C., and Seebauer, M. (2016). Reputation formation in economic transactions. *Journal of Economic Behavior & Organization*, 121, 1–14.
- Afilipoaie, A., and Shortis, P. (2018). Crypto-Market Enforcement-New Strategy and Tactics. *Policy*, 54, 87-98.
- Akerlof, G. A. (1970). The market for" lemons": Quality uncertainty and the market mechanism. *The quarterly journal of economics*, 488-500.
- Aldridge, J., and Askew, R. (2017). Delivery dilemmas: How drug cryptomarket users identify and seek to reduce their risk of detection by law enforcement. *International Journal of Drug Policy*, 41, 101-109.
- Aldridge, J., and Décary-Héту, D. (2014). Not an 'eBay for Drugs': The Cryptomarket 'Silk Road' as a Paradigm Shifting Criminal Innovation. SSRN: <https://ssrn.com/abstract=2436643>.
- Aldridge, J., and Décary-Héту, D. (2016). Hidden wholesale: The drug diffusing capacity of online drug cryptomarkets. *International Journal of Drug Policy*, 35, 7-15.
- Aldridge, J., and Décary-Héту, D. (2016b). Cryptomarkets and the future of illicit drug markets. In *Internet and drug markets, EMCDDA insights* (pp. 23-30). Publications Office of the European Union, Luxembourg.
- Allison, P. D. (2009). *Fixed Effects Regression Models*. Thousand Oaks, California: SAGE.
- Allison, P. D., and Waterman, R. P. (2002). Fixed-effects negative binomial regression models. *Sociological Methodology*. 32(1), 247-265.
- Arrow, K. J. (1974). *The Limits of Organization*. New York: Norton.
- Axelrod, R. (1984). *The Evolution of Cooperation*. New York: Basic Books.
- Bacharach, M., and Gambetta, D. (2001). Trust as type detection. In Castelfranchi, C., and Tan, Y. (eds). *Trust and deception in virtual societies*. Dordrecht, NL: Springer, pp. 1-26.
- Bakken, S. A., Moeller, K., and Sandberg, S. (2018). Coordination problems in cryptomarkets: Changes in cooperation, competition and valuation. *European Journal of Criminology*, 15(4), 442-460.
- Bakos, Y., and Dellarocas, C. (2011). Cooperation Without Enforcement? A Comparative Analysis of Litigation and Online Reputation as Quality Assurance Mechanisms. *Management Science*, 57(11), 1944-1962.
- Balliet, D. (2010). Communication and cooperation in social dilemmas: A meta-analytic review. *Journal of Conflict Resolution*, 54(1), 39-57.
- Bancroft, A., and Scott Reid, P. (2017). Challenging the techno-politics of anonymity: the case of cryptomarket users. *Information, Communication and Society*, 20(4), 497-512.

- Barratt, M. J., and Aldridge, J. (2016). Everything you always wanted to know about drug cryptomarkets* (*but were afraid to ask). *International Journal of Drug Policy*, 35, 1-6.
- Barratt, M. J., Ferris, J. A., and Winstock, A. R. (2016a). Safer scoring? Cryptomarkets, social supply and drug market violence. *International Journal of Drug Policy*, 35, 24-31.
- Barratt, M. J., Lenton, S., Maddox, A., and Allen, M. (2016b). "What if you live on top of a bakery and you like cakes?" – Drug use and harm trajectories before, during and after the emergence of Silk Road. *International Journal of Drug Policy*, 35, 50-57.
- Barrera, D. (2008). The social mechanisms of trust. *Sociologica*, 2(2), 1-32.
- Barrera, D., and Buskens, V. (2009). Third-party effects. In Cook, K. S., Snijders, C., Buskens, V., and Cheshire, C. (eds). *eTrust: Forming relationships in the online world*. Russell Sage Foundation, pp. 37-72.
- Barrera, D., and van de Bunt, G. (2009). Learning to trust: networks effects through time. *European Sociological Review*, 25(6), 709-721.
- Bartlett, J. (2014). *The Dark Net: Inside the Digital Underworld*. London: Melville House.
- Bauerly, R. J. (2009). Online Auction Fraud and eBay. *Marketing Management Journal*, 19(1), 133-143.
- Beckert, J. (2009). The social order of markets. *Theory and Society*, 38(3), 245-269.
- Beckert, J., and Wehinger, F. (2013). In the shadow: illegal markets and economic sociology. *Socio-economic review*, 11(1), 5-30.
- Bente, G., Baptist, O., and Leuschner, H. (2012). To buy or not to buy: influence of seller photos and reputation on buyer trust and purchase behavior. *International Journal of Human-Computer Studies*, 70(1), 1-13.
- Bockstedt, J. C., Goh, K. H., and Ng, S. (2012). Effects of simultaneous auctions on willingness-to-pay in online auctions. In *Proceedings of the 14th Annual International Conference on Electronic Commerce*, ACM, pp. 153-154.
- Bolton, G. E., Greiner, B., and Ockenfels, A. (2013). Engineering Trust: Reciprocity in the Production of Reputation Information. *Management Science*, 59(2), 265-285.
- Bolton, G. E., Katok, E., and Ockenfels, A. (2004). How effective are electronic reputation mechanisms? An experimental investigation. *Management science*, 50(11), 1587-1602.
- Bouchard, M., and Ouellet, F. (2011). Is small beautiful? The link between risks and size in illegal drug markets. *Global Crime*, 12(1), 70-86.
- Bowles, S., and Gintis, H. (2011). *A Cooperative Species: Human Reciprocity and its Evolution*. Princeton: Princeton University Press.
- Bozoyan, C., and Vogt, S. (2016). The impact of third-party information on trust: valence, source, and reliability. *PloS one*, 11, e0149542.

- Bracht, J., and Feltovich, N. (2009). Whatever you say, your reputation precedes you: Observation and cheap talk in the trust game. *Journal of Public Economics*, 93(9-10), 1036-1044.
- Bradbury, D. (2014). Unveiling the Dark Web. *Network Security*, 4, 14-17.
- Branwen, G. (2016). *Black-market risks: Analysis of lifespans, deaths, and predictive factors*, gwern.net Blogs. Retrieved at <http://www.gwern.net/Black-market%20survival>.
- Branwen, G. (2017). *Tor DNM-related arrests, 2011-2015* (Updated 30 Sep, 2017). Retrieved at <https://www.gwern.net/DNM-arrests>.
- Branwen, G. (2019). *Darknet Market mortality risks*. Retrieved at <https://www.gwern.net/DNM-survival>.
- Branwen, G., Christin, N., Décary-Héту, D., Munksgaard, R., StExo, El Presidente, Anonymous, Lau, D., Cakic, V., van Buskirk, J. (2015). *Dark Net Market Archives 2011-2015*. Retrieved at www.gwern.net/DNM%20archives.
- Broséus, J., Rhumorbarbe, D., Mireault, C., Ouellette, V., Crispino, F., and Décary-Héту, D. (2016). Studying illicit drug trafficking on Darknet markets: structure and organization from a Canadian perspective. *Forensic science international*, 264, 7-14.
- Broséus, J., Rhumorbarbe, D., Morelato, M., Staehli, L., and Rossy, Q. (2017). A geographical analysis of trafficking on a popular darknet market. *Forensic Science International*, 277, 88-102.
- Brynjolfsson, E., and Smith, M. D. (2000). Frictionless commerce? A comparison of Internet and conventional retailers. *Management science*, 46(4), 563-585.
- Buskens, V. (2002). *Social networks and trust*. New York: Springer Science & Business Media.
- Buskens, V. (2003). Trust in triads: effects of exit, control, and learning. *Games and Economic Behavior*, 42(2), 235-252.
- Buskens, V., and Raub, W. (2002). Embedded trust: Control and learning. In *Advances in group processes*. Emerald Group Publishing Limited, pp. 167-202.
- Buskens, V., and Raub, W. (2013). Rational choice research on social dilemmas: embeddedness effects on trust. In Wittek, R., Snijders, T. A., and Nee, V. (eds). *The handbook of rational choice social research*, Stanford University Press, pp. 113-150.
- Buskens, V., Frey, V., and Raub, W. (2018). Trust Games. In Uslaner, E. M. (ed). *The Oxford Handbook of Social and Political Trust*, pp. 305-336.
- Buskens, V., Raub, W., and van der Veer, J. (2010). Trust in triads: An experimental study. *Social Networks*, 32(4), 301-312.
- van Buskirk, J., Bruno, R., Dobbins, T., Breen, C., Burns, L., Naicker, S., and Roxburgh, A. (2017). The recovery of online drug markets following law enforcement and other disruptions. *Drug and alcohol dependence*, 173, 159-162.

- van Buskirk, J., Naicker, S., Roxburgh, A., Bruno, R., and Burns, L. (2016). Who sells what? Country specific differences in substance availability on the Agora cryptomarket. *International Journal of Drug Policy*, 35, 16-23.
- van Buskirk, J., Roxburgh, A., Farrell, M., and Burns, L. (2014). The closure of the Silk Road: What has this meant for online drug trading? *Addiction*, 109(4), 517-518.
- Calkins, M. M., Nikitkov, A., and Richardson, V. (2008). Mineshafts on Treasure Island: A Relief Map of the eBay Fraud Landscape. *Pittsburgh Journal of Technology Law & Policy*, 8, 1-52.
- Cambini, C., Meccheri, N., Silvestri, V., Torino, P., Duca, C., and Pisa, U. (2011). Competition, efficiency and market structure in online digital markets. An overview and policy implications. *European Review of Industrial Economics and Policy*, 2, 1-27.
- Carruthers, B. G. (2013). From uncertainty toward risk: the case of credit ratings. *Socio-Economic Review*, 11(3), 525-551.
- Chalmers, J., and Bradford, D. (2013). Methamphetamine users' perceptions of exchanging drugs for money: Does trust matter? *Journal of Drug Issues*, 43(3), 256-269.
- Christin, N. (2013). Traveling the Silk Road: A measurement analysis of a large anonymous online marketplace'. In *Proceedings of the 22nd international conference on World Wide Web*, ACM, pp. 213-224.
- Christin, N. (2014). Commentary on Barratt *et al.* (2014): Steps towards characterizing online anonymous drug marketplace customers. *Addiction*, 109(5), 784-785.
- Coleman, J. S. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94, S95-S120.
- Coleman, J. S. (1990). *Foundations of social theory*. Cambridge, Mass: Belknap Press of Harvard University Press.
- Corten, R., Rosenkranz, S., Buskens, V., and Cook, K. S. (2016). Reputation Effects in Social Networks Do Not Promote Cooperation: An Experimental Test of the Raub and Weesie Model. *PLoS ONE*, 11, e0155703.
- Cunliffe, J., Martin, J., Décary-Héту, D., and Aldridge, J. (2017). An island apart? Risks and prices in the Australian cryptomarket drug trade. *International Journal of Drug Policy*, 50, 64-73.
- Dasgupta, P. (1988). Trust as a Commodity. In Gambetta, D. (ed). *Trust: Making and Breaking Cooperative Relations*. Oxford: Basil Blackwell.
- Décary-Héту, D., and Aldridge, J. (2015). Sifting through the Net: Monitoring of Online Offenders by Researchers. *The European Review of Organised Crime*, 2(2), 122-141.
- Décary-Héту, D., and Giommoni, L. (2017). Do police crackdowns disrupt drug cryptomarkets? A longitudinal analysis of the effects of Operation Onymous. *Crime, Law and Social Change*, 67(1), 55-75.

- Décary-Hétu, D., and Quessy-Doré, O. (2017). Are repeat buyers in cryptomarkets loyal customers? Repeat business between dyads of cryptomarket vendors and users. *American Behavioral Scientist*, 61(11), 1341-1357.
- Décary-Hétu, D., Paquet-Clouston, M., and Aldridge, J. (2016). Going international? Risk taking by cryptomarket drug vendors. *International Journal of Drug Policy*, 35, 69-76.
- Dellarocas, C. (2003). The Digitization of Word of Mouth: Promise and Challenges of Online Feedback Mechanisms. *Management Science*, 49(10), 1407-1424.
- Demant, J., Munksgaard, R., and Houborg, E. (2016). Personal Use, Social Supply or Redistribution? Cryptomarket Demand on Silk Road 2 and Agora. *Trends in Organized Crime*, 21(1), 1-20.
- Diekmann, A., and Przepiorka, W. (2019). Trust and Reputation in Markets. In Giardini, F., and Wittek, R. (eds). *The Oxford Handbook of Gossip and Reputation*. Oxford: Oxford University Press, pp. 383-400.
- Diekmann, A., Jann, B., and Wyder, D. (2009). Trust and Reputation in Internet Auctions. In Cook, K. S., Snijders, C., Buskens, V., and Cheshire, C. (eds). *eTrust: Forming relationships in the online world*, Russell Sage Foundation, pp. 139-165.
- Diekmann, A., Jann, B., Przepiorka, W., and Wehrli, S. (2014). Reputation formation and the evolution of cooperation in anonymous online markets. *American Sociological Review*, 79(1), 65-85.
- DiMaggio, P., and Louch, H. (1998). Socially embedded consumer transactions: for what kinds of purchases do people most often use networks? *American sociological review*, 63(5), 619-637.
- Duffy, J., and Feltovich, N. (2002). Do actions speak louder than words? An experimental comparison of observation and cheap talk. *Games and Economic Behavior*, 39(1), 1-27.
- Dunbar, R. I. M. (2004). Gossip in Evolutionary Perspective. *Review of General Psychology*, 8(2), 100-110.
- Duxbury, S. W., and Haynie, D. L. (2018a). The Network Structure of Opioid Distribution on a Darknet Cryptomarket. *Journal of Quantitative Criminology*, 34(4), 921-941.
- Duxbury, S. W., and Haynie, D. L. (2018b). Building them up, breaking them down: Topology, vendor selection patterns, and a digital drug market's robustness to disruption. *Social Networks*, 52, 238-250.
- Ellickson, R. C. (1991). *Order Without Law: How Neighbors Settle Disputes*. Cambridge: Harvard University Press.
- Ert, E., Fleischer, A., and Magen, N. (2016). Trust and reputation in the sharing economy: The role of personal photos in Airbnb. *Tourism Management*, 55, 62-73.
- Europol (2014). *Global Action Against Dark Markets on Tor Network (Press release)*. Retrieved at <https://www.europol.europa.eu/newsroom/news/global-action-against-dark-markets-tor-network>.

- Europol (2017). *Massive Blow to Criminal Dark Web Activities after Globally Coordinated Operation* (Press release). Retrieved at <https://www.europol.europa.eu/newsroom/news/massive-blow-to-criminal-dark-web-activities-after-globally-coordinated-operation>.
- Falk, A., and Heckman, J. J. (2009). Lab Experiments Are a Major Source of Knowledge in the Social Sciences, *Science*, 326(5952), 535-538.
- Fehrler, S., and Przepiorka, W. (2013). Charitable giving as a signal of trustworthiness: Disentangling the signaling benefits of altruistic acts. *Evolution and Human Behavior*, 34(2), 139-145.
- Feinberg, M., Willer, R., and Schultz, M. (2014). Gossip and ostracism promote cooperation in groups, *Psychological Science*, 25(3), 656-664.
- Fligstein, N. (2001). *The Architecture of Markets: An Economic Sociology of Twenty-First-Century Capitalist Societies*. Princeton, NJ: Princeton University Press.
- Frey, V., and van de Rijt, A. (2016). Arbitrary Inequality in Reputation Systems, *Scientific Reports*, 6, 38304.
- Friedman, E. J., and Resnick, P. (2001). The social cost of cheap pseudonyms. *Journal of Economics & Management Strategy*, 10(2), 173-199.
- Galenianos, M., Pacula, R. L., and Persico, N. (2012). A search-theoretic model of the retail market for illicit drugs. *The Review of Economic Studies*, 79(3), 1239-1269.
- Gambetta, D. (2005). Deceptive Mimicry in Humans. In Hurley, S., and Chater, N. (eds), *Perspectives on Imitation: Imitation, human development, and culture*, Cambridge, Mass: The MIT Press, pp. 221-242.
- Gambetta, D. (2009a). *Codes of the Underworld: How Criminals Communicate*. Princeton: Princeton University Press.
- Gambetta, D. (2009b). Signaling. In Hedström, P., and Bearman, P. (eds), *The Oxford Handbook in Analytical Sociology*. Oxford: Oxford University Press, pp. 168-194.
- Gambetta, D., and Przepiorka, W. (2014). Natural and strategic generosity as signals of trustworthiness. *PloS one*, 9(5), e97533.
- Global Drug Survey. (2016). Key findings from the Global Drug Survey 2016, London: Global Drug Survey. Retrieved at <https://www.globaldrugsurvey.com/past-findings/the-global-drug-survey-2016-findings>.
- Glückler, J., and Armbrüster, T. (2003). Bridging uncertainty in management consulting: The mechanisms of trust and networked reputation. *Organization Studies*, 24(2), 269-297.
- Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. *American journal of sociology*, 91(3), 481-510.

- Granovetter, M. (1992). Problems of Explanation in Economic Sociology. In Nohria, N., and Eccles, R. G. (eds), *Networks and Organizations: Structure, Form, and Action*, Boston: Harvard Business School Press, pp. 25-56.
- Greif, A. (1989). Reputation and Coalitions in Medieval Trade: Evidence on the Maghribi Traders, *Journal of Economic History*, 49, 857-882.
- Greiner, B., and Ockenfels, A. (2009). Vom Labor ins Feld: Die Ökonomik des Vertrauens, *Kölner Zeitschrift für Soziologie und Sozialpsychologie, Sonderheft*, 49, 219-242.
- Grimalda, G., Ponderfer, A., and Tracer, D. P. (2016). Social image concerns promote cooperation more than altruistic punishment. *Nature Communications*, 7, 12288.
- Guala, F. (2012). Reciprocity: weak or strong? What punishment experiments do (and do not) demonstrate. *Behavioral and Brain Sciences*, 35, 1-15.
- Güth, W., and Ockenfels, A. (2003). The Coevolution of Trust and Institutions in Anonymous and Non-anonymous Communities. In Holler, M. J., Kliemt, H., Schmidtchen, D., and Streit, M. (eds), *Jahrbuch für Neue Politische Ökonomie*. Tübingen: Mohr Siebeck, pp. 157-174.
- Handcock, M. S., Hunter, D. R., Butts, C. T., Goodreau, S. M., and Morris, M. (2008). statnet: Software tools for the representation, visualization, analysis and simulation of network data. *Journal of statistical software*, 24(1), 1548.
- van Hardeveld, G. J., Webber, C., & O'Hara, K. (2017). Deviating from the cybercriminal script: exploring tools of anonymity (mis) used by carders on cryptomarkets. *American Behavioral Scientist*, 61(11), 1244-1266.
- Hardy, R. A., and Norgaard, J. R. (2016). Reputation in the Internet black market: an empirical and theoretical analysis of the Deep Web. *Journal of Institutional Economics*, 12, 515-539.
- Hijikata, Y., Ohno, H., Kusumura, Y., and Nishida, S. (2007). Social summarization of text feedback for online auctions and interactive presentation of the summary. *Knowledge-Based Systems*, 20(6), 527-541.
- Hillmann, H. (2013). Economic Institutions and the State: Insights from Economic History, *Annual Review of Sociology*, 39, 251-273.
- Hillmann, H., and Aven, B. L. (2011). Fragmented Networks and Entrepreneurship in Late Imperial Russia. *American Journal of Sociology*, 117(2), 484-538.
- Holt, T. J., Strumsky, D., Smirnova, O., and Kilger, M. (2012). Examining the social networks of malware writers and hackers. *International Journal of Cyber Criminology*, 6(1), 891.
- Horton-Eddison, M., and Di Cristofaro, M. (2017). Hard Interventions and Innovation in Crypto-Drug Markets: The ESCROW Example. *Policy Brief*, 11. Retrieved at <https://www.swansea.ac.uk/media/Hard-Interventions-and-Innovation-in-CryptoDrug-Markets-The-escrow-example.pdf>

- van Hout, M. C., & Hearne, E. (2017). New psychoactive substances (NPS) on cryptomarket fora: an exploratory study of characteristics of forum activity between NPS buyers and vendors. *International Journal of Drug Policy*, 40, 102-110.
- van Hout, M. C., and Bingham, T. (2013). 'Silk Road', the virtual drug marketplace: A single case study of user experiences. *International Journal of Drug Policy*, 24(5), 385-391.
- van Hout, M. C., and Bingham, T. (2014). Responsible sellers, intelligent consumers: Silk Road, the online revolution of drug trading. *International Journal of Drug Policy*, 25(2), 183-189.
- ter Huurne, M., Ronteltap, A., Corten, R., and Buskens, V. (2017). Antecedents of trust in the sharing economy: A systematic review. *Journal of Consumer Behaviour*, 16(6), 485-498.
- ter Huurne, M., Ronteltap, A., Corten, R., and Buskens, V. (2018). Reputation Effects in Socially Driven Sharing Economy Transactions. *Sustainability*, 10(8), 2674.
- Jacomy, M. (2009). Force-atlas graph layout algorithm. Retrieved at <http://gephi.org/2011/forceatlas2-the-new-version-of-our-home-brew-layout>.
- Jacques, S., Allen, A., and Wright, R. (2014). Drug dealers' rational choices on which customers to rip-off. *International Journal of Drug Policy*, 25, 251-256.
- Jacques, S., and Wright, R. (2011). Informal control and illicit drug trade. *Criminology*, 49(3), 729-765.
- Jacques, S., Wright, R., and Allen, A. (2014). Drug dealers, retaliation, and deterrence. *International Journal of Drug Policy*, 25, 656-662.
- Jappelli, T., and Pagano, M. (2002). Information sharing, lending and defaults: Cross-country evidence, *Journal of Banking & Finance*, 26, 2017-2045.
- Kenney, M. (2007). The architecture of drug trafficking: network forms of organization in the Colombian cocaine trade. *Global crime*, 8(3), 233-259.
- Kokkodis, M., and Ipeirotis, P. G. (2015). Reputation transferability in online labor markets. *Management Science*, 62(6), 1687-1706.
- Kollock, P. (1993). An eye for an eye leaves everyone blind: Cooperation and Accounting Systems. *American Sociological Review*, 58(6), 768-786.
- Kollock, P. (1994). The Emergence of Exchange Structures: An Experimental Study of Uncertainty, Commitment, and Trust, *American Journal of Sociology*, 100(2), 313-345.
- Kollock, P. (1999). The Production of Trust in Online Markets. In Lawler, E. J., and Macy, M. W. (eds). *Advances in Group Processes*, 16. Amsterdam: JAI Press, pp. 99-123.
- Kreps, D. M. (1990). Corporate culture and economic theory. In: Alt, J., and Shepsle, K. (eds), *Perspectives on positive political economy*. New York: Cambridge University Press, pp. 90-142.
- Kreps, D. M., and Wilson, R. (1982). Reputation and Imperfect Information, *Journal of Economic Theory*, 27, 253-279.

- Kreps, D. M., Milgrom, P., Roberts, J., and Wilson, R. (1982). Rational Cooperation in the Finitely Repeated Prisoners' Dilemma. *Journal of Economic Theory*, 27, 245-252.
- Kruithof, K., Aldridge, J., Décary-Hétu, D., Sim, M., Dujso, E., and Hoorens, S. (2016). *Internet-facilitated drugs trade. An Analysis of the size, scope and the role of the Netherlands: Summary*. Cambridge, UK: RAND Corporation.
- Kuwabara, K. (2015). Do Reputation Systems Undermine Trust? Divergent Effects of Enforcement Type on Generalized Trust and Trustworthiness, *American Journal of Sociology*, 120(5), 1390-1428.
- Labianca, G., and Brass, D. J. (2006). Exploring the social ledger: Negative relationships and negative asymmetry in social networks in organizations. *Academy of Management Review*, 31(3), 596-614.
- Ladegaard, I. (2017a). "I Pray That We Will Find a Way to Carry on This Dream": How a Law Enforcement Crackdown United an Online Community. *Critical Sociology*, 45(4-5), 631-646.
- Ladegaard, I. (2017b). We know where you are, what you are doing, and we will catch you: Testing deterrence theory in digital drug markets. *The British Journal of Criminology*, 58(2), 414-433.
- Ladegaard, I. (2018). Instantly hooked? Freebies and samples of opioids, cannabis, MDMA, and other drugs in an illicit E-commerce market. *Journal of Drug Issues*, 48(2), 226-245.
- Ladegaard, I. (2019). Crime displacement in digital drug markets. *International Journal of Drug Policy*, 63, 113-121.
- Lawler, E. J. (2001). An affect theory of social exchange. *American Journal of Sociology*, 107(2), 321-352.
- Lindenberg, S. (2017). The Dependence of Human Cognitive and Motivational Processes on Institutional Systems. In Jann, B., and Przepiorka, W. (eds) *Social dilemmas, institutions and the evolution of cooperation*. Berlin: De Gruyter Oldenburg, pp. 85-106.
- Lu, Y., Luo, X., Polgar, M., and Cao, Y. (2010). Social network analysis of a criminal hacker community. *Journal of Computer Information Systems*, 51(2), 31-41.
- Lusthaus, J. (2012). Trust in the world of cybercrime. *Global Crime*, 13(2): 71-94.
- Ma, X., Hancock, J. T., Lim Mingjie, K., and Naaman, M. (2017). Self-disclosure and perceived trustworthiness of Airbnb host profiles. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, pp. 2397-2409. ACM.
- Maddox, A., Barratt, M. J., Allen, M., and Lenton, S. (2016). Constructive activism in the dark web: cryptomarkets and illicit drugs in the digital 'demimonde'. *Information, Communication & Society*, 19(1), 111-126.
- Malm, A., and Bichler, G. (2011). Networks of collaborating criminals: Assessing the structural vulnerability of drug markets. *Journal of Research in Crime and Delinquency*, 48(2), 271-297.

- Martin, J. (2014a). Lost on the Silk Road: Online drug distribution and the cryptomarket. *Criminology & Criminal Justice*, 14(3), 351-367.
- Martin, J. (2014b). *Drugs on the Dark Net. How Cryptomarkets Are Transforming the Global Trade in Illicit Drugs*. Hampshire, UK: Palgrave Pivot, Palgrave Macmillan.
- Masson, K., and Bancroft, A. (2018). 'Nice people doing shady things': Drugs and the morality of exchange in the darknet cryptomarkets. *International Journal of Drug Policy*, 58, 78-84.
- Matzat, U., and Snijders, C. (2012). Rebuilding Trust in Online Shops on Consumer Review Sites: Sellers' Responses to User-Generated Complaints, *Journal of Computer-Mediated Communication*, 18(1), 62-79.
- May, T., and Hough, M. (2004). Drug markets and distribution systems. *Addiction Research & Theory*, 12(6), 549-563.
- McFadden, D. (1974). The measurement of urban travel demand. *Journal of public economics*, 3(4), 303-328.
- Milgrom, P. R., North, D. C., and Weingast, B. R. (1990). The Role of Institutions in the Revival of Trade: The Law Merchant, Private Judges, and the Champagne Fairs. *Economics and Politics*, 2(1), 1-23.
- Milinski, M. (2016). Reputation, a universal currency for human social interactions. *Philosophical Transactions of the Royal Society B*, 371, 20150100.
- Milinski, M., Semmann, D., and Krambeck, H.-J. (2002). Reputation helps solve the 'tragedy of the commons', *Nature*, 415, 424-426.
- Moeller, K., Munksgaard, R., and Demant, J. (2017). Flow my FE the vendor said: Exploring violent and fraudulent resource exchanges on cryptomarkets for illicit drugs. *American Behavioral Scientist*, 61(11), 1427-1450.
- Monsma, E., Buskens, V., Soudijn, M., and Nieuwebeerta, P. (2013). Partners in cybercrime. In *Advances in cyber security: technology, operation, and experiences*. New York: Fordham University Press, pp. 146-170.
- Morselli, C. (2009). *Inside criminal networks*. New York: Springer.
- Morselli, C., Décary-Héty, D., Paquet-Clouston, M., & Aldridge, J. (2017). Conflict management in illicit drug cryptomarkets. *International Criminal Justice Review*, 27(4), 237-254.
- Morselli, C., Giguère, C., and Petit, K. (2007). The efficiency/security trade-off in criminal networks. *Social Networks*, 29(1), 143-153.
- Motoyama, M., McCoy, D., Levchenko, K., Savage, S., and Voelker, G. M. (2011). An analysis of underground forums. In *Proceedings of the 2011 ACM SIGCOMM conference on Internet measurement conference* (pp. 71-80). ACM.
- Munksgaard, R., and Demant, J. J. (2016). Mixing politics and crime – The prevalence and decline of political discourse on the cryptomarket. *International Journal of Drug Policy*, 35, 77-83.

- Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. Retrieved at <http://www.cryptovest.co.uk/resources/Bitcoin%20paper%20Original.pdf>.
- Natarajan, M. (2006). Understanding the structure of a large heroin distribution network: A quantitative analysis of qualitative data. *Journal of Quantitative Criminology*, 22(2), 171-192.
- Nee, V. (2005). The New Institutionalisms in Economics and Sociology. In Smelser, N. J., and Swedberg, R. (eds). *The Handbook of Economic Sociology*. Princeton, NJ: Princeton University Press, pp. 49-74.
- Newman, M. (2010). *Networks: an introduction*. Oxford: Oxford university press.
- Nowak, M. A. (2006). Five rules for the evolution of cooperation. *Science*, 314(5805): 1560-1563.
- Nurmi, J., Kaskela, T., Perälä, J., and Oksanen, A. (2017). Seller's reputation and capacity on the illicit drug markets: 11-month study on the Finnish version of the Silk Road. *Drug and alcohol dependence*, 178, 201-207.
- O'Donovan, J., Smyth, B., Evrim, V., and McLeod, D. (2007). Extracting and Visualizing Trust Relationships from Online Auction Feedback Comments. In *IJCAI* (Vol. 7), pp. 2826-2831.
- Paquet-Clouston, M., Décary-Héту, D., and Morselli, C. (2018). Assessing market competition and vendors' size and scope on AlphaBay. *International Journal of Drug Policy*, 54, 87-98.
- Pavlou, P. A., and Gefen, D. (2004). Building Effective Online Marketplaces with Institution-Based Trust, *Information Systems Research*, 15, 37-59.
- Peeters, G., and Czapinski, J. (1990). Positive-negative asymmetry in evaluations: The distinction between affective and informational negativity effects. *European review of social psychology*, 1(1), 33-60.
- Przepiorka, W. (2013). Buyers pay for and sellers invest in a good reputation: More evidence from eBay. *The Journal of Socio-Economics*, 42, 31-42.
- Przepiorka, W., and Aksoy, O. (2017). Social order in online markets and the 'collapse' of institutions, Unpublished manuscript, Department of Sociology/ICS, Utrecht University, the Netherlands.
- Przepiorka, W., and Berger, J. (2017). Signaling theory evolving: Signals and signs of trustworthiness in social exchange. In Jann, B., and Przepiorka, W. (eds). *Social dilemmas, institutions and the evolution of cooperation*. Berlin: De Gruyter Oldenburg, pp. 373-392.
- Przepiorka, W., Norbutas, L., and Corten, R. (2017). 'Order without law: Reputation promotes cooperation in a cryptomarket for illegal drugs', *European Sociological Review*, 33(6), 752-764.
- Raub, W., and Buskens, V. (2008). Theory and empirical research in analytical sociology: The case of cooperation in problematic social situations. *Analyse & Kritik*, 30(2), 689-722.

- Raub, W., Buskens, V., and Corten, R. (2014). Social dilemmas and cooperation. In Braun, N., and Saam, N. J. (eds). *Handbuch Modellbildung und Simulation in den Sozialwissenschaften*. Springer Fachmedien Wiesbaden, pp. 597-626.
- Resnick, P., and Zeckhauser, R. (2002). Trust among strangers in internet transactions: empirical analysis of eBay's reputation system. In Baye, M. R. (ed). *The Economics of the Internet and E-Commerce*. Amsterdam: Elsevier, pp. 127-157.
- Reuter, P. (1983). *Disorganized crime: The economics of the visible hand*. Cambridge, MA: MIT press.
- Reuter, P., and Caulkins, J. P. (2004). Illegal 'lemons': price dispersion in cocaine and heroin markets. *Bulletin on Narcotics*, 56(1-2), 141-165.
- Roberts, G. (1998). Competitive altruism: from reciprocity to the handicap principle. *Proceedings of the Royal Society of London B: Biological Sciences* 265(1394): 427-431.
- Robins, G., Pattison, P., Kalish, Y., and Lusher, D. (2007a). An introduction to exponential random graph (p*) models for social networks. *Social networks*, 29(2), 173-191.
- Robins, G., Snijders, T., Wang, P., Handcock, M., and Pattison, P. (2007b). Recent developments in exponential random graph (p*) models for social networks. *Social networks*, 29(2), 192-215.
- Robinson, S. L. (1996). Trust and breach of the psychological contract. *Administrative science quarterly*, 41(4), 574-599.
- Romero, D. M., Uzzi, B., and Kleinberg, J. (2016). Social networks under stress. In *Proceedings of the 25th International Conference on World Wide Web*, International World Wide Web Conferences Steering Committee, pp. 9-20.
- Sally, D. (1995). Conversation and cooperation in social dilemmas a meta-analysis of experiments from 1958 to 1992. *Rationality and Society*, 7(1): 58-92.
- Schuessler, R. (1989). Exit threats and cooperation under anonymity. *Journal of Conflict Resolution*, 33(4), 728-749.
- Shapiro, C. (1983). Premiums for High Quality Products as Return to Reputation. *Quarterly Journal of Economics*, 98, 659-680.
- Snijders, C., and Weesie, J. (2009). Online programming markets. In Cook, K. S., Snijders, C., Buskens, V., and Cheshire, C. (eds). *eTrust: Forming relationships in the online world*, Russell Sage Foundation, pp. 166-185.
- Sommerfeld, R. D., Krambeck, H.-J., Semmann, D., and Milinski, M. (2007). Gossip as an alternative for direct observation in games of indirect reciprocity, *Proceedings of the National Academy of Sciences of the U.S.A.*, 104, 17435-17440.
- Sorenson, O., and Waguespack, D. M. (2006). Social structure and exchange: Self-confirming dynamics in Hollywood. *Administrative Science Quarterly*, 51(4), 560-589.

- Soska, K., and Christin N. (2015). Measuring the Longitudinal Evolution of the Online Anonymous Marketplace Ecosystem. In *24th USENIX Security Symposium (USENIX Security 15)*. Washington, D.C.: USENIX Association, pp. 33-48.
- Sotirakopoulos, N. (2018). Cryptomarkets as a libertarian counter-conduct of resistance. *European Journal of Social Theory*, 21(2), 189-206.
- Standifird, S. S. (2001). Reputation and e-commerce: eBay auctions and the asymmetrical impact of positive and negative ratings. *Journal of management*, 27(3), 279-295.
- StataCorp. (2015). Stata 14 Base Reference Manual. Xtnbreg – Fixed-effects, random-effects, & population-averaged negative binomial models. Stata Press, College Station, TX.
- Sylwester, K., and Roberts, G. (2010). Cooperators benefit through reputation-based partner choice in economic games. *Biology Letters*, 6(5): 659-662.
- Sylwester, K., and Roberts, G. (2013). Reputation-based partner choice is an effective alternative to indirect reciprocity in solving social dilemmas, *Evolution and Human Behavior*, 34, 201-206.
- Taylor, S. E. (1991). Asymmetrical effects of positive and negative events: the mobilization-minimization hypothesis. *Psychological bulletin*, 110(1), 67-85.
- Teubner, T., Hawlitschek, F., and Dann, D. (2017). Price determinants on Airbnb: how reputation pays off in the sharing economy. *Journal of Self-Governance & Management Economics*, 5(4), 53-80.
- Tzanetakis M. (2019) Informal Governance on Cryptomarkets for Illicit Drugs. In Polese A., Russo A., Strazzari F. (eds) *Governance Beyond the Law*. International Political Economy Series. Palgrave Macmillan, Cham.
- Tzanetakis, M., Kamphausen, G., Werse, B., and von Laufenberg, R. (2016). The transparency paradox. Building trust, resolving disputes and optimizing logistics on conventional and online drugs markets. *International Journal of Drug Policy*, 35, 58-68.
- Utz, S. (2009). Rebuilding trust after negative feedback: The role of communication. In Cook, K. S., Snijders, C., Buskens, V., and Cheshire, C. (eds). *eTrust: Forming relationships in the online world*, Russell Sage Foundation, pp. 139-165.
- Utz, S., Matzat, U., and Snijders, C. (2009). On-line reputation systems: The effects of feedback comments and reactions on building and rebuilding trust in on-line auctions. *International Journal of Electronics & Communications*, 13(3), 95-118.
- Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embeddedness. *Administrative science quarterly*, 42(1), 35-67.
- Wadsworth, E., Drummond, C., & Deluca, P. (2018). The dynamic environment of crypto markets: the lifespan of new psychoactive substances (NPS) and vendors selling NPS. *Brain sciences*, 8(3), 46.

- van Wegberg, R., and Verburgh, T. (2018). Lost in the Dream? Measuring the effects of Operation Bayonet on vendors migrating to Dream Market. In *Proceedings of the Evolution of the Darknet Workshop*, pp. 1-5.
- Wibral, M. (2015). Identity changes and the efficiency of reputation systems. *Experimental Economics*, 18(3), 408-431.
- Willer, R. (2009). Groups Reward Individual Sacrifice: The Status Solution to the Collective Action Problem, *American Sociological Review*, 74(1), 23-43.
- Winstock, A., Barratt, M., Ferris, J., and Maier, L. (2017). *Global Drug Survey. Global Overview and Highlights*. Retrieved at https://www.globaldrugsurvey.com/wp-content/themes/globaldrugsurvey/results/GDS2017_key-findings-report_final.pdf
- Wood, G. (2017). The Structure and Vulnerability of a Drug Trafficking Collaboration Network. *Social Networks*, 48, 1-9
- Wu, J., Balliet, D., and van Lange, P. A. M. (2016). Gossip Versus Punishment: The Efficiency of Reputation to Promote and Maintain Cooperation, *Scientific Reports*, 6, 23919.
- Yamagishi, T. (1988). Exit from the group as an individualistic solution to the free rider problem in the United States and Japan. *Journal of Experimental Social Psychology*, 24(6), 530-542.
- Yamagishi, T., Hayashi, N., and Jin, N. (1984). Prisoner's dilemma networks: selection strategy versus action strategy. In Schulz, U., Wulf, A., and Mueller, U. (eds). *Social dilemmas and cooperation*, Berlin, Heidelberg: Springer, pp. 233-250.
- Yamagishi, T., Matsuda, M., Yoshikai, N., Takahashi, H., and Usui, Y. (2009). Solving the Lemons Problem with Reputation. In Cook, K. S., Snijders, C., Buskens, V., and Cheshire, C. (eds). *eTrust: Forming Relationships in the Online World*. New York: Russell Sage Foundation, pp. 73-108.
- Ye, Q., Xu, M., Kiang, M., Wu, W., and Sun, F. (2013). In-depth analysis of the seller reputation and price premium relationship: a comparison between eBay US and Taobao China. *Journal of Electronic Commerce Research*, 14(1), 1-10.

Acknowledgements

ACKNOWLEDGEMENTS

The last four years were the most intense period of professional and personal growth for me. I have to admit that at times it was also the biggest emotional rollercoaster I have ever been on. From the day when I received an email saying that the project received funding, to the day when I struggled to find sentences that could conclude the final chapter - it was a great journey. Now, looking back, I feel very grateful for having had the opportunity and privilege to write this dissertation. Although I spent a lot of time in Vilnius, Utrecht has become a second home and it will always be a very special place for me.

First and foremost, I would like to thank my supervisors Rense and Stijn. You were the people that taught me the most about trust and you did so by example. Your continuous support was very important to me, and your passion for science inspired me to move forward. Thank you for providing me with plenty of space to grow and nudging me in the right direction when I lacked confidence. Thank you for keeping the bar high and showing no doubts that I can make it. I learned a great deal from you as a researcher and as a person.

I would like to thank all the people I met and worked with in the Sociology department of Utrecht University. Wojtek, thank you for being the person who always had the time to hear my ideas and doubts. It was a great experience to work with you. To all the people who read my work and helped me make it better - Vincent, Werner, Jeroen, Arnout, Vincenz, Joyce, your comments and your own work influenced this dissertation substantially. Thank you for that. I owe my thanks to all the people I met in the NSCR - it was a great feeling to be welcome in the community of criminologists.

I would like to say a special thank you to Ineke Maas and Tanja van der Lippe. Ineke, you were the first person in the department who showed confidence in me as a researcher. It played a big role in shaping my decision to pursue a PhD. Tanja, without your encouragement the project would probably not have started. I sincerely thank you both for all the support throughout the years.

My colleagues (ex-) PhD candidates have also been very important to me. Jelle, Margriet, Sara - you were the best office-mates ever. Thank you for always making me feel welcome, for all the conversations, jokes, advice and help I received from you. Jelle, I am ready for that squash rematch whenever you are. Thank you for always having my back. Marcus, Jannes, Joris, Lex, Femke, Eva, Judith, Siyang, it was great to go through this journey together with you. I wish I could have enjoyed your company more often. I am thankful that you kept inviting me to go out for lunch and walks, ignoring my constant hesitation. I am glad I could share my accomplishments and

fears with you. A special shout out goes to those of you who let me crash at your places! Nikki, Leonie, Müge, thank you for all the coffee breaks and your mentorship. Your smiles and great mood were often the first things I would see when coming back to Utrecht. I am also grateful for all the time I spent with my colleagues in Groningen, Nijmegen and Amsterdam - I enjoyed working with you and having the evening drinks afterwards, too.

Thank you to all the people who greeted me in Stanford University and made my visit there very special. I owe my thanks to Karen Cook and Paolo Parigi for being so welcoming and supportive. Bas, it was truly inspiring to work with you in Utrecht and also to see a familiar face so far away from the Netherlands. I wish you all the best. I am grateful to Afrooz and Valentina for not letting me sit between the four walls all the time. Thank you for showing me around, all the lunch breaks and great moments.

Finally, I owe the most to my family. Mama, tėti, Jūsų meilė ir nuolatinis tikėjimas mano jėgomis buvo ir yra stiprus pamatas mano gyvenime. Esu be galo dėkingas galėdamas nuolat į Jus atsiremti. Ačiū už neblėstančią šilumą.

Darja, this dissertation would have never been completed without you. Utrecht was one of the biggest challenges for us and this four year journey was also our journey. I am forever grateful for your unconditional love and support. I am very proud and thankful to have you beside me. Thank you for being my home.

Curriculum Vitae

CURRICULUM VITAE

Lukas Norbutas was born in Kaunas, Lithuania, on October 19, 1990. In 2013, he obtained his bachelor's degree in Sociology at Vilnius University. He obtained his research master's degree in Sociology and Social Research (*cum laude*) at Utrecht University in 2015. In 2015, he was awarded the Netherlands Organisation for Scientific Research (NWO) Talent Grant and started working as a Ph.D. candidate at the Interuniversity Centre for Social Science Theory and Methodology (ICS) at the Department of Sociology at Utrecht University, where he wrote this dissertation under the supervision of Stijn Ruiter and Rense Corten. Between 2016 and 2019, he taught in the "Internet, Social Media and Networks" course and supervised Bachelor theses. As part of his training, he visited prof. Karen Cook in Stanford University. His work has been published in *Social Networks*, *European Sociological Review* and *International Journal of Drug Policy*, among others.

ICS dissertation series

ICS DISSERTATION SERIES

“Cooperation and social control: Effects of preferences, institutions, and social structure” The ICS series presents dissertations of the Interuniversity Center for Social Science Theory and Methodology. Each of these studies aims at integrating explicit theory formation with state of the art empirical research or at the development of advanced methods for empirical research. The ICS was founded in 1986 as a cooperative effort of the universities of Groningen and Utrecht. Since 1992, the ICS expanded to the University of Nijmegen and since 2017 to the University of Amsterdam (UvA). Most of the projects are financed by the participating universities or by the Netherlands Organization for Scientific Research (NWO). The international composition of the ICS graduate students is mirrored in the increasing international orientation of the projects and thus of the ICS series itself.

1. Kees van Liere (1990), *“Lastige Leerlingen. Een empirisch onderzoek naar sociale oorzaken van probleemgedrag op basisscholen.”* Amsterdam: Thesis Publishers
2. Marco van Leeuwen (1990), *“Bijstand in Amsterdam, ca. 1800 - 1850. Armenzorg als beheersings en overlevingsstrategie.”* ICS-dissertation, Utrecht
3. Ineke Maas (1990), *“Deelname aan podiumkunsten via de podia, de media en actieve beoefening. Substitutie of leereffecten?”* Amsterdam: Thesis Publishers
4. Marjolein Broese van Groenou (1991), *“Gescheiden Netwerken. De relaties met vrienden en verwanten na echtscheiding”* Amsterdam: Thesis Publishers
5. Jan van den Bos (1991), *“Dutch EC Policy Making. A Model Guided Approach to Coordination and Negotiation.”* Amsterdam: Thesis Publishers
6. Karin Sanders (1991), *“Vrouwelijke Pioniers. Vrouwen en mannen met een ‘mannelijke’ hogere beroepsopleiding aan het begin van hun loopbaan.”* Amsterdam: Thesis Publishers
7. Sjerp de Vries (1991), *“Egoism, Altruism, and Social Justice. Theory and Experiments on Cooperation in Social Dilemmas.”* Amsterdam: Thesis Publishers
8. Ronald Batenburg (1991), *“Automatisering in bedrijf.”* Amsterdam: Thesis Publishers
9. Rudi Wielers (1991), *“Selectie en allocatie op de arbeidsmarkt. Een uitwerking voor de informele en geïnstitutionaliseerde kinderopvang.”* Amsterdam: Thesis Publishers
10. Gert Westert (1991), *“Verschillen in ziekenhuisgebruik.”* ICS-dissertation, Groningen
11. Hanneke Hermsen (1992), *“Votes and Policy Preferences. Equilibria in Party Systems.”* Amsterdam: Thesis Publishers
12. Cora Maas (1992), *“Probleemleerlingen in het basisonderwijs”* Amsterdam: Thesis Publishers
13. Ed Boxman (1992), *“Contacten en carrière. Een empirisch theoretisch onderzoek naar de relatie tussen sociale netwerken en arbeidsmarktposities”* Amsterdam: Thesis Publishers

14. Conny Taes (1992), *"Kijken naar banen. Een onderzoek naar de inschatting van arbeidsmarktkansen bij schoolverlaters uit het middelbaar beroepsonderwijs."* Amsterdam: Thesis Publishers
15. Peter van Roozendaal (1992), *"Cabinets in Multi Party Democracies. The Effect of Dominant and Central Parties on Cabinet Composition and Durability."* Amsterdam: Thesis Publishers
16. Marcel van Dam (1992), *"Regio zonder regie. Verschillen in en effectiviteit van gemeentelijk arbeidsmarktbeleid."* Amsterdam: Thesis Publishers
17. Tanja van der Lippe (1993), *"Arbeidsverdeling tussen mannen en vrouwen."* Amsterdam: Thesis Publishers
18. Marc Jacobs (1993), *"Software: Kopen of Kopiëren? Een sociaal wetenschappelijk onderzoek onder PC gebruikers."* Amsterdam: Thesis Publishers
19. Peter van der Meer (1993), *"Verdringing op de Nederlandse arbeidsmarkt. Sector- en sekseverschillen."* Amsterdam: Thesis Publishers
20. Gerbert Kraaykamp (1993), *"Over lezen gesproken. Een studie naar sociale differentiatie in leesgedrag."* Amsterdam: Thesis Publishers
21. Evelien Zeggelink (1993), *"Strangers into Friends. The Evolution of Friendship Networks Using an Individual Oriented Modeling Approach."* Amsterdam: Thesis Publishers
22. Jaco Berveling (1994), *"Het stempel op de besluitvorming. Macht, invloed en besluitvorming op twee Amsterdamse beleidsterreinen."* Amsterdam: Thesis Publishers
23. Wim Bernasco (1994), *"Coupled Careers. The Effects of Spouse's Resources on Success at Work."* Amsterdam: Thesis Publishers
24. Liset van Dijk (1994), *"Choices in Child Care. The Distribution of Child Care Among Mothers, Fathers and Non Parental Care Providers."* Amsterdam: Thesis Publishers
25. Jos de Haan (1994), *"Research Groups in Dutch Sociology."* Amsterdam: Thesis Publishers
26. Kwasi Boahene (1995), *"Innovation Adoption as a Socio Economic Process. The Case of the Ghanaian Cocoa Industry."* Amsterdam: Thesis Publishers
27. Paul Ligthart (1995), *"Solidarity in Economic Transactions. An Experimental Study of Framing Effects in Bargaining and Contracting."* Amsterdam: Thesis Publishers
28. Roger Leenders (1995), *"Structure and Influence. Statistical Models for the Dynamics of Actor Attributes, Network Structure, and their Interdependence."* Amsterdam: Thesis Publishers
29. Beate Volker (1995), *"Should Auld Acquaintance Be Forgotten...? Institutions of Communism, the Transition to Capitalism and Personal Networks: the Case of East Germany."* Amsterdam: Thesis Publishers
30. Anneke Cancrinus-Matthijssse (1995), *"Tussen hulpverlening en ondernemerschap. Beroepsuitoefening en taakopvattingen van openbare apothekers in een aantal West Europese landen."* Amsterdam: Thesis Publishers
31. Nardi Steverink (1996), *"Zo lang mogelijk zelfstandig. Naar een verklaring van verschillen in oriëntatie ten aanzien van opname in een verzorgingstehuis onder fysiek kwetsbare ouderen."* Amsterdam: Thesis Publishers
32. Ellen Lindeman (1996), *"Participatie in vrijwilligerswerk."* Amsterdam: Thesis Publishers
33. Chris Snijders (1996), *"Trust and Commitments."* Amsterdam: Thesis Publishers

34. Koos Postma (1996), *"Changing Prejudice in Hungary. A Study on the Collapse of State Socialism and Its Impact on Prejudice Against Gypsies and Jews."* Amsterdam: Thesis Publishers
35. Jooske van Busschbach (1996), *"Uit het oog, uit het hart? Stabiliteit en verandering in persoonlijke relaties."* Amsterdam: Thesis Publishers
36. René Torenvlied (1996), *"Besluiten in uitvoering. Theorieën over beleidsuitvoering modelmatig getoetst op sociale vernieuwing in drie gemeenten."* Amsterdam: Thesis Publishers
37. Andreas Flache (1996), *"The Double Edge of Networks. An Analysis of the Effect of Informal Networks on Cooperation in Social Dilemmas."* Amsterdam: Thesis Publishers
38. Kees van Veen (1997), *"Inside an Internal Labor Market: Formal Rules, Flexibility and Career Lines in a Dutch Manufacturing Company."* Amsterdam: Thesis Publishers
39. Lucienne van Eijk (1997), *"Activity and Well being in the Elderly."* Amsterdam: Thesis Publishers
40. Róbert Gál (1997), *"Unreliability. Contract Discipline and Contract Governance under Economic Transition."* Amsterdam: Thesis Publishers
41. Anne-Geerte van de Goor (1997), *"Effects of Regulation on Disability Duration."* ICS-dissertation, Utrecht
42. Boris Blumberg (1997), *"Das Management von Technologiekooperationen. Partnersuche und Verhandlungen mit dem Partner aus Empirisch Theoretischer Perspektive."* ICS-dissertation, Utrecht
43. Marijke von Bergh (1997), *"Loopbanen van oudere werknemers."* Amsterdam: Thesis Publishers
44. Anna Petra Nieboer (1997), *"Life Events and Well Being: A Prospective Study on Changes in Well Being of Elderly People Due to a Serious Illness Event or Death of the Spouse."* Amsterdam: Thesis Publishers
45. Jacques Niehof (1997), *"Resources and Social Reproduction: The Effects of Cultural and Material Resources on Educational and Occupational Careers in Industrial Nations at the End of the Twentieth Century."* ICS-dissertation, Nijmegen
46. Ariana Need (1997), *"The Kindred Vote. Individual and Family Effects of Social Class and Religion on Electoral Change in the Netherlands, 1956 1994."* ICS-dissertation, Nijmegen
47. Jim Allen (1997), *"Sector Composition and the Effect of Education on Wages: an International Comparison."* Amsterdam: Thesis Publishers
48. Jack Hutten (1998), *"Workload and Provision of Care in General Practice. An Empirical Study of the Relation Between Workload of Dutch General Practitioners and the Content and Quality of their Care."* ICS-dissertation, Utrecht
49. Per Kropp (1998), *"Berufserfolg im Transformationsprozeß. Eine theoretisch empirische Studie über die Gewinner und Verlierer der Wende in Ostdeutschland."* ICS-dissertation, Utrecht
50. Maarten Wolbers (1998), *"Diploma-inflatie en verdringing op de arbeidsmarkt. Een studie naar ontwikkelingen in de opbrengsten van diploma's in Nederland."* ICS-dissertation, Nijmegen
51. Wilma Smeenk (1998), *"Opportunity and Marriage. The Impact of Individual Resources and Marriage Market Structure on First Marriage Timing and Partner Choice in the Netherlands."* ICS-dissertation, Nijmegen

52. Marinus Spreen (1999), *"Sampling Personal Network Structures: Statistical Inference in Ego-Graphs."* ICS-dissertation, Groningen
53. Vincent Buskens (1999), *"Social Networks and Trust."* ICS-dissertation, Utrecht
54. Susanne Rijken (1999), *"Educational Expansion and Status Attainment. A Cross-National and Over-Time Comparison."* ICS-dissertation, Utrecht
55. Mérove Gijsberts (1999), *"The Legitimation of Inequality in State-Socialist and Market Societies, 1987-1996."* ICS-dissertation, Utrecht
56. Gerhard van de Bunt (1999), *"Friends by Choice. An Actor-Oriented Statistical Network Model for Friendship Networks Through Time."* ICS-dissertation, Groningen
57. Robert Thomson (1999), *"The Party Mandate: Election Pledges and Government Actions in the Netherlands, 1986-1998."* Amsterdam: Thela Thesis
58. Corine Baarda (1999), *"Politieke besluiten en boeren beslissingen. Het draagvlak van het mestbeleid tot 2000."* ICS-dissertation, Groningen
59. Rafael Wittek (1999), *"Interdependence and Informal Control in Organizations."* ICS-dissertation, Groningen
60. Diane Payne (1999), *"Policy Making in the European Union: an Analysis of the Impact of the Reform of the Structural Funds in Ireland."* ICS-dissertation, Groningen
61. René Veenstra (1999), *"Leerlingen Klassen Scholen. Prestaties en vorderingen van leerlingen in het voortgezet onderwijs."* Amsterdam, Thela Thesis
62. Marjolein Achterkamp (1999), *"Influence Strategies in Collective Decision Making. A Comparison of Two Models."* ICS-dissertation, Groningen
63. Peter Mühlau (2000), *"The Governance of the Employment Relation. A Relational Signaling Perspective."* ICS-dissertation, Groningen
64. Agnes Akkerman (2000), *"Verdeelde vakbeweging en stakingen. Concurrentie om leden."* ICS-dissertation, Groningen
65. Sandra van Thiel (2000), *"Quangocratization: Trends, Causes and Consequences."* ICS-dissertation, Utrecht
66. Sylvia Peacock-Korupp (2000), *"Mothers and the Process of Social Stratification."* ICS-dissertation, Utrecht
67. Rudi Turksema (2000), *"Supply of Day Care."* ICS-dissertation, Utrecht
68. Bernard Nijstad (2000), *"How the Group Affects the Mind: Effects of Communication in Idea Generating Groups."* ICS-dissertation, Utrecht
69. Inge de Wolf (2000), *"Opleidingsspecialisatie en arbeidsmarktsucces van sociale wetenschappers."* ICS-dissertation, Utrecht
70. Jan Kratzer (2001), *"Communication and Performance: An Empirical Study in Innovation Teams."* ICS-dissertation, Groningen
71. Madelon Kroneman (2001), *"Healthcare Systems and Hospital Bed Use."* ICS/NIVEL-dissertation, Utrecht
72. Herman van de Werfhorst (2001), *"Field of Study and Social Inequality. Four Types of Educational Resources in the Process of Stratification in the Netherlands."* ICS-dissertation, Nijmegen
73. Tamás Bartus (2001), *"Social Capital and Earnings Inequalities. The Role of Informal Job Search in Hungary."* ICS-dissertation Groningen

74. Hester Moerbeek (2001), *"Friends and Foes in the Occupational Career. The Influence of Sweet and Sour Social Capital on the Labour Market."* ICS-dissertation, Nijmegen
75. Marcel van Assen (2001), *"Essays on Actor Perspectives in Exchange Networks and Social Dilemmas."* ICS-dissertation, Groningen
76. Inge Sieben (2001), *"Sibling Similarities and Social Stratification. The Impact of Family Background across Countries and Cohorts."* ICS-dissertation, Nijmegen
77. Alinda van Bruggen (2001), *"Individual Production of Social Well Being. An Exploratory Study."* ICS-dissertation, Groningen
78. Marcel Coenders (2001), *"Nationalistic Attitudes and Ethnic Exclusionism in a Comparative Perspective: An Empirical Study of Attitudes Toward the Country and Ethnic Immigrants in 22 Countries."* ICS-dissertation, Nijmegen
79. Marcel Lubbers (2001), *"Exclusionistic Electorates. Extreme Right Wing Voting in Western Europe."* ICS-dissertation, Nijmegen
80. Uwe Matzat (2001), *"Social Networks and Cooperation in Electronic Communities. A theoretical-empirical Analysis of Academic Communication and Internet Discussion Groups."* ICS-dissertation, Groningen
81. Jacques Janssen (2002), *"Do Opposites Attract Divorce? Dimensions of Mixed Marriage and the Risk of Divorce in the Netherlands."* ICS-dissertation, Nijmegen
82. Miranda Jansen (2002), *"Waardenoriëntaties en partnerrelaties. Een panelstudie naar wederzijdse invloeden."* ICS-dissertation, Utrecht
83. Anne-Rigt Poortman (2002), *"Socioeconomic Causes and Consequences of Divorce."* ICS-dissertation, Utrecht
84. Alexander Gattig (2002), *"Intertemporal Decision Making."* ICS-dissertation, Groningen
85. Gerrit Rooks (2000), *"Contract en Conflict: Strategisch Management van Inkooptransacties."* ICS-dissertation, Utrecht
86. Károly Takács (2002), *"Social Networks and Intergroup Conflict."* ICS-dissertation, Groningen
87. Thomas Gautschi (2002), *"Trust and Exchange, Effects of Temporal Embeddedness and Network Embeddedness on Providing and Dividing a Surplus."* ICS-dissertation, Utrecht
88. Hilde Bras (2002), *"Zeeuwse meiden. Dienen in de levensloop van vrouwen, ca. 1850 –1950."* Aksant Academic Publishers, Amsterdam
89. Merijn Rengers (2002), *"Economic Lives of Artists. Studies into Careers and the Labour Market in the Cultural Sector."* ICS-dissertation, Utrecht
90. Annelies Kassenberg (2002), *"Wat scholieren bindt. Sociale gemeenschap in scholen."* ICS-dissertation, Groningen
91. Marc Verboord (2003), *"Moet de meester dalen of de leerling klimmen? De invloed van literatuuronderwijs en ouders op het lezen van boeken tussen 1975 en 2000."* ICS-dissertation, Utrecht
92. Marcel van Egmond (2003), *"Rain Falls on All of Us (but Some Manage to Get More Wet than Others): Political Context and Electoral Participation."* ICS-dissertation, Nijmegen
93. Justine Horgan (2003), *"High Performance Human Resource Management in Ireland and the Netherlands: Adoption and Effectiveness."* ICS-dissertation, Groningen
94. Corine Hoebe (2003), *"LET'S Be a Community. Community in Local Exchange Trading Systems."* ICS-dissertation, Groningen

95. Christian Steglich (2003), *"The Framing of Decision Situations. Automatic Goal Selection and Rational Goal Pursuit."* ICS-dissertation, Groningen
96. Johan van Wilsem (2003), *"Crime and Context. The Impact of Individual, Neighborhood, City and Country Characteristics on Victimization."* ICS-dissertation, Nijmegen
97. Christiaan Monden (2003), *"Education, Inequality and Health. The Impact of Partners and Life Course."* ICS-dissertation, Nijmegen
98. Evelyn Hello (2003), *"Educational Attainment and Ethnic Attitudes. How to Explain their Relationship."* ICS-dissertation, Nijmegen
99. Marnix Croes en Peter Tammes (2004). Gif laten wij niet voortbestaan. Een onderzoek naar de overlevingskansen van joden in de Nederlandse gemeenten, 1940-1945. Aksant Academic Publishers, Amsterdam.
100. Ineke Nagel (2004), *"Cultuurdeelname in de levensloop."* ICS-dissertation, Utrecht
101. Marieke van der Wal (2004), *"Competencies to Participate in Life. Measurement and the Impact of School."* ICS-dissertation, Groningen
102. Vivian Meertens (2004), *"Depressive Symptoms in the General Population: a Multifactorial Social Approach."* ICS-dissertation, Nijmegen
103. Hanneke Schuurmans (2004), *"Promoting Well-Being in Frail Elderly People. Theory and Intervention."* ICS-dissertation, Groningen
104. Javier Arregui Moreno (2004), *"Negotiation in Legislative Decision-Making in the European Union."* ICS-dissertation, Groningen
105. Tamar Fischer (2004), *"Parental Divorce, Conflict and Resources. The Effects on Children's Behaviour Problems, Socioeconomic Attainment, and Transitions in the Demographic Career."* ICS-dissertation, Nijmegen
106. René Bekkers (2004), *"Giving and Volunteering in the Netherlands: Sociological and Psychological Perspectives."* ICS-dissertation, Utrecht
107. Renée van der Hulst (2004), *"Gender Differences in Workplace Authority: An Empirical Study on Social Networks."* ICS-dissertation, Groningen
108. Rita Smaniotta (2004), *"'You Scratch My Back and I Scratch Yours' Versus 'Love Thy Neighbour'. Two Proximate Mechanisms of Reciprocal Altruism."* ICS-dissertation, Groningen
109. Maurice Gesthuizen (2004), *"The Life-Course of the Low-Educated in the Netherlands: Social and Economic Risks."* ICS-dissertation, Nijmegen
110. Carlijne Philips (2005), *"Vakantiegemeenschappen. Kwalitatief en Kwantitatief Onderzoek naar Gelegenheid en Refreshergemeenschap tijdens de Vakantie."* ICS-dissertation, Groningen
111. Esther de Ruijter (2005), *"Household Outsourcing."* ICS-dissertation, Utrecht
112. Frank van Tubergen (2005), *"The Integration of Immigrants in Cross-National Perspective: Origin, Destination, and Community Effects."* ICS-dissertation, Utrecht
113. Ferry Koster (2005), *"For the Time Being. Accounting for Inconclusive Findings Concerning the Effects of Temporary Employment Relationships on Solidary Behavior of Employees."* ICS-dissertation, Groningen
114. Carolien Klein Haarhus (2005), *"Promoting Anti-Corruption Reforms. Evaluating the Implementation of a World Bank Anti-Corruption Program in Seven African Countries (1999-2001)."* ICS-dissertation, Utrecht

115. Martin van der Gaag (2005), *"Measurement of Individual Social Capital."* ICS-dissertation, Groningen
116. Johan Hansen (2005), *"Shaping Careers of Men and Women in Organizational Contexts."* ICS-dissertation, Utrecht
117. Davide Barrera (2005), *"Trust in Embedded Settings."* ICS-dissertation, Utrecht
118. Mattijs Lambooi (2005), *"Promoting Cooperation. Studies into the Effects of Long-Term and Short-Term Rewards on Cooperation of Employees."* ICS-dissertation, Utrecht
119. Lotte Vermeij (2006), *"What's Cooking? Cultural Boundaries among Dutch Teenagers of Different Ethnic Origins in the Context of School."* ICS-dissertation, Utrecht
120. Mathilde Strating (2006), *"Facing the Challenge of Rheumatoid Arthritis. A 13-year Prospective Study among Patients and Cross-Sectional Study among Their Partners."* ICS-dissertation, Groningen
121. Jannes de Vries (2006), *"Measurement Error in Family Background Variables: The Bias in the Intergenerational Transmission of Status, Cultural Consumption, Party Preference, and Religiosity."* ICS-dissertation, Nijmegen
122. Stefan Thau (2006), *"Workplace Deviance: Four Studies on Employee Motives and Self-Regulation."* ICS-dissertation, Groningen
123. Mirjam Plantinga (2006), *"Employee Motivation and Employee Performance in Child Care. The effects of the Introduction of Market Forces on Employees in the Dutch Child-Care Sector."* ICS-dissertation, Groningen
124. Helga de Valk (2006), *"Pathways into Adulthood. A Comparative Study on Family Life Transitions among Migrant and Dutch Youth."* ICS-dissertation, Utrecht
125. Henrike Elzen (2006), *"Self-Management for Chronically Ill Older People."* ICS-Dissertation, Groningen
126. Ayse Güveli (2007), *"New Social Classes within the Service Class in the Netherlands and Britain. Adjusting the EGP Class Schema for the Technocrats and the Social and Cultural Specialists."* ICS-dissertation, Nijmegen
127. Willem-Jan Verhoeven (2007), *"Income Attainment in Post-Communist Societies."* ICS-dissertation, Utrecht
128. Marieke Voorpostel (2007), *"Sibling support: The Exchange of Help among Brothers and Sisters in the Netherlands."* ICS-dissertation, Utrecht
129. Jacob Dijkstra (2007), *"The Effects of Externalities on Partner Choice and Payoffs in Exchange Networks."* ICS-dissertation, Groningen
130. Patricia van Echtelt (2007), *"Time-Greedy Employment Relationships: Four Studies on the Time Claims of Post-Fordist Work."* ICS-dissertation, Groningen
131. Sonja Vogt (2007), *"Heterogeneity in Social Dilemmas: The Case of Social Support."* ICS-dissertation, Utrecht
132. Michael Schweinberger (2007), *"Statistical Methods for Studying the Evolution of Networks and Behavior."* ICS-dissertation, Groningen
133. István Henrik Back (2007), *"Commitment and Evolution: Connecting Emotion and Reason in Long-term Relationships."* ICS-dissertation, Groningen
134. Ruben van Gaalen (2007), *"Solidarity and Ambivalence in Parent-Child Relationships."* ICS-dissertation, Utrecht
135. Jan Reitsma (2007), *"Religiosity and Solidarity – Dimensions and Relationships Disentangled and Tested."* ICS-dissertation, Nijmegen

136. Jan Kornelis Dijkstra (2007), *"Status and Affection among (Pre)Adolescents and Their Relation with Antisocial and Prosocial Behavior."* ICS-dissertation, Groningen
137. Wouter van Gils (2007), *"Full-time Working Couples in the Netherlands. Causes and Consequences."* ICS-dissertation, Nijmegen
138. Djamila Schans (2007), *"Ethnic Diversity in Intergenerational Solidarity."* ICS-dissertation, Utrecht
139. Ruud van der Meulen (2007), *"Brug over Woelig Water: Lidmaatschap van Sportverenigingen, Vriendschappen, Kennissenkringen en Veralgemeend Vertrouwen."* ICS-dissertation, Nijmegen
140. Andrea Knecht (2008), *"Friendship Selection and Friends' Influence. Dynamics of Networks and Actor Attributes in Early Adolescence."* ICS-dissertation, Utrecht
141. Ingrid Doorten (2008), *"The Division of Unpaid Work in the Household: A Stubborn Pattern?"* ICS-dissertation, Utrecht
142. Stijn Ruiter (2008), *"Association in Context and Association as Context: Causes and Consequences of Voluntary Association Involvement."* ICS-dissertation, Nijmegen
143. Janneke Joly (2008), *"People on Our Minds: When Humanized Contexts Activate Social Norms."* ICS-dissertation, Groningen
144. Margreet Frieling (2008), *"Joint production' als motor voor actief burgerschap in de buurt."* ICS-dissertation, Groningen
145. Ellen Verbakel (2008), *"The Partner as Resource or Restriction? Labour Market Careers of Husbands and Wives and the Consequences for Inequality Between Couples."* ICS-dissertation, Nijmegen
146. Gijs van Houten (2008), *"Beleidsuitvoering in gelaagde stelsels. De doorwerking van aanbevelingen van de Stichting van de Arbeid in het CAO-overleg."* ICS-dissertation, Utrecht
147. Eva Jaspers (2008), *"Intolerance over Time. Macro and Micro Level Questions on Attitudes Towards Euthanasia, Homosexuality and Ethnic Minorities."* ICS-dissertation, Nijmegen
148. Gijs Weijters (2008), *"Youth Delinquency in Dutch Cities and Schools: A Multilevel Approach."* ICS-dissertation, Nijmegen
149. Jessica Nooij (2009), *"The Self in Social Rejection."* ICS-dissertation, Groningen
150. Gerald Mollenhorst (2009), *"Networks in Contexts. How Meeting Opportunities Affect Personal Relationships."* ICS-dissertation, Utrecht
151. Tom van der Meer (2009), *"States of Freely Associating Citizens: Comparative Studies into the Impact of State Institutions on Social, Civic and Political Participation."* ICS-dissertation, Nijmegen
152. Manuela Vieth (2009), *"Commitments and Reciprocity in Trust Situations. Experimental Studies on Obligation, Indignation, and Self-Consistency."* ICS-dissertation, Utrecht
153. Rense Corten (2009), *"Co-evolution of Social Networks and Behavior in Social Dilemmas: Theoretical and Empirical Perspectives."* ICS-dissertation, Utrecht
154. Arieke Rijken (2009), *"Happy Families, High Fertility? Childbearing Choices in the Context of Family and Partner Relationships."* ICS-dissertation, Utrecht

155. Jochem Tolsma (2009), *"Ethnic Hostility among Ethnic Majority and Minority Groups in the Netherlands. An Investigation into the Impact of Social Mobility Experiences, the Local Living Environment and Educational Attainment on Ethnic Hostility."* ICS-dissertation, Nijmegen
156. Freek Bucx (2009), *"Linked Lives: Young Adults' Life Course and Relations With Parents."* ICS-dissertation, Utrecht
157. Philip Wotschack (2009), *"Household Governance and Time Allocation. Four studies on the combination of work and care."* ICS-dissertation, Groningen
158. Nienke Moor (2009), *"Explaining Worldwide Religious Diversity. The Relationship between Subsistence Technologies and Ideas about the Unknown in Pre-industrial and (Post-)industrial Societies."* ICS-dissertation, Nijmegen
159. Lieke ten Brummelhuis (2009), *"Family Matters at Work. Depleting and Enriching Effects of Employees' Family lives on Work Outcomes."* ICS-dissertation, Utrecht
160. Renske Keizer (2010), *"Remaining Childless. Causes and Consequences from a Life Course Perspective."* ICS-dissertation, Utrecht
161. Miranda Sentse (2010), *"Bridging Contexts: The interplay between Family, Child, and Peers in Explaining Problem Behavior in Early Adolescence."* ICS-dissertation, Groningen
162. Nicole Tieben (2010), *"Transitions, Tracks and Transformations. Social Inequality in Transitions into, through and out of Secondary Education in the Netherlands for Cohorts Born Between 1914 and 1985."* ICS-dissertation, Nijmegen
163. Birgit Pauksztat (2010), *"Speaking up in Organizations: Four Studies on Employee Voice."* ICS-dissertation, Groningen
164. Richard Zijdemans (2010), *"Status Attainment in the Netherlands, 1811-1941. Spatial and Temporal Variation Before and During Industrialization."* ICS-dissertation, Utrecht
165. Rianne Kloosterman (2010), *"Social Background and Children's Educational Careers. The Primary and Secondary Effects of Social Background over Transitions and over Time in the Netherlands."* ICS-dissertation, Nijmegen
166. Olav Aarts (2010), *"Religious Diversity and Religious Involvement. A Study of Religious Markets in Western Societies at the End of the Twentieth Century."* ICS-dissertation, Nijmegen
167. Stephanie Wiesmann (2010), *"24/7 Negotiation in Couples Transition to Parenthood."* ICS-dissertation, Utrecht
168. Borja Martinovic (2010), *"Interethnic Contacts: A Dynamic Analysis of Interaction Between Immigrants and Natives in Western Countries."* ICS-dissertation, Utrecht
169. Anne Roeters (2010), *"Family Life Under Pressure? Parents' Paid Work and the Quantity and Quality of Parent-Child and Family Time."* ICS-dissertation, Utrecht
170. Jelle Sijtsema (2010), *"Adolescent Aggressive Behavior: Status and Stimulation Goals in Relation to the Peer Context."* ICS-dissertation, Groningen
171. Kees Keizer (2010), *"The Spreading of Disorder."* ICS-dissertation, Groningen
172. Michael Mäs (2010), *"The Diversity Puzzle. Explaining Clustering and Polarization of Opinions."* ICS-dissertation, Groningen
173. Marie-Louise Damen (2010), *"Cultuurdeelname en CKV. Studies naar effecten van kunsteducatie op de cultuurdeelname van leerlingen tijdens en na het voortgezet onderwijs."* ICS-dissertation, Utrecht

174. Marieke van de Rakt (2011), *"Two generations of Crime: The Intergenerational Transmission of Convictions over the Life Course."* ICS-dissertation, Nijmegen
175. Willem Huijnk (2011), *"Family Life and Ethnic Attitudes. The Role of the Family for Attitudes Towards Inter-marriage and Acculturation Among Minority and Majority Groups."* ICS-dissertation, Utrecht
176. Tim Huijts (2011), *"Social Ties and Health in Europe. Individual Associations, Cross-National Variations, and Contextual Explanations."* ICS-dissertation, Nijmegen
177. Wouter Steenbeek (2011), *"Social and Physical Disorder. How Community, Business Presence and Entrepreneurs Influence Disorder in Dutch Neighborhoods."* ICS-dissertation, Utrecht
178. Miranda Vervoort (2011), *"Living Together Apart? Ethnic Concentration in the Neighborhood and Ethnic Minorities' Social Contacts and Language Practices."* ICS-dissertation, Utrecht
179. Agnieszka Kanas (2011), *"The Economic Performance of Immigrants. The Role of Human and Social Capital."* ICS-dissertation, Utrecht
180. Lea Ellwardt (2011), *"Gossip in Organizations. A Social Network Study."* ICS-dissertation, Groningen
181. Annemarije Oosterwaal (2011), *"The Gap between Decision and Implementation. Decision making, Delegation and Compliance in Governmental and Organizational Settings."* ICS-dissertation, Utrecht
182. Natascha Notten (2011), *"Parents and the Media. Causes and Consequences of Parental Media Socialization."* ICS-dissertation, Nijmegen
183. Tobias Stark (2011), *"Integration in Schools. A Process Perspective on Students' Interethnic Attitudes and Interpersonal Relationships."* ICS-dissertation, Groningen
184. Giedo Jansen (2011), *"Social Cleavages and Political Choices. Large-scale Comparisons of Social Class, Religion and Voting Behavior in Western Democracies."* ICS-dissertation, Nijmegen
185. Ruud van der Horst (2011), *"Network Effects on Treatment Results in a Closed Forensic Psychiatric Setting."* ICS-dissertation, Groningen
186. Mark Levels (2011), *"Abortion Laws in European Countries between 1960 and 2010. Legislative Developments and Their Consequences for Women's Reproductive Decision-making."* ICS-dissertation, Nijmegen
187. Marieke van Londen (2012), *"Exclusion of ethnic minorities in the Netherlands. The effects of individual and situational characteristics on opposition to ethnic policy and ethnically mixed neighbourhoods."* ICS-dissertation, Nijmegen
188. Sigrid Mohnen (2012), *"Neighborhood context and health: How neighborhood social capital affects individual health."* ICS-dissertation, Utrecht
189. Asya Zhelyazkova (2012), *"Compliance under Controversy: Analysis of the Transposition of European Directives and their Provisions."* ICS-dissertation, Utrecht
190. Valeska Korff (2012), *"Between Cause and Control: Management in a Humanitarian Organization."* ICS-dissertation, Groningen
191. Maike Gieling (2012), *"Dealing with Diversity: adolescents' support for civil liberties and immigrant rights."* ICS-dissertation, Utrecht
192. Katya Ivanova (2012), *"From Parents to Partners: The Impact of Family on Romantic Relationships in Adolescence and Emerging Adulthood."* ICS-dissertation, Groningen

193. Jelmer Schalk (2012), *"The Performance of Public Corporate Actors: Essays on Effects of Institutional and Network Embeddedness in Supranational, National, and Local Collaborative Contexts."* ICS-dissertation, Utrecht
194. Alona Labun (2012), *"Social Networks and Informal Power in Organizations."* ICS-dissertation, Groningen
195. Michal Bojanowski (2012), *"Essays on Social Network Formation in Heterogeneous Populations: Models, Methods, and Empirical Analyses."* ICS-dissertation, Utrecht
196. Anca Minescu (2012), *"Relative Group Position and Intergroup Attitudes in Russia."* ICS-dissertation, Utrecht
197. Marieke van Schellen (2012), *"Marriage and crime over the life course. The criminal careers of convicts and their spouses."* ICS-dissertation, Utrecht
198. Mieke Maliepaard (2012), *"Religious Trends and Social Integration: Muslim Minorities in the Netherlands."* ICS-dissertation, Utrecht
199. Fransje Smits (2012), *"Turks and Moroccans in the Low Countries around the year 2000: determinants of religiosity, trend in religiosity and determinants of the trend."* ICS-dissertation, Nijmegen
200. Roderick Sluiter (2012), *"The Diffusion of Morality Policies among Western European Countries between 1960 and 2010. A Comparison of Temporal and Spatial Diffusion Patterns of Six Morality and Eleven Non-morality Policies."* ICS-dissertation, Nijmegen
201. Nicoletta Balbo (2012), *"Family, Friends and Fertility."* ICS-dissertation, Groningen
202. Anke Munniksma (2013), *"Crossing ethnic boundaries: Parental resistance to and consequences of adolescents' cross-ethnic peer relations"* ICS-dissertation, Groningen
203. Anja-Kristin Abendroth (2013), *"Working Women in Europe. How the Country, Workplace, and Family Context Matter."* ICS-dissertation, Utrecht
204. Katia Begall (2013), *"Occupational Hazard? The Relationship between Working Conditions and Fertility."* ICS-dissertation, Groningen
205. Hidde Bekhuis (2013), *"The Popularity of Domestic Cultural Products: Cross-national Differences and the Relation to Globalization."* ICS-dissertation, Utrecht
206. Lieselotte Blommaert (2013), *"Are Joris and Renske more employable than Rashid and Samira? A study on the prevalence and sources of ethnic discrimination in recruitment in the Netherlands using experimental and survey data."* ICS-dissertation, Utrecht
207. Wiebke Schulz (2013), *"Careers of Men and Women in the 19th and 20th Centuries."* ICS-dissertation, Utrecht
208. Ozan Aksoy (2013), *"Essays on Social Preferences and Beliefs in Non-embedded Social Dilemmas."* ICS-dissertation, Utrecht
209. Dominik Morbitzer (2013), *"Limited Farsightedness in Network Formation."* ICS-dissertation, Utrecht
210. Thomas de Vroome (2013), *"Earning Your Place: The Relation Between Immigrants' Economic and Psychological Integration in the Netherlands."* ICS-dissertation, Utrecht
211. Marloes de Lange (2013), *"Causes and Consequences of Employment Flexibility Among Young People. Recent Developments in the Netherlands and Europe."* ICS-dissertation, Nijmegen
212. Roza Meuleman (2014), *"Consuming the Nation. Domestic cultural consumption: its stratification and relation with nationalist attitudes."* ICS-dissertation, Utrecht

213. Esther Havekes (2014), *"Putting interethnic attitudes in context. The relationship between neighbourhood characteristics, interethnic attitudes and residential behaviour."* ICS-dissertation, Utrecht
214. Zoltán Lippényi (2014), *"Transitions toward an open society? Intergenerational occupational mobility in Hungary in the 19th and 20th centuries."* ICS-dissertation, Utrecht
215. Anouk Smeekes (2014), *"The presence of the past: Historical rooting of national identity and current group dynamics."* ICS-dissertation, Utrecht
216. Michael Savelkoul (2014), *"Ethnic Diversity and Social capital. Testing Underlying Explanations Derived from Conflict and Contact Theories in Europe and the United States."* ICS-dissertation, Nijmegen
217. Martijn Hogerbrugge (2014), *"Misfortune and family: How negative events, family ties, and lives are linked."* ICS-dissertation, Utrecht
218. Gina-Felicia Potarca (2014), *"Modern Love. Comparative Insights in Online Dating Preferences and Assortative Mating."* ICS dissertation, Groningen
219. Mariska van der Horst (2014), *"Gender, Aspirations, and Achievements: Relating work and family aspirations to occupational outcomes."* ICS-dissertation, Utrecht
220. Gijs Huitsing (2014), *"A Social network perspective on bullying"* ICS dissertation, Groningen
221. Thomas Kowalewski (2015), *"Personal growth in organizational contexts."* ICS-dissertation, Groningen
222. Manuel Muñoz-Herrera (2015), *"The impact of individual differences on network relations: Social exclusion and inequality in productive exchange and coordination games."* ICS-dissertation, Groningen
223. Tim Immerzeel (2015), *"Voting for a change. The democratic lure of populist radical right parties in voting behavior."* ICS-dissertation, Utrecht
224. Fernando Nieto Morales (2015), *"The control imperative: Studies on reorganization in the public and private sectors."* ICS-dissertation, Groningen
225. Jellie Sierksma (2015), *"Bounded helping: How morality and intergroup relations shape children's reasoning about helping."* ICS-dissertation, Utrecht
226. Tinka Veldhuis (2015), *"Captivated by fear. An evaluation of terrorism detention policy."* ICS-dissertation, Groningen
227. Miranda Visser (2015), *"Loyalty in humanity. Turnover among expatriate humanitarian aid workers."* ICS-dissertation, Groningen
228. Sarah Westphal (2015), *"Are the kids alright? Essays on postdivorce residence arrangements and children's well-being."* ICS-dissertation, Utrecht
229. Britta Rüschhoff (2015), *"Peers in careers: Peer relationships in the transition from school to work."* ICS dissertation, Groningen
230. Nynke van Miltenburg (2015), *"Cooperation under peer sanctioning institutions: Collective decisions, noise, and endogenous implementation."* ICS-dissertation, Utrecht
231. Antonie Knigge (2015), *"Sources of sibling similarity. Status attainment in the Netherlands during modernization."* ICS-dissertation, Utrecht
232. Sanne Smith (2015), *"Ethnic segregation in friendship networks. Studies of its determinants in English, German, Dutch, and Swedish school classes."* ICS-dissertation, Utrecht

233. Patrick Präg (2015), *"Social stratification and health. Four essays on social determinants of health and wellbeing."* ICS dissertation, Groningen
234. Wike Been (2015), *"European top managers' support for work-life arrangements"* ICS-dissertation, Utrecht
235. André Grow (2016), *"Status differentiation: New insights from agent-based modeling and social network analysis"* ICS-dissertation, Groningen
236. Jesper Røzer (2016), *"Family and personal networks. How a partner and children affect social relationships"* ICS-dissertation, Utrecht
237. Kim Pattiselanno (2016), *"At your own risk: The importance of group dynamics and peer processes in adolescent peer groups for adolescents' involvement in risk behaviors"* ICS- dissertation, Groningen
238. Vincenz Frey (2016), *"Network formation and trust"* ICS-dissertation, Utrecht
239. Rozemarijn van der Ploeg (2016), *"Be a buddy, not a bully? Four studies on social and emotional processes related to bullying, defending, and victimization"* ICS-dissertation, Groningen
240. Tali Spiegel (2016), *"Identity, career trajectories and wellbeing: A closer look at individuals with degenerative eye conditions"* ICS- dissertation, Groningen
241. Felix Christian Tropf (2016), *"Social Science Genetics and Fertility"* ICS-dissertation, Groningen
242. Sara Geven (2016), *"Adolescent problem behavior in school: the role of peer networks"* ICS-dissertation, Utrecht
243. Josja Rokven (2016), *"The victimization-offending relationship from a longitudinal perspective"* ICS-dissertation, Nijmegen
244. Maja Djundeva (2016), *"Healthy ageing in context: Family welfare state and the life course"* ICS-dissertation, Groningen
245. Mark Visser (2017), *"Inequality between older workers and older couples in the Netherlands. A dynamic life course perspective on educational and social class differences in the late career"* ICS-dissertation, Nijmegen
246. Beau Oldenburg (2017), *"Bullying in schools: The role of teachers and classmates"* ICS-dissertation, Groningen
247. Tatang Muttaqin (2017), *"The education divide in Indonesia: Four essays on determinants of unequal access to and quality of education"* ICS-dissertation, Groningen
248. Margriet van Hek (2017), *"Gender inequality in educational attainment and reading performance. A contextual approach."* ICS-dissertation, Nijmegen
249. Melissa Verhoef-van Dorp (2017), *"Work schedules, childcare and well-being. Essays on the associations between modern-day job characteristics, childcare arrangements and the well-being of parents and children"* ICS-dissertation, Utrecht
250. Timo Septer (2017), *"Goal priorities, cognition and conflict: Analyses of cognitive maps concerning organizational change"* ICS-dissertation, Groningen
251. Bas Hofstra (2017), *"Online Social Networks: Essays on Membership, Privacy, and Structure"* ICS-dissertation, Utrecht
252. Yassine Khoudja (2018), *"Women's labor market participation across ethnic groups: The role of household conditions, gender role attitudes, and religiosity in different national contexts"* ICS-dissertation, Utrecht

253. Joran Laméris (2018), *"Living together in diversity. Whether, why and where ethnic diversity affects social cohesion"* ICS-dissertation, Nijmegen
254. Maaïke van der Vleuten (2018), *"Gendered Choices. Fields of study of adolescents in the Netherlands"* ICS-dissertation, Utrecht
255. Mala Sondang Silitonga (2018), *"Corruption in Indonesia: The impact of institutional change, norms, and networks"* ICS-dissertation, Groningen
256. Manja Coopmans (2018), *"Rituals of the past in the context of the present. The role of Remembrance Day and Liberation Day in Dutch society"* ICS-dissertation, Utrecht
257. Paul Hindriks (2018), *"The Struggle for Power: Attitudes towards the political participation of ethnic minorities"* ICS-dissertation, Utrecht
258. Nynke Niezink (2018), *"Modeling the dynamics of networks and continuous behavior"* ICS-dissertation, Groningen
259. Simon de Bruijn (2018), *"Reaching agreement after divorce and separation. Essays on the effectiveness of parenting plans and divorce mediation"* ICS-dissertation, Utrecht
260. Susanne van 't Hoff-de Goede (2018), *"While you were locked up. An empirical study on the characteristics, social surroundings and wellbeing of partners of prisoners in The Netherlands"* ICS-dissertation, Utrecht
261. Loes van Rijsewijk (2018), *"Antecedents and Consequences of Helping among Adolescents"* ICS-dissertation, Groningen
262. Mariola Gremmen (2018), *"Social network processes and academic functioning. The role of peers in students' school well-being, academic engagement, and academic achievement"* ICS-dissertation, Groningen
263. Jeanette Renema (2018), *"Immigrants' support for welfare spending. The causes and consequences of welfare usage and welfare knowledgeability"* ICS-dissertation, Nijmegen
264. Suwatin Miharti (2018), *"Community health centers in Indonesia in the era of decentralization. The impact of structure, staff composition and management on health outcomes"* ICS-dissertation, Groningen
265. Chaïm la Roi (2019), *"Stigma and stress: Studies on attitudes towards sexual minority orientations and the association between sexual orientation and mental health"* ICS-dissertation, Groningen
266. Jelle Lössbroek (2019), *"Turning grey into gold. Employer-employee interplay in an ageing workforce"* ICS-dissertation, Utrecht
267. Nikki van Gerwen (2019), *"Employee cooperation through training. A multi-method approach"* ICS-dissertation, Utrecht
268. Paula Thijs (2019), *"Trends in cultural conservatism: The role of educational expansion, secularisation, and changing national contexts"* ICS-dissertation, Nijmegen
269. Renske Verweij (2019), *"Understanding childlessness: Unravelling the link with genes and the socio-environment"* ICS-dissertation, Groningen
270. Niels Blom (2019), *"Partner relationship quality under pressing work conditions. Longitudinal and cross-national investigation"* ICS-dissertation, Nijmegen
271. Müge Simsek (2019), *"The dynamics of religion among native and immigrant youth in Western Europe"* ICS-dissertation, Utrecht
272. Leonie van Breeschoten (2019), *"Combining a career and childcare: The use and usefulness of work-family policies in European organizations"* ICS-dissertation, Utrecht

- 273. Roos van der Zwan (2019), *"The political representation of ethnic minorities and their vote choice"* ICS dissertation, Nijmegen
- 274. Ashwin Rambaran (2019), *"The classroom as context for bullying: A social network approach"* ICS dissertation, Groningen
- 275. Dieko Bakker (2019), *"Cooperation and social control: Effects of preferences, institutions, and social structure"* ICS-dissertation, Groningen
- 276. Femke van der Werf (2019), *"Shadow of a rainbow? National and ethnic belonging in Mauritius"* ICS dissertation, Utrecht
- 277. Robert Krause (2019), *"Multiple Imputation for Missing Network Data"* ICS-dissertation, Groningen
- 278. Take Sipma (2020), *"Economic insecurity and populist radical right voting"* ICS-dissertation, Nijmegen
- 279. Mathijs Kros (2020), *"The nature of negative contact: studies on interethnic relations in western societies"* ICS dissertation, Utrecht
- 280. Lonneke van den Berg (2020), *"Time to leave: Individual and contextual explanations for the timing of leaving home"* ICS dissertation, Amsterdam
- 281. Marianne Hooijsma (2020), *"Clashrooms: Interethnic peer relationships in schools"* ICS-dissertation, Groningen
- 282. Marina Tulin (2020), *"Blind Spots in Social Resource Theory: Essays on the Creation, Maintenance and Returns of Social Capital"* ICS-dissertation, Amsterdam
- 283. Tessa Kaufman (2020), *"Toward Tailored Interventions: Explaining, Assessing, and Preventing Persistent Victimization of Bullying"* ICS-dissertation, Groningen
- 284. Lex Thijssen (2020), *"Racial and Ethnic Discrimination in Western Labor Markets: Empirical Evidence from Field Experiments"* ICS dissertation, Utrecht
- 285. Lukas Norbutas (2020), *"Trust on the Dark Web: An analysis of illegal online drug markets"* ICS dissertation, Utrecht

Why would anyone engage in risky business with a total stranger? In many types of social and economic interactions, the presence of trust obviates the use of more formal and costly means of protection against opportunistic behavior by interaction partners. But what if your business is illegal and formal protection is unavailable? This dissertation delves into illegal online drug trade networks on the Dark Web to provide answers on how individuals overcome uncertainty and build trust under extremely risky conditions. Digital footprints left by drug buyers and sellers in illegal online marketplaces provide a perfect opportunity to observe how people build and maintain trust in an environment where everyone is anonymous, anyone can disappear with the partner's money or get them arrested. The results of five empirical chapters in this study shed light on what can be learned from illegal cooperation in the darker corners of the Internet.

Lukas Norbutas obtained his Research Master's degree in Sociology and Social Research (cum laude) at Utrecht University in 2015. This dissertation was written as part of his Ph.D. research project at the Interuniversity Centre for Social Science Theory and Methodology (ICS), the Department of Sociology at Utrecht University and the Netherlands Institute for the Study of Crime and Law Enforcement.