Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? [*]

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Abstract

Cryptocurrencies are among the largest unregulated markets in the world. We find that approximately one-quarter of bitcoin users and one-half of bitcoin transactions are associated with illegal activity. Around $72 billion of illegal activity per year involves bitcoin, which is close to the scale of the US and European markets for illegal drugs. The illegal share of bitcoin activity declines with mainstream interest in bitcoin and with the emergence of more opaque cryptocurrencies. The techniques developed in this paper have applications in cryptocurrency surveillance. Our findings suggest that cryptocurrencies are transforming the way black markets operate by enabling "black e-commerce".

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1. Introduction

Cryptocurrencies have grown rapidly in price, popularity, and mainstream adoption. The total market capitalization of bitcoin alone exceeds $250 billion as at January 2018, with a further $400 billion in over 1,000 other cryptocurrencies. The numerous online cryptocurrency exchanges and markets have daily dollar volume of around $50 billion.[2] Over 170 "cryptofunds" have emerged (hedge funds that invest solely in cryptocurrencies), attracting around $2.3 billion in assets under management.[3] Recently, bitcoin futures have commenced trading on the CME and CBOE, catering to institutional demand for trading and hedging bitcoin.[4] What was once a fringe asset is quickly maturing.

The rapid growth in cryptocurrencies and the anonymity that they provide users has created considerable regulatory challenges. An application for a $100 million cryptocurrency Exchange Traded Fund (ETF) was rejected by the US SEC in March 2017 (and again in 2018) amid concerns including the lack of regulation. China has banned residents from trading cryptocurrencies and made initial coin offerings (ICOs) illegal. Central bank heads have publically expressed concerns about cryptocurrencies. While cryptocurrencies have many potential benefits including faster and more efficient settlement, regulatory concerns center around their use in illegal trade (drugs, hacks and thefts, illegal pornography, even murder-for-hire), potential to fund terrorism, launder money, and avoid capital controls. There is little doubt that by providing a digital and anonymous payment mechanism, cryptocurrencies such as bitcoin have facilitated the growth of "darknet" online marketplaces in which illegal goods and services are traded. The recent FBI seizure of over $4 million of bitcoin from one such marketplace, the "Silk Road", provides some idea of the scale of the problem faced by regulators.

This paper seeks to quantify and characterize the illegal trade facilitated by bitcoin. In doing so, we hope to better understand the nature and scale of the "problem" facing this nascent technology. We develop methods for identifying illegal activity in bitcoin. These methods can also be used in analyzing many other blockchains.

Several recent seizures of bitcoin by law enforcement agencies (including the US FBI's seizure of the "Silk Road" marketplace), combined with the public nature of the blockchain, provide us with a unique laboratory in which to analyze the illegal ecosystem that has evolved in the bitcoin network. Although individual identities are masked by the pseudo-anonymity of a 26-35 character alpha-numeric address, the public nature of the blockchain allows us to link bitcoin transactions to individual "users" (market participants) and then further identify the users that had bitcoin seized by authorities. Bitcoin

[2] SEC Release No. 34-79103, March 10, 2017; and https://coinmarketcap.com

[3] Source: financial research firm Autonomous Next and cnbc.com.

[4] Bitcoin futures commenced trading on the CME (Chicago Mercantile Exchange) on December 18, 2017 and on the Chicago Board Options Exchange (CBOE) on December 10, 2017. A bitcoin futures contract on CBOE is for one bitcoin, whereas on CBOE it is five bitcoins. At a price of approximately $20,000 per bitcoin at the time the CME bitcoin futures launched, one CME bitcoin futures contract has a notional value of around $100,000.

seizures (combined with a few other sources) provide us with a sample of users known to be involved in illegal activity. This is the starting point for our analysis, from which we apply two different empirical approaches to go from the sample to the estimated population of illegal activity.

Our first approach exploits the trade networks of users known to be involved in illegal activity ("illegal users"). We use the bitcoin blockchain to reconstruct the complete network of transactions between market participants. We then applying a type of network cluster analysis to identify two distinct communities in the data—the legal and illegal communities. Our second approach exploits certain characteristics that distinguish between legal and illegal bitcoin users, applying detection controlled estimation models (simultaneous equation models with latent variables). For example, we measure the extent to which individual bitcoin users take actions to conceal their identity and trading records, which is a predictor of involvement in illegal activity.

We find that illegal activity accounts for a substantial proportion of the users and trading activity in bitcoin. For example, approximately one-quarter of all users (25%) and close to one-half of bitcoin transactions (44%) are associated with illegal activity. Furthermore, approximately one-fifth (20%) of the total dollar value of transactions and approximately one-half of bitcoin holdings (51%) through time are associated with illegal activity. Our estimates suggest that in the most recent part of our sample (April 2017), there are an estimated 24 million bitcoin market participants that use bitcoin primarily for illegal purposes. These users annually conduct around 36 million transactions, with a value of around $72 billion, and collectively hold around $8 billion worth of bitcoin.

To give these numbers some context, a report to the US White House Office of National Drug Control Policy estimates that drug users in the United States in 2010 spend in the order of $100 billion annually on illicit drugs.[5] Using different methods, the size of the European market for illegal drugs is estimated to be at least €24 billion per year.[6] While comparisons between such estimates and ours are imprecise for a number of reasons (and the illegal activity captured by our estimates is broader than just illegal drugs), they do provide a sense that the scale of the illegal activity involving bitcoin is not only meaningful as a proportion of bitcoin activity, but also in absolute dollar terms.

The use of bitcoin in illegal trade has interesting time-series patterns. In recent years (since 2015), the proportion of bitcoin activity associated with illegal trade has declined. We attribute this trend to two main factors. The first is an increase in mainstream and speculative interest in bitcoin. For example, we find that the proportion of illegal activity in bitcoin is inversely related to the Google search intensity for

[5] The report, prepared by the RAND Corporation, estimates the user of cocaine, crack, heroin, marijuana, and methamphetamine, and is available at (www.rand.org/t/RR534). A significant share of the illegal activity involving bitcoin is likely associated with buying/selling illegal drugs online (e.g., Soska and Christin, 2015), which is what motivates the comparison with the size of the market for illegal drugs.

[6] The estimate is from the European Monitoring Centre for Drugs and Drug Addiction / Europol "EU Drug Markets Report" for the year 2013. (http://www.emcdda.europa.eu/attachements.cfm/att_194336_EN_TD3112366ENC.pdf)

the keyword "bitcoin". Furthermore, while the *proportion* of illegal bitcoin activity has declined, the *absolute amount* of such activity has continued to increase, indicating that the declining proportion is due to rapid growth in legal bitcoin use. The second factor is the emergence of alternative cryptocurrencies that are more opaque and better at concealing a user's activity (e.g., Dash, Monero, and ZCash). We find that the emergence of such alternative cryptocurrencies is also associated with a decrease in the proportion of illegal activity in bitcoin. Despite these two factors affecting the use of bitcoin in illegal activity, as well as numerous darknet marketplace seizures by law enforcement agencies, the *amount* of illegal activity involving bitcoin at the end of our sample in April 2017 remains close to its all-time high.

Bitcoin users that are involved in illegal activity differ from other users in several characteristics. Differences in transactional characteristics are generally consistent with the notion that while illegal users predominantly (or solely) use bitcoin as a payment system to facilitate trade in illegal goods/services, some legal users treat bitcoin as an investment or speculative asset. Specifically, illegal users tend to transact more, but in smaller transactions. They are also more likely to repeatedly transact with a given counterparty. Despite transacting more, illegal users tend to hold less bitcoin, consistent with them facing risks of having bitcoin holdings seized by authorities.

We find several other robust predictors of involvement in illegal activity. A user is more likely to be involved in illegal activity if they trade when there are many darknet marketplaces in operation, few shadow coins in existence, little bitcoin hype or mainstream interest, and immediately following darknet marketplaces seizures or scams. A user is also more likely to be involved in illegal activity if they use "tumbling" and/or "wash trades"—trading techniques that help conceal one's activity.

The network of bitcoin transactions between illegal users is three to four times denser, with users much more connected with one another through transactions. The higher density is consistent with illegal users transacting more and using bitcoin primarily as a payment system in buying/selling goods.

It is important to consider the differences between cryptocurrencies and cash. After all, cash is also largely anonymous (traceable only through serial numbers) and has therefore traditionally played an important role in facilitating crime and illegal trade (e.g., Rogoff, 2016). The key difference is that cryptocurrencies (similar to PayPal and credit cards) enable digital transactions and thus e-commerce. Arguably, the ability to make digital payments revolutionized retail and wholesale trade. Online shopping substantially impacted the structure of retailing, consumption patterns, choice and hence welfare, marketing, competition, and ultimately supply and demand. Until cryptocurrencies, such impacts were largely limited to legal goods and services due to the traceability of digital payments. Cryptocurrencies have changed this, by combining the anonymity of cash with digitization, which enables efficient anonymous online and cross-border commerce. Cryptocurrencies therefore have the potential to cause an important structural shift in how the black market operates.

While the emergence of illegal darknet marketplaces illustrates that this shift has commenced, it is not obvious to what extent the black market will adopt the opportunities for e-commerce and digital payments via cryptocurrencies—this is an important empirical question. Our findings illustrate the dynamics of this adoption process and suggest that eight years after the introduction of the first cryptocurrency, the black market has indeed adopted this form of electronic payment on a meaningful scale. Thus, our results suggest that cryptocurrencies are having a material impact on the way the black market for illegal goods and services operates.

Our findings have a number of further implications, which we discuss in Section 6. Blockchain technology and the systems/protocols that can be implemented on a blockchain have the potential for revolutionizing numerous industries. In shedding light on the dark side of cryptocurrencies, we hope this research will reduce some of the regulatory uncertainty about the negative consequences and risks of this innovation, facilitating more informed policy decisions that assess both the costs and benefits. In turn, we hope this contributes to these technologies reaching their potential. Second, our paper contributes to understanding the intrinsic value of bitcoin, highlighting that a significant component of its value as a payment system derives from its use in facilitating illegal trade. This has ethical implications for bitcoin as an investment, as well as valuation implications. Third, our paper moves the literature closer to understanding the welfare consequences of the growth in illegal online trade. A crucial piece of this puzzle is understanding the extent to which illegal online trade simply reflects a migration of activity that would have otherwise occurred on the street, versus the alternative that by making illegal goods more accessible, convenient to buy, and less risky to buy due to anonymity, "black e-commerce" could lead to growth in the aggregate black market. Our estimates contribute to understanding this issue, but further research is required to relate these estimates to trends in the offline black market to further our understanding of the welfare consequences.

This paper also makes a methodological contribution. The techniques developed in this paper can be used in cryptocurrency surveillance in a number of ways, including monitoring trends in illegal activity, its response to regulatory interventions, and how its characteristics change through time. The methods can also be used to identify key bitcoin users (e.g., "hubs" in the illegal trade network) which, when combined with other sources of information, can be linked to specific individuals. The techniques in this paper can also be used to study other types of activity in bitcoin or other cryptocurrencies / blockchains.

Our paper contributes to a few areas of recent literature, which we discuss in more detail in Section 6. We add to the literature on the economics of cryptocurrencies and applications of blockchain technology to securities markets by showing that one of the major uses of cryptocurrencies as a payment

system is in settings where anonymity is valued (e.g., illegal trade).[7] Our paper also contributes to the computer science literature that analyzes the degree of anonymity in bitcoin by developing algorithms that identify entities/users/activities in bitcoin's blockchain.[8] We exploit algorithms from this literature to identify individual users in the data, and we add new methods to the literature that go beyond observing individuals, to identification of communities and estimation of populations of users. Finally, our paper is also related to studies of darknet marketplaces and the online drug trade, including papers from computer science and drug policy.[9] We contribute to this literature by quantifying the amount of illegal activity that involves bitcoin, rather than studying a single market (e.g., Silk Road) or indirect lower-bound measures of darknet activity such as the feedback left by buyers. Empirically, we confirm that the estimated population of illegal activity is several times larger than what can be "observed" through studying observable darknet marketplaces and their customers.

The next section provides institutional details about bitcoin and the blockchain, darknet marketplaces in which illegal goods and services are bought/sold using bitcoin, and law enforcement efforts to monitor and disrupt illegal online activity. Section 3 describes the blockchain data used in this paper. Section 4 explains three approaches that we use to construct a sample of illegal activity and characterizes that sample. The sample forms the input to our empirical methods in Section 5 that quantify the total amount of illegal activity, its trends, and its characteristics. A discussion of the implications of the results and how they relate to existing studies is in Section 6, while Section 7 concludes.

2. Institutional details

2.1. The structure of the bitcoin blockchain

Bitcoin is an international currency, not associated with any country or central bank, backed only by its limited total supply and the willingness of bitcoin users to recognize its value.[10] Bitcoins are "mined" (created) by solving cryptographic puzzles that deterministically increase in difficulty and once solved can be easily verified. Each solution results in a new "block" and provides the miner with the "block reward" (currently 12.5 bitcoins), which incentivizes the miner. The difficulty of the cryptographic puzzles is adjusted after every 2,016 blocks (approximately 14 days) by an amount that ensures the average time between blocks remains ten minutes.

[7] See: Malinova and Park, 2016; Khapko and Zoican, 2016; Yermack, 2017; Huberman et al., 2017; Easley et al., 2017.
[8] See: Meiklejohn et al., 2013; Ron and Shamir, 2013; Androulaki et al., 2013; Tasca et al., 2016.
[9] See: Soska and Christin, 2015; Barratt et al., 2016a; Aldridge and Décary-Hétu, 2016; Van Buskirk et al., 2016.
[10] As of January 2017, over 16 million bitcoins had been mined out of a maximum of 21 million. This maximum limit is built into the protocol (Nakamoto, 2008).

Each block, as well as expanding the supply of bitcoin, confirms a collection of recent transactions (transactions since the last block). Each block also contains a reference to the last block, thereby forming a "chain", giving rise to the term "blockchain". The blockchain thus forms a complete and sequential record of all transactions and is publically available to any participant in the network.

Bitcoins are divisible to the "Satoshi", being one hundred millionth of one bitcoin (currently worth less than two hundredths of a cent). Each bitcoin holding (or parcel) is identified by an address, analogous to the serial number of a banknote. Unlike banknotes, bitcoin does not have to be held in round units (e.g., 5, 10, 50). Unless a holding of bitcoin with a given address is exactly spent in a transaction, the "change" from the transaction is returned to a new address forming a new parcel of bitcoin.

A bitcoin "user" (a participant in the network) stores the addresses associated with each parcel of bitcoin that they own in a "wallet". Similar to a conventional cash wallet, a bitcoin wallet balance is the sum of the balances of all the addresses inside the wallet. While individual bitcoin addresses are designed to be anonymous, it is possible to link addresses belonging to the same wallet when more than one address is used to make a purchase.

2.2. Darknet marketplaces and their microstructure

The "darknet" is a network like the internet, but that can only be accessed through particular communications protocols that provide greater anonymity than the internet. The darknet contains online marketplaces, much like EBay, but with anonymous communications, which also makes these marketplaces less accessible than online stores on the internet. Darknet marketplaces are particularly popular for trading illegal goods and services because the identities of buyers and sellers are concealed. The darknet is estimated to contain approximately 30,000 domains (Lewman, 2016).

To access a darknet marketplace, a user is generally required to establish an account (usually free) at the marketplace in order to browse vendor products (Martin, 2014a; Van Slobbe, 2016). Similar to the way PayPal propelled EBay, the secure, decentralized, and anonymous nature of cryptocurrencies has played an important role in the success of darknet marketplaces. While bitcoin is the most widespread cryptocurrency used in such marketplaces, other currencies have occasionally been adopted, either due to their popularity (such as *Ethereum*) or improved anonymity (such as *Monero*). Despite the availability of alternate currencies on some marketplaces, the vast majority of transactions on the darknet are still undertaken in bitcoin.[11]

A user that wants to buy goods or services on a darknet marketplace must first acquire cryptocurrency (typically from an online exchange or broker) and then deposit this in an address

[11] A recent estimate from a darknet marketplace operator identified bitcoin as accounting for 98% of transactions: https://www.wired.com/2017/01/monero-drug-dealers-cryptocurrency-choice-fire/.

belonging to the darknet marketplace (often termed a "hot wallet"). These funds are held in "escrow" by the marketplace. Vendor prices on darknet markets are often quoted inclusive of a marketplace fee. The escrow system also assists marketplace administrators in mediating disputes between buyers and sellers and minimizing scams in which money is collected without the intention of ever shipping any goods (Aldridge and Décary-Hétu, 2014; Christin, 2013). Funds are released when the vendor indicates the goods have been sent. In some marketplaces, the funds are held until the buyer indicates that the goods have been received. The escrow function of the darknet marketplaces sometimes leads to "exit scams", whereby a marketplace ceases operations but does not return bitcoin held in escrow. Many such scams have been perpetrated by marketplaces in the last five years, including *Sheep Marketplace* (2013), *Pirate Market* (2014), *Evolution* (2015), and *Nucleus* (2016).

The evolution of dark marketplaces allows sellers of illegal goods and services to reach global audiences (Van Buskirk et al., 2016). This internationalization of illegal trade necessitates more complex methods of communications and logistics to avoid detection. To this end, buyers placing an order with an online seller typically communicate using PGP (Pretty Good Privacy) encryption, which encodes and decodes messages using a pair of public and private keys (Cox, 2016). On some (typically more recent) marketplaces, this functionality is built into the site. Logistically, items are typically delivered by mail and the process by which this occurs has been widely documented (Christin, 2013; Van Hout and Bingham, 2013; Lavorgna, 2016; Van Slobbe, 2016). Many methods are used to minimize the chance of such deliveries being intercepted by law enforcement, including professional logos, vacuum sealed bags, posting small quantities of product, and including a (fake) return address (Christin, 2013; Basu, 2014; Tzanetakis et al., 2016). Customers are advised by marketplaces to avoid using their real name or address to minimize the risk of being caught by law enforcement agencies (Martin, 2014b).

After receiving their goods, buyers are encouraged to leave feedback about the seller, commenting on the arrival (or otherwise) of the goods, their quality, and overall service (Van Slobbe, 2016). Such feedback is paramount for developing a reputation in a marketplace that is primarily based on trust between participants, with few ramifications for "scamming" purchasers (Aldridge and Décary-Hétu, 2014; Tzanetakis et al., 2016).

To get a sense of how a buyer navigates a darknet marketplace, Figure 1 provides screenshots from one of the first darknet marketplaces, "Silk Road". Panel A provides an example of the "Drugs" page illustrating that a wide variety of illegal drugs, weapons, and forgeries can be purchased using bitcoin. Panel B provides an example of information about individual items and sellers. Clicking on the appropriate headings, one can obtain further information about the items (detailed description, insurance/refund policies, available postage methods and locations, security and encryption, and so on) and about the seller (their rating from buyers, detailed feedback from buyers, history of sales, and so on).

Panel C shows the interface for depositing bitcoin to Silk Road's escrow account, how to transfer bitcoins to a given seller, and how to withdraw bitcoins from escrow.

< Figure 1 >

By providing an anonymous, digital method of payment, bitcoin did for darknet marketplaces what PayPal did for EBay—provide a reliable, scalable, and convenient payment mechanism. What was also required was an anonymous way of hosting and accessing those illegal marketplaces. This issue is solved through the use of The Onion Router (TOR), originally developed by the US Navy. By routing the message through several nodes in the TOR network, TOR obfuscates the path (and hence the IP address) of a message sent between two clients.

The combination of TOR for covert communications and bitcoin for covert payments has led to the proliferation of darknet marketplaces. The most well-known marketplace was the "Silk Road" started in 2011. Since its shutdown by the FBI in 2013, numerous other marketplaces have sprung up (see Table A2 in Appendix A for a list). Despite frequent shutdowns, seizures and scams, measures of darknet marketplace activity indicate steady growth in the number of market participants and products (Matthews et al., 2017). For example, one of the largest marketplaces in 2017, "AlphaBay", had over 350,000 items available for sale in categories such as drugs, weapons, malware, and illegal pornography.

2.3. Surveillance and cryptocurrency seizures from darknet marketplaces

Cryptocurrencies have proven effective not only in facilitating illegal trade, but also in the detection of illegal activity due to the public nature of the blockchain. Even though bitcoin has been used extensively in illegal activity, some argue that the blockchain actually makes it easier for law enforcement to detect illegal activity, despite the currency's anonymity. Koshy, Koshy, and McDaniel (2014) show that by monitoring transactions transmitted from computers to the blockchain, they are able to link individual transactions to the IP address of the sender. Meiklejohn et al. (2013) describe how tracing a bitcoin theft on the blockchain to bitcoin exchanges could be used by authorities with subpoena powers to potentially identify perpetrators. Yermack (2017) hypothesizes that the growing popularity of bitcoin will inevitably lead to a growing market for de-anonymizing technologies, leading to increased transparency of the users making transactions on the blockchain. In response to these pressures, supporters of the anonymity provided by cryptocurrencies are actively developing new currencies that challenge law enforcement's detection methods. Such currencies include *Monero*, which hides user's public keys among a group of public keys that contain the same amount (known as "Ring Signatures"), and *ZCash* (launched

in 2016), which uses zero-knowledge proofs that hide sender, recipient, and transaction amount (Noether, 2015; Ben-Sasson et al., 2014).

Recently, law enforcement agencies have been successful in seizing bitcoin from a number of darknet marketplaces. For example, the Silk Road marketplace was raided by the FBI on October 2, 2013, seizing bitcoin from customer and supplier escrow accounts (hot wallets) and from the owner/operator, Ross William Ulbricht. After the closure of the Silk Road, law enforcement agencies successfully seized bitcoin from several other illegal sites/individuals (see Table A1 of Appendix A). Numerous darknet sites were raided and shut down in "Operation Onymous"; an international collaboration between US and European law enforcement agencies that targeted illegal darknet sites. Despite the seizures, illegal darknet marketplaces continue to operate, with many new ones being created since the seizures.

The seized bitcoin from these operations allows us to identify bitcoin users (customers, suppliers, and marketplace operators) involved in illegal activity. These observations provide a starting point from which to estimate the extent of illegal activity involving bitcoin.

Law enforcement agencies use a number of strategies to detect illegal activity on the darknet, ranging from cyber-surveillance to forensic analysis. Given that detected illegal activity feeds into our identification techniques, it is important to understand law enforcement strategies. Christin (2013) and Kruithof et al. (2016) describe a number of such strategies, including: infiltrating the TOR network to determine individual IP addresses, decoding the financial infrastructure of bitcoin to identify individuals, and using traditional forensic and investigative techniques on seized packages. Law enforcement agencies monitor suspicious packages passing through the postal service. Agencies also order drugs on darknet marketplaces to investigate the return address on the package. For example, an unusual amount of outgoing mail from a large Australian drug dealer led authorities to seize over 24,000 in bitcoin, along with a wide array of drugs and cash. Investigators also sometimes pose as suppliers to gather addresses of customers and reveal their identities. Finally, by conducting major seizures, agencies can create distrust in the online trade of illegal drugs among participants (Van Slobbe, 2016; Christin, 2013). Large-scale initiatives such as "Operation Onymous", in which law enforcement agencies shut down several illegal marketplaces and made 17 arrests across 17 countries, can discourage illegal online activity by increasing the risk of detection (Franklin, Paxson, Perrig, and Savage, 2007).

3. Data and descriptive statistics

We extract the complete record of bitcoin transactions from the public bitcoin blockchain, from the first block on January 3, 2009, to the end of April 2017. For each transaction, we collect the transaction ID, sender and recipient address, timestamp, block ID, transaction fee, and transaction amount.

3.1 Identifying users in transaction-level bitcoin data

The data that make up the bitcoin blockchain reveal "addresses" (identifiers for parcels of bitcoin) but not the "users" (individuals) that control those addresses. A user typically controls several addresses. This one-to-many mapping occurs partly as a result of various activities that users employ to preserve their anonymity and partly due to transaction mechanics (e.g., when a user receives "change" in a transaction, the change is given a new address).[12] We find addresses connected to a single user with the Union-Find algorithm, which is developed by Cormen, Leiserson, Rivest, and Stein (2001) and Ron and Shamir (2013) and used in several related papers such as Meiklejohn et al. (2013). This algorithm transforms the transaction-level data into user-level data, linking each transaction to the associated users.

The following illustrates how the Union-Find algorithm works. A transaction usually involves several addresses from one user. For example, the payer ("sender") of bitcoin might send bitcoin from multiple addresses and also receive change to a new address. Because a user must control the private key of each address from which bitcoin is sent in a given transaction, all of the sender's addresses in one transaction are almost certainly associated with one user. Transitivity is then used to link the addresses of a user across multiple transactions. For example, suppose two separate transactions are observed; one in which bitcoin is sent from addresses A and B and another in which bitcoin is sent from addresses B and C. The first transaction identifies addresses A and B as belonging to the one user, while the second identifies B and C as belonging to the same user. By transitivity, all three addresses (A, B, and C) belong to the same user.

None of the existing algorithms that cluster bitcoin addresses by user has perfect accuracy.[13] The Union-Find algorithm is the most widely used approach, primarily because the errors it makes (too little clustering of addresses rather than too much clustering) are conservative in most applications (Meiklejohn et al, 2013). The Union-Find algorithm might fail to cluster together two sets of addresses controlled by the one user if the user never makes a transaction that uses an address from each set. In such instances, two or more address clusters might in fact correspond to one user.[14] In contrast, the Union-Find algorithm (unlike other approaches such as those that exploit the change from transactions) is very unlikely to make the opposite and more severe error of incorrectly clustering together sets of addresses that involve *more* than one user. In our application, too little clustering (and thus having instances where two or more clusters correspond to one actual user) is unlikely to have severe consequences for our empirical methods,

[12] For example, individuals can send bitcoin to a "tumbling" service which then returns the bitcoin (minus a fee) to a new address, or by sending bitcoin to oneself using a newly generated address as the recipient of the transaction (Ron and Shamir, 2013).

[13] For example, Androulaki et al. (2013) examine two approaches using simulations and find that many, but not all, of the users can be correctly identified by clustering algorithms even when users try to enhance their privacy by creating new addresses.

[14] Meiklejohn et al. (2013) empirically find that this error is "not too common" in bitcoin blockchain analysis.

whereas incorrectly joining multiple users into a single cluster would be far more problematic.[15] Therefore, the Union-Find algorithm is a suitable choice given our requirements.

3.2 Filters

In this study, we are primarily interested in quantifying the amount of illegal trade that uses bitcoin. Currency conversion transactions (between bitcoin and fiat currency or other cryptocurrencies), which are mainly done via bitcoin exchanges, are also recorded on the bitcoin blockchain but do not involve trade in the sense of buying or selling goods or services. In our baseline analysis, we therefore remove bitcoin exchanges (and their transactions) from the data to avoid inflating activity with currency conversion transactions. We also remove the major known bitcoin "miners" as their role in the network is one of providing transaction confirmations, i.e., the infrastructure of the bitcoin network. They receive block creation rewards and fees in the process of providing transaction confirmation services and we remove these from the sample.[16] The exchanges and miners are identified via "Wallet Explorer".[17]

We also exclude transactions that have a value of less than $1 on the day of the transaction.[18] Such transactions reflect negligible transfers of value and are therefore used for purposes such as messages, test transactions, and tips. Failure to exclude these transactions could significantly skew our data, particularly measures of the proportion of transactions. Other than these exclusions, we include all other bitcoin users and transaction activity on the bitcoin blockchain.

3.3 Descriptive statistics of user-level variables

Our sample has a total of approximately 106 million bitcoin users, who collectively conduct approximately 606 million transactions, transferring around $1.9 trillion.[19] For each user, we calculate a collection of variables that characterize features of their bitcoin transaction activity (e.g., transaction count, transaction size, transaction frequency, and number of counterparties). We also calculate a range of user-level variables that are more specific indicators of the nature of the activity in which a user is likely to be engaged, such as the number of illegal darknet marketplaces that operate at the time the user transacts, the extent to which the user engages in transactions designed to conceal their activity, and the

[15] For example, if a single actual user appears in the data as two or more clusters, all of those clusters could be correctly classified with the user's actual type (illegal or legal), whereas if a legal and illegal user are incorrectly clustered together, there is no way to assign a correct classification to the cluster.
[16] We remove 83 exchanges and 28 miners, collectively accounting for 15.3% of the total number of transactions.
[17] Wallet Explorer joins transactions into "wallets" (the equivalent of our "users") using a similar procedure to the one described above and then classifies a large number of wallets by type either on the basis of (i) having observed an address being advertised as part of a given entity (e.g., a known address from a bitcoin exchange), or (ii) having identified an entity's wallet by sending a small amount of bitcoin to the entity, where that address is linked to the larger wallet of the entity (similar to Meiklejohn et al., 2013). Data available from https://www.walletexplorer.com.
[18] These small transactions represent 23.9% of all transactions, but less than 0.0001% of total bitcoin volume.
[19] Exact numbers are in Table 3.

degree of interest in bitcoin at the time the user transacts (using Google search intensity). The detailed definitions of these variables are reported in Table 1.

< Table 1 >

Table 2 reports descriptive statistics about the user-level variables. Focusing on the variables that characterize a user's bitcoin transaction activity (Panel A), we see that a typical (median) user engages in three bitcoin transactions (mean *Transaction Count* is 5.7 transactions) with three different counterparties (mean of *Counterparties* is 4.2). Thus, a typical user has a low degree of concentration in counterparties, in that they do not repeatedly transact with the same counterparty (our measure of *Concentration*, which is a normalized Herfindahl–Hirschman Index, has a median of zero). There are a small number of highly active entities, with the most active having 11.4 million transactions and 4.4 million counterparties.

The average transaction size is around $5,000, but a typical transaction (the median *Transaction Size*) is much smaller at $112. Some transactions are very large, with the largest exceeding $90 million. For most users, their first and last bitcoin transaction occurs within the same month (the median *Existence Time* is one month), although some users are present for many years (the maximum *Existence Time* is 101 months, or just over eight years).

The other variables (Panel B) are more specific indicators of the nature of the activity in which a user is likely to be engaged and are thus important in our empirical models. We therefore define and discuss these variables when we turn to the empirical models.

< Table 2 >

4. Identifying a sample of illegal users

We identify a sample of addresses (and therefore users) involved in illegal activity using three approaches described below.

4.1. First approach: Bitcoin seizures by law enforcement agencies

Our first approach exploits bitcoin seizures by law enforcement agencies such as the US FBI. We manually identifying bitcoin seizures from news articles (via searches using Factiva) and US court records (via searches of the digital PACER records). Table A1 in Appendix A reports the list of seizures that we use. For each seizure, we extract information from court records and law enforcement agency disclosures about any identified bitcoin addresses or transactions (amounts and dates). From these details

we uniquely identify the users involved in the illegal activity, by matching up the bitcoin address or transaction identifier with our user-level data constructed from the bitcoin blockchain.

In some cases (e.g., the US FBI's seizure of Silk Road and Ross Ulbricht's holdings, and the Australian law enforcement's seizure of Richard Pollard's holdings) the law enforcement agency auctioned the seized bitcoin to the public. Given the public nature of the auctions, we are able to identify the auction transactions on the bitcoin blockchain and work backwards to identify the seized bitcoin addresses, which in turn identify those individuals that were involved in illegal activity and had some or all of their bitcoin holdings seized by law enforcement agencies. Using this approach we are able to identify 1,016 known illegal users, which we refer to as "*Seized Users*".

4.2. Second approach: Illegal darknet marketplaces and their users

Our second approach exploits the known "hot wallets" of major illegal darknet marketplaces. These are central accounts, many of which operate like escrow accounts, into which users of darknet marketplaces deposit or withdraw funds. We are able to identify 17 such marketplaces using data from the Wallet Explorer service, which in turn identifies these marketplaces using an approach similar to Meiklejohn et al. (2013), i.e., on the basis of small "probing" transactions undertaken with a given entity.

From these hot wallets, we identify slightly over 6 million darknet marketplace users as individuals that send to and/or receive bitcoin from a known darknet marketplace. We refer to the darknet marketplace hot wallets and their contributors/recipients as "*Black Market Users*".

An underlying assumption is that the trade that occurs in darknet marketplaces is illegal. This assumption is supported by ample anecdotal evidence, objective empirical evidence in the form of darknet market scrapes that show the goods and services traded there (e.g., Christin, 2013; Aldridge Décary-Hétu, 2014; Van Buskirk et al., 2014; Soska and Christin, 2015), as well as actions by law enforcement agencies, including indiscriminate seizures of *all* bitcoin from such markets.

4.3. Third approach: Users identified in darknet forums

Our third approach exploits information contained in the darknet, in particular the bitcoin addresses of users identified in darknet forums as selling goods/services. We use systematic scrapes of darknet forums from 2013 to 2017.[20] This allows us to identify users that might never have been caught by authorities and might not be otherwise identified in the data through transactions with known darknet marketplaces. Users often post bitcoin addresses in cases such as fraud (they did not receive their goods), quality checking, and for the purposes of advertising the address to which funds should be sent, including

[20] A list of known darknet markets is in Table A2 of Appendix. An archive of darknet forums during 2013-2015 is available at https://www.gwern.net/index. We scrape information from active darknet sites during 2016-2017.

in privately negotiated trade. While other studies have also scraped darknet marketplaces for certain types of information (e.g., Soska and Christin, 2015; Van Buskirk et al., 2016), as far as we know no other study has used scrapes to identify the bitcoin addresses of illegal users.

Using this approach, ee identify an additional 448 users that were not already identified in either of the previous two approaches. We refer to these as "*Forum Users*".

4.4. The sample of illegal users

Table 3 shows the number of illegal users identified using the three approaches above and various measures of their activity.[21] Together, there are 6,223,337 "observed" illegal users, representing 5.86% of all bitcoin participants. They account for an even larger share of transactions—a total of 196 million transactions, or around one-third of all transactions (32.38%). They also account for an even larger share of bitcoin holdings—throughout the sample period, the average dollar value of the bitcoin holdings of observed illegal users is around $1.3 billion, which is close to half (45.28%) of the average dollar value of holdings for all users.[22] Observed illegal users control around one-quarter (26.33%) of all bitcoin addresses, and the dollar value of their transactions is approximately 12.96% of the total dollar value of bitcoin transactions.

Within the three subgroups of illegal users, the largest group in terms of number of users is the "*Black market users*", followed by "*Seized users*" and then "*Forum users*". *Seized users* and *Forum users* are nevertheless meaningful subgroups, for example, they account for 3.93% and 2.47% of all transactions, respectively.

< Table 3 >

The results in Table 3 indicate that the sample of "observed" illegal users is already a substantial proportion of users and bitcoin transaction activity, without yet having applied methods to estimate the population of illegal users/activity. Capturing a relatively large sample of illegal activity is important because it provides rich information to our empirical methods that estimate the totality of illegal activity. The fact that the sample of illegal activity is drawn from three different approaches is also likely to help the subsequent empirical models by providing a more diverse sample.

[21] Given a transaction has two sides (a sender and a receiver) and it is possible for the different sides to be users from different groups, throughout the paper we (double) count the number of transactions and volume by considering each transaction from the perspective of the sender and receiver.

[22] The average holdings numbers are considerably lower than current holdings because for the first few years of bitcoin's existence, its market capitalization was much lower than it is currently.

Finally, given the nature of illegal activity could change through time, it is also important that our sample of observed illegal users spans different time periods and is not completely concentrated at one point in time. Figure 2 indicates that this is the case for our sample of observed illegal users and their activity. Figure 2 plots the time-series of the observed illegal users and their activity as a percentage of: total users (Panel A), total number of transaction (Panel B), the dollar value of all transactions (Panel C), and the dollar value of all bitcoin holdings (Panel D).

These time-series show that the observed illegal users are present during all points in time throughout our sample period. Their share of activity is highest at the start of the sample in 2009, and then again during a period from 2012 to the end of 2015. The first of these periods (the year 2009) is not particularly economically meaningful as the first year or two of bitcoin's existence involves a very small number of users and transactions compared to subsequent years. In contrast, the activity in the second period, 2012-2015, is meaningful. This period corresponds to the time when illegal darknet marketplaces grew rapidly in number and popularity. Silk Road 1 was established in January 2011 and soon became a popular venue in which to buy and sell illegal goods and services (e.g., Soska and Christin, 2015). After Silk Road 1 was shut down by the US FBI in October of 2013, a large number of other illegal darknet marketplaces commenced operating throughout 2013-2015 (see Table A2 of Appendix A). Thus, perhaps somewhat unsurprisingly, the peak activity of our sample of observed illegal users coincides with substantial darknet marketplace activity. However, we also observe a reasonable number of illegal users and illegal activity outside of this peak window.

< Figure 2 >

5. Quantifying and characterizing all illegal activity

Having identified a substantial sample of bitcoin users that are involved in illegal activity, our next step is to use the information in this sample to estimate the totality of illegal activity that uses bitcoin. We use two different methods to classify users into those that are primarily involved in illegal activity ("illegal users") and those that are primarily involved in legal activity ("legal users"). Subsequently, we measure the size and activity of the two groups.

At an intuitive level, the first method exploits the network topology—the information about who trades with whom. Trade networks reveal "communities" of users and can thereby identify other illegal users that were not part of our initial sample. In contrast, the second method exploits characteristics that distinguish illegal users from legal users (controlling for non-random detection). Both methods allow a user that was initially classified as an "observed" illegal user to be reclassified as a user that is predominantly engaged in legal activity (a "legal user"). This feature of the methods allows for the

possibility that some of the users identified in the previous stage as having engaged in illegal activity actually engaged in more legal activity than illegal activity.

The two methods provide independent estimates of the illegal activity and its characteristics. Given that the methods rely on completely different assumptions and exploit different information, their concurrent use provides robustness and the ability to cross-validate results. The methods are described below in separate subsections. We then report the results of how many users and how much trade is estimated to be associated with illegal activity, after which we characterize the nature of the illegal users and their trading activity compared to legal users.

5.1. Method 1: Network cluster analysis

The first method exploits network topology to identify "communities" of users based on the transactions between users. In simple terms, the method works as follows. If users A, B, and C are known to be involved in illegal activity (e.g., their bitcoin was seized by law enforcement agencies), a user X that trades exclusively or predominantly with users A, B, or C is likely to also be involved in illegal activity. Similarly, a user Y that trades predominantly with users that are not identified as illegal is likely to be a legal user. This intuition drives the classification of users into legal and illegal on the basis of their transaction partners.

More formally, the method we apply is a network cluster analysis algorithm that takes as inputs the set of users ("nodes" in network terminology) and the trades between users ("edges" or "links" in network terminology). The output of the algorithm is an assignment of users to communities such that the "modularity" of the communities (density of links within communities and sparsity of links between communities) is maximized. The method labels a user as illegal (legal) if the disproportionate share of their transactions is with members of the illegal (legal) community. The method does not assume that users only engage in either legal or illegal activity—users can do both. Therefore, there will be some trades between the legal and illegal communities.

We apply a variant of the Smart Local Moving (SLM) algorithm developed by Waltman and van Eck (2013), adapted to our specific application. The algorithm's name ("smart moving") comes from the fact that the algorithm finds the underlying community structure in the network by moving nodes from one community to another, if such a move improves the model fit. The SLM algorithm is among the leading network cluster analysis algorithms.[23]

Applied to our data, the algorithm is as follows.

[23] For example, Emmons et al. (2016) in their comparison of multiple methods find that the SLM algorithm performs the best in terms of maximizing cluster quality metrics.

- Step 1: Assign all the observed illegal users to the illegal community and all of the remaining users to the legal community.
- Step 2: Loop through each user, performing the following action on each:
    - If the user disproportionately transacts with members of the user's currently assigned community, then leave the user in that community[24];
    - Otherwise, move the user to the other community (if the user is assigned to the illegal community, move the user to legal community, and vice versa).
- Step 3: Repeat Step 2 until, in a complete loop through all users, no user switches between communities. At that point the assignment to communities is stable and ensures that each member trades disproportionately with other members of the same community.

Note that due to the iterative moving in the algorithm, not all of the "observed" illegal users will necessarily remain in the illegal community. For example, it is possible that some of the users that had bitcoin seized by authorities were involved in some illegal activity (hence getting bitcoin seized) but were mainly using bitcoin for legal purposes. This will be recognized by the algorithm in Step 2 and the user will be moved to the legal community.

5.2. Method 2: Detection controlled estimation (DCE)

The second method we use to estimate the population of users involved in illegal activity ("illegal users") is detection controlled estimation (DCE). Intuitively, this method exploits the differences in the characteristics of legal and illegal users of bitcoin to probabilistically identify the population of illegal users. If we had a random sample of illegal users and a set of characteristics that differ between legal and illegal users (e.g., measures of the extent to which a user has employed tools to conceal their activity), this task would be relatively simple and could be achieved with standard techniques (regression, discriminant analysis, and so on). A complication is that detection (as in most settings where violators attempt to conceal their illegal activity from authorities) is not random, and this non-randomness must be accounted for to obtain unbiased estimators.[25] We use "detection" in the broad sense of an illegal user having been identified by any of the three approaches described in the previous section (had bitcoin seized by a law enforcement agency, was identified in darknet forums, or was observed in the blockchain data as having

[24] "Disproportionately" is if the proportion of transactions the user makes with other members of the same community is greater than or equal to the community's proportion of total transactions. In robustness tests we consider the proportion of volume rather than transactions and find consistent results.

[25] A further complication is that the determinants of this non-randomness are not separately observed (unlike, for example, non-respondents in a survey, or people that choose not to participate in the labor force) and therefore the classic tools to deal with sample selection bias (e.g., Heckman models) cannot be applied.

transacted with a known illegal darknet marketplace). Thus, "detected" illegal users are the observed illegal users described in Section 4.

Fortunately this econometric challenge is not unique to illegal activity in bitcoin and methods to overcome this challenge exist. The same challenge occurs in quantifying other forms of misconduct such as tax evasion, fraud, insider trading, and market manipulation, as well as contexts such as nuclear power plant safety regulation breaches, cancer detection by mammograms, and so on. The standard tool for these settings is DCE. Since its development by Feinstein (1989, 1990), DCE models have been applied to various financial misconduct settings including tax evasion (Feinstein, 1991), corporate fraud (Wang et al., 2010), and market manipulation (Comerton-Forde and Putniņš, 2014). By explicitly modelling both underlying processes (violation and detection) simultaneously, one can obtain unbiased estimates of the illegal activity, which is otherwise only partially observed.

< Figure 3 here >

Figure 3 illustrates the two-stage DCE model that we estimate. On the left is the starting point, the data, which in our case is the set of all bitcoin users. In the middle we have the two processes, violation (undertaking illegal activity) and detection (e.g., bitcoin seizures). On the right-hand side are the joint outcomes of those processes: the observable classifications of users into detected illegal users (the set A) and other users (the complement set A^C, comprising legal users and undetected illegal users).

The first branch models whether a bitcoin user, i, is predominantly involved in illegal or legal activity. This branch is modelled as an unobservable binary process (L_{1i}) driven by a continuous latent function (Y_{1i}) of a vector of characteristics, x_{1i}, that can distinguish between legal and illegal users:

$$Y_{1i} = \beta_1 x_{1i} + \epsilon_{1i} \tag{1}$$

$$L_{1i} = \begin{cases} 1 & (Illegal\ user) \\ 0 & (Legal\ user) \end{cases} \text{ if } \begin{matrix} Y_{1i} > 0 \\ Y_{1i} \leq 0 \end{matrix} \tag{2}$$

The second branch models whether or not an illegal user is "detected" (they enter our sample of observed illegal users). This detection process is modelled as another unobservable binary process (L_{2i}) driven by a different continuous latent function (Y_{2i}) of a vector of characteristics, x_{2i}, that affect the probability that an illegal user is detected:

$$Y_{2i} = x_{2i}\beta_2 + \epsilon_{2i} \tag{3}$$

$$L_{2i} = \begin{cases} 1 & (Detected) \\ 0 & (Not\ detected) \end{cases} if \begin{matrix} Y_{2i} > 0 \\ Y_{2i} \leq 0 \end{matrix} \tag{4}$$

Both stages of the model are estimated simultaneously using maximum likelihood. The likelihood function for the model is derived in Appendix B. Intuitively, this process finds estimates for the vectors of

model parameters, β_1 and β_2, that maximize the likelihood of the observed data (the classification of users into sets A and A^C). From the estimates of β_1 and β_2, we compute each user's probability of being involved in illegal activity and construct a binary classification of legal and illegal users.

Similar to the SLM approach, the DCE model does not assume that detected illegal users were engaged solely or predominantly in illegal activity. Once the DCE model is estimated, the classification of users into legal and illegal categories can result in some detected illegal users being re-classified as predominantly legal users.[26]

Similar to Heckman models, identification in a DCE model without instruments is possible, relying on functional form and distributional assumptions. However, more robust identification is achieved through instrumental variables that affect one process but not the other. We take the more robust route of using instrumental variables. The next subsection describes the instrumental variables and their descriptive statistics.

5.3. Variables used in the DCE model and their descriptive statistics

One of the instrumental variables associated with illegal activity is the extent to which the user employs methods to conceal their identity or obfuscate their transaction history. For example, to partially conceal their identities from an observer of the bitcoin blockchain, users can use "tumbling" and "wash trades" to alter the addresses of their bitcoin holdings, increasing the difficulty of tracing their activity. Tumbling, in its simplest form, involves a user sending bitcoin to a tumbling provider who (in return for a small fee) returns the balance to a different address controlled by the user. Wash trades involve a user sending bitcoin from one address to another (new) address that they also control. Legal users have little reason to take such actions to conceal their actions (and incur associated costs). In contrast, users involved in illegal activity are likely to use these concealment techniques. As such, the use of tumbling services and wash trades is likely to be a predictor of whether a user is involved in illegal activity. Importantly (for this to be an instrumental variable), using wash trades and tumbling does not alter the probability of "detection" by law enforcement agencies via the seizures of bitcoin from darknet sites. The seizures confiscated all bitcoin held in darknet marketplace escrow accounts ("hot wallets") irrespective of whether the user employed tumbling or wash trades. For each user, we measure the percentage of their transactions that are tumbling or wash trades and call this variable *Tumbling*.

[26] For example, suppose a user was involved in some illegal activity and had bitcoin seized by authorities but was mainly using bitcoin for legal purposes. Such a user will have characteristics that are similar to those of legal users and not very similar to illegal users, which would lead to a classification by the DCE model into the legal user category. In contrast, a predominantly illegal user, even if not detected or observed, is likely to have characteristics similar to other illegal users and therefore (after controlling for the differences in characteristics due to non-random detection) the user is likely to be classified as illegal by the DCE model.

Another set of instruments for the likelihood that a user is involved in illegal activity involves time-series variables that are likely to correlate with the type of activity in which bitcoin users are engaged. For example, for each user we construct a measure of the average number of operational illegal darknet marketplaces at the time the user transacts (we label the variable *Darknet Sites*). All else equal, illegal transactions (and thus users involved in illegal activity) are more likely when there is a lot of illegal darknet marketplace activity than when there is little or no illegal darknet activity.

In a similar spirit, we construct a measure of the average number of opaque cryptocurrencies in existence (Dash, Monero, and ZCash) at the time the user participates in bitcoin (labelled *Shadow Coins*). These major alternative "shadow coins" were developed, at least in part, to provide more privacy than bitcoin. If some of the online black market starts using these shadow coins instead of bitcoin, the number of such coins in existence at the time a user transacts in bitcoin is likely to inversely correlate with the user's likelihood of being involved in illegal activity.

For each user, we also construct a measure of the amount of mainstream interest and hype associated with bitcoin at the time of their participation in bitcoin (we label the variable *Bitcoin Hype*). We take the average Google Trends search intensity for the keyword "bitcoin" at the time of the user's bitcoin transactions. If Google search intensity for "bitcoin" correlates with speculative trading in bitcoin and mainstream (legal) use, this variable will have an inverse association with the likelihood of the user being involved in illegal activity.

Our final instrument for involvement in illegal activity exploits the anecdotal evidence that significant darknet marketplace shocks such as seizures of darknet marketplaces by law enforcement agencies or closures of such marketplaces for scams or hacks result in a brief spike of transaction activity by illegal users as they turn to alternative marketplaces or relocate their holdings in response to the shock. At the same time, shocks to darknet marketplaces are unlikely to materially affect the activity of legal users. Therefore, for each user, we measure the fraction of the user's transaction value that occurs in the one week period after each major darknet marketplace shock (marketplace "raids", "scams", and "hacks" in Table A2 of Appendix A). We label this variable *Darknet Shock Volume*.

As determinants of the probability of detection, we include a binary variable for whether the user started using bitcoin (date of first bitcoin transaction) before the first seizure of bitcoin by law enforcement agencies from Silk Road 1 (we label the variable *Pre-Silk-Road User*). Because users that enter the bitcoin network after the first seizure can only be detected in subsequent seizures, post-Silk-Road-seizure users are likely to have a lower detection probability.

A few things are worth noting about the variables used in the DCE model. First, while the instrumental variables help identify the model, they are not the only characteristics that help separate legal and illegal users—the full set of characteristics used in the model serve that purpose, including variables

common to both detection and violation equations (they have different coefficients in each equation). The full list of variables is presented in Table 1. Second, identification of the model requires only one variable that is associated with either the probability of being involved in illegal activity or the probability of detection, but not both. We have more candidate instrumental variables than this minimum of one, and in robustness tests we examine how sensitive the results are to the assumptions about these instruments. We do so by relaxing the assumed exclusion restrictions on a subset of the instruments one at a time, from which we conclude that the results are not particularly sensitive to any individual instrumental variable's exclusion restriction.

Table 2 Panel B reports descriptive statistics about the variables that serve as instruments. *Darknet Sites* indicates that for the average bitcoin participant, there are on average 17 operational darknet marketplaces around the time of their transactions. This number ranges from a minimum of zero to a maximum of 27. *Tumbling* indicates that only a relatively small proportion of users (less than 25%) engage in "tumbling" and/or "wash trades", which are used to obscure the user's holdings. Thus, while techniques exist to help a bitcoin user conceal their activity, it appears that few bitcoin users adopt such techniques.

The variable *Shadow Coins* indicates that for the average bitcoin participant, there are around two opaque alternative cryptocurrencies in existence at the time of their transactions. The variable *Darknet Shock Volume* indicates that while most users do not trade in the period immediately following darknet shocks (median of zero), some users conduct a large fraction of their trading during these periods, with the average bitcoin user undertaking 17% of their trading following darknet shocks.

The variable *Bitcoin Hype* indicates that for the average user, the intensity of Google searches for "bitcoin" is around 28% of its maximum of 100%. The *Pre-Silk-Road User* dummy indicates that only around 7% of all bitcoin participants started transacting before October 2013, when the first darknet marketplace seizure by law enforcement agencies occurred (the seizure of Silk Road 1 by the FBI).

5.4. How much illegal activity involves bitcoin?

Both methods—network cluster analysis (SLM) and detection controlled estimation (DCE)—arrive at probabilistic classifications of bitcoin users into those primarily involved in legal activity and those primarily involved in illegal activity. Once the users have been partitioned into the legal and illegal "communities", we use those categorizations to quantify the size and activity of the two groups.

Table 4 presents the main results at the aggregate level, for the whole sample period. Panel A reports the estimated size of the groups and their level of activity, while Panel B re-expresses these values as percentages for each group. First, the percentage of bitcoin users estimated to be predominantly involved in illegal activity is 29.12% using the SLM and 21.37% using the DCE, giving a midpoint

estimate of about one-quarter of bitcoin users (25.24%, the average of the estimates from the two models). The 99% confidence interval around this estimate is 21.73% to 28.76%.[27] The midpoint estimate suggests around 26.82 million bitcoin users are predominantly involved in illegal activity, versus 79.42 million legal users.

The estimated number of illegal users is around four times larger than our sample of observed illegal users. Given our sample of observed illegal users is based on a comprehensive approach and includes all users that can be observed transacting with one of the known darknet marketplaces, the results suggest that without empirical methods such as the SLM or DCE, illegal activity that can be inferred from involvement with known darknet marketplaces represents only a small (and likely non-random) fraction of all illegal activity. Thus, our results suggest that studies of known/identifiable darknet markets (e.g., Soska and Christin, 2015; Meiklejohn et al., 2013) only scratch the surface of all illegal activity involving bitcoin.

< Table 4 >

Table 4 also indicates that illegal users account for an even larger share of all transactions—around 44.33% (45.67% using the SLM and 42.99% using the DCE) or approximately 269 million transactions. Thus, the average illegal user is involved in more transactions than a legal user. This result is consistent with the notion that illegal users are likely to use bitcoin as a payment system (which involves actively transacting), whereas legal users may hold bitcoin for reasons such as speculation. A similar proportion is observed for holding values—illegal users on average hold around one-half (51.28%) of the outstanding bitcoin. One reason for the large share of illegal user holdings (relative to their share of the number of users) is related to the calculation of this variable as a time-series average. A high fraction of illegal users in the early parts of the sample (when there are fewer bitcoin users) can generate such a result even if the holdings *per user* are lower among illegal users compared to legal users.

Illegal users are estimated to control around 38.21% of bitcoin addresses and account for about one-fifth (20.30%) of the dollar volume of bitcoin transactions. In dollar terms, illegal users conduct approximately $378 billion worth of bitcoin transactions. Because illegal users account for a larger share of transactions than their share of dollar volume, they tend to make smaller value transactions than legal

[27] We use a form of bootstrapped standard errors to form the confidence interval. First we obtain standard errors from the DCE model using a bootstrap of 200 samples in which, for computational reasons, we are forced to reduce the sample size by taking a random sample (this is a conservative step as it inflates the estimated standard errors relative to the standard errors for the full sample size). We then apply the conservative bootstrapped DCE standard errors to approximate the error in the midpoint estimate. This step assumes the SLM standard errors (which we cannot compute as a bootstrap would not be appropriate when one needs to use the transaction network in the model) are similar in magnitude to the DCE standard errors.

users. This result is consistent with illegal users primarily using bitcoin as a payment system rather than holding it as an investment or speculative asset.

Three general conclusions can be drawn from the results in Table 4. First, illegal users account for a sizeable proportion of both users and trading activity in bitcoin, with the exact proportion varying across different measures of activity and the two estimation models. Second, the estimates from both the SLM and DCE are fairly similar across the various activity measures, despite relying on completely different assumptions and information. Third, even a fairly comprehensive approach to identifying illegal activity directly (such as the approach used in the previous section and that used in other darknet market studies) only captures a small fraction of the total illegal activity, highlighting the importance of extrapolation beyond a directly observed sample.

5.5. How does the illegal activity vary through time?

There is interesting time-series variation in the amount of illegal activity and its share of all bitcoin activity. Figures 4 to 7 plot the estimated amount of illegal activity that uses bitcoin through time from the first block in 2009 to 2017. The figures show the estimated number of illegal users, the number and dollar value of their transactions, and the value of their bitcoin holdings. Panel B of each of the figures shows these activity measures as a percentage of the total across all bitcoin participants.[28]

< Figure 4 here >

< Figure 5 here >

< Figure 6 here >

< Figure 7 here >

A pattern that is observed across all activity measures is that illegal activity, as a percentage of total bitcoin activity, tends to be high at the start of the sample in 2009, and then again from 2012 to the end of 2015, after which it steadily declines through to 2017. The activity levels indicate that there is only a very small (negligible) level of activity in bitcoin until about the middle of 2011, so the activity at the start of the sample is not economically meaningful. In contrast, the high relative level of illegal activity between 2012 and 2015 is noteworthy and coincides with the growth in the number of illegal darknet marketplaces, starting with the Silk Road in 2011. After the Silk Road was shut down in October of 2013, a large number of other illegal darknet marketplaces commenced operating between 2013 and 2015 (Table A2 of Appendix A).

[28] Figures 4-7 use the average of the SLM and DCE model estimates. The SLM and DCE time-series estimates are separately reported in Figures A1-A8 of the Online Appendix.

What could drive the decline in the relative level of illegal activity from the end of 2015 onwards? The first thing to note is that the decline is observed in relative terms (that is, illegal activity as a fraction of total bitcoin activity), but *not* in absolute terms. Thus, it is not the case that the level of illegal activity in bitcoin has declined in recent years, rather, there has been a disproportionate increase in the legal use of bitcoin since the end of 2015. For example, from the end of 2015 to April 2017, the estimated number of illegal bitcoin users increases from around 16 million to around 24 million, reflecting growth of around 50%, whereas the estimated number of legal bitcoin users increases from around 15 million to around 58 million, reflecting growth of around 290%. The rapid growth of legal use is likely driven by factors such as increased interest from investors and speculators (e.g., the emergence of "cryptofunds", and more recently bitcoin futures) and increased mainstream adoption as a payment system (e.g., cafes and internet merchants accepting bitcoin).

The time-series of legal and illegal activity levels show strong growth in both illegal and legal activity throughout the sample period, in particular since 2012. Interestingly, the strong growth in illegal activity precedes the strong growth in legal activity—by about three or four years. Thus it seems illegal users were relatively early adopters of bitcoin as a payment system.

Finally, because of the rapid growth in the legal use of bitcoin in the final two years of the sample, the aggregate measures of the illegal proportion of bitcoin activity reported in the previous subsection understate the proportion seen throughout most of the sample period. For example, for most of the sample period, the estimated proportion of illegal users is closer to one-half than one-quarter (the aggregate estimate). The aggregate estimate is heavily influenced by the large number of legal users that enter in the last two years of the sample. Similarly, for much of the sample period, the estimated proportion of bitcoin transactions involved in illegal activity is between 60% and 80%, contrasting with the aggregate estimate of around 44%.

The most recent estimates of illegal activity (at the end of our sample in April 2017) suggest there are around 24 million illegal users of bitcoin. These users conduct around 36 million bitcoin transactions annually, valued at around $72 billion, and collectively hold around $8 billion in bitcoin.[29]

5.6. What are the characteristics of illegal users?

We assess the differences between legal and illegal user characteristics in two ways: univariate statistics that compare observed or estimated illegal users with their legal counterparts, and multivariate tests exploiting the coefficients of the estimated DCE model.

[29] For these estimates, we have halved the double-counted volumes so that the estimates can be interpreted as the volume/value of goods/services bought/sold by the illegal users.

< Table 5 >

Starting with a univariate difference in means, Table 5 compares the characteristics of the sample of "observed" illegal users with the characteristics of other users. Note that the "other users" are not all legal users—they contain a mix of legal users and undetected illegal users. Therefore, the table also compares the characteristics of users classified by the SLM and DCE models as being involved in illegal activity with those of users classified as legal. Interestingly, despite being based on completely different assumptions, the SLM and DCE models generally agree on how the characteristics of legal users differ from illegal users. This is true for the signs of the mean differences for all but one characteristic (*Transaction Frequency*).

The SLM and DCE models agree that illegal users tend to transact more (have a two to three times higher *Transaction Count*), but use smaller sized transactions (about half the average size of legal transactions). This result could be a reflection of illegal users predominantly using bitcoin to buy and sell goods and services, whereas some legal users also use bitcoin for investment and speculation.[30]

The models also agree that illegal users tend to hold less bitcoin (measured in dollar value) than legal users; their average *Holding Value* is about half that of legal users. This characteristic is consistent with the previous conjecture—legal users might tend to hold larger bitcoin balances because some use bitcoin for investment/speculation purposes, whereas for an illegal user that buys/sells illegal goods and services using bitcoin, holding a large balance is costly due to (i) opportunity costs of capital, and (ii) risks associated with having holdings seized by authorities. For these reasons, illegal users are likely to prefer holding less bitcoin and this tendency is supported by the data.

Illegal users tend to have more counterparties in total, reflecting their larger number of transactions, but tend to have a higher counterparty concentration. This suggests that illegal users are more likely to repeatedly transact with a given counterparty. This characteristic might be a reflection of illegal users repeatedly transacting with a given illegal darknet marketplace or other illegal user once trust is established from a successful initial exchange. Illegal users have a longer *Existence Time* (time between their first and last transactions in bitcoin), consistent with our observations from the time-series that illegal users tend to become involved in bitcoin earlier than legal users. Similarly, the differences in means also show that there is a higher proportion of Pre-Silk-Road users among the illegal users than the legal users (as indicated by the variable *Pre-Silk-Road User*).

[30] While the result could also reflect illegal users engaging in techniques to conceal their trading, this is less likely to be an explanation because a similar result holds in multivariate (DCE) tests that control for tumbling and wash trades.

The more specific indicators of illegal activity also show significant differences between the two groups. Illegal users tend to be more active during periods in which there are many illegal darknet marketplaces operating (a higher mean for the variable *Darknet Sites*). They make greater use of tumbling and wash trades to conceal their activity (two to four times more *Tumbling*). On average, a larger proportion of illegal volume, compared to legal volume, is transacted immediately following shocks to darknet marketplaces (*Darknet Shock Volume*). This finding is consistent with anecdotal evidence that illegal users turn to alternative marketplaces in response to darknet marketplace seizures or scams.

Interestingly, illegal users are more likely to transact with bitcoin when there are fewer opaque "shadow coins" in existence, suggesting such coins do get used as alternatives to bitcoin in illegal transactions. This result (for the variable *Shadow Coins*) is consistent with anecdotal accounts of shadow coins becoming recognized by the illegal community for their increased privacy, as well as recent examples of hackers demanding ransom payments in shadow coins rather than bitcoin.

Another interesting result is that legal users tend to be more active in bitcoin when there is less *Bitcoin Hype*, measured by the Google search intensity for "bitcoin". It therefore appears that Google searches for "bitcoin" are associated with mainstream (legal) adoption of bitcoin for payments, and/or speculative/investment interest in bitcoin.

In summary, the comparison of transactional characteristics (number and size of transactions, holdings, and counterparties) is consistent with the notion that illegal users predominantly use bitcoin for payments, whereas legal users are more likely to treat bitcoin as an investment asset. Furthermore, legal and illegal users differ with respect to when they are most active in bitcoin, with illegal users being most active when there are more darknet marketplaces, fewer shadow coins, less bitcoin hype, and immediately following shocks to darknet marketplaces. The differences in characteristics for the instrumental variables are consistent with the hypothesized differences, lending support to their use as instruments.

< Table 6 >

The DCE model coefficients reported in Table 6 provide multivariate tests of how the characteristics relate to the likelihood that a user is involved in illegal activity. The results confirm most of the observations made in the simple comparison of means. The effects of all of the instrumental variables are consistent with their hypothesized effects. A user is more likely to be involved in illegal activity if they trade when: (i) there are many darknet marketplaces operating, (ii) there are fewer shadow coins in existence, (iii) there is little bitcoin hype, and (iv) darknet marketplaces experience seizures or scams. A user is also more likely to be involved in illegal activity if they use tumbling and/or wash trades, transact frequently in small sized transactions, and tend to repeatedly transact with a given counterparty.

The marginal effects in Table 6, reported in parentheses below the coefficient estimates, provide a sense of the magnitudes of the effects and their relative importance.[31] For example, the marginal effects indicate that a one standard deviation increase in the number of illegal darknet marketplaces at the time a user transacts in bitcoin increases the probability of that user being involved in illegal activity by a factor of 0.435, or 43.5% of what their probability would otherwise be.[32] The magnitudes generally show that most of the determinants of involvement in illegal activity and determinants of the detection probability are economically meaningful. In particular, the instrumental variables of *Darknet Sites*, *Shadow Coins*, *Bitcoin Hype*, and *Darknet Shock Volume* all have strong relations with the probability that a user is involved in illegal activity.

The DCE model also sheds light on the determinants of the likelihood that an illegal user is "detected" by either of our three approaches. The main instrument, *Pre-Silk-Road User* has a strong relation with detection, indicating that illegal users that commence transacting in bitcoin prior to the first darknet marketplace seizure in October 2013 have a higher probability of being detected. Similarly, those users that transact in bitcoin for a longer period of time (higher *Existence Time*), trade more frequently (higher *Transaction Frequency*), or tend to trade repeatedly with a given counterparty such as a darknet marketplace (higher *Concentration*) have a significantly higher detection probability.

Model 2 in Table 6 adds further control variables to the models, including *Holding Value* and *Transaction Count*, and finds that the main results do not change much in response to additional control variables. A risk of adding too many transactional control variables is co-linearity between such variables.

5.7. What are the characteristics of the illegal user network?

Exploiting the fact that the bitcoin blockchain provides us with a complete record of every transaction between every pair of counterparties, we briefly explore how the trade network of illegal users differs from that of legal users. Our approach is to compute a few descriptive network metrics that capture different aspects of network topology and structure for each of the two groups or "communities" separately and then compare the values between the two communities. In mapping the networks, users form the "nodes", and transactions between users form the "edges" or "links" between nodes.

< Table 7 >

[31] To make the comparisons and interpretation easier, before estimating the DCE models, we standardize all variables to have mean zero and standard deviation of one. We also log transform the right skewed variables (*Transaction Frequency*, *Size*, and *Count*, and *Holding Value*) and winsorize the variables at +/- three standard deviations to reduce the influence of extreme values.

[32] As an example of how to interpret the marginal effect of 0.435, if a user's illegal probability is say 20%, the predicted effect of a one standard deviation increase in *Darknet Sites*, holding all else constant, is to increase the user's probability to 20% × 1.435 = 28.7%, an increase of 43.5% of what their probability would otherwise be.

Table 7 reports the results. The first metric, *Density*, takes the range [0,1] and indicates how highly connected the users are within a community (versus how sparse the connections are between users); it is the actual number of links between users within the given community (a "link" between two users means that they have transacted with one another) divided by the total potential number of links. It shows that the illegal trade network is three to four times denser in the sense that users are much more connected to one another through transactions. This observation is consistent with the fact that illegal users tend to transact more than legal users. It is also consistent with the notion that in the illegal community, bitcoin's dominant role is likely that of a payment system in buying/selling goods, whereas in the legal community, bitcoin is also used as an investment or for speculation.

Reciprocity takes the range [0,1] and indicates the tendency for users to engage in two-way interactions; it is the number of two-way links between users within the given community (a two-way link is when two users send and receive bitcoin to and from one another) divided by the total number of links within the given community (two-way and one-way). While *Reciprocity* is higher among illegal users than it is among legal users, it is generally very low in both communities (1% among legal users and 3% among illegal users). Thus, interactions between bitcoin users are generally only one-way interactions with one counterparty receiving bitcoin from the other but not vice versa.

Entropy measures the amount of heterogeneity among users in their number of links to other members of the community. It takes its minimum value of zero when all users have the same number of links (same degree).[33] The results suggest that illegal users are a more heterogeneous group in terms of the number of links each user has with other members of the community. A driver of that heterogeneity could be that the illegal community at one end of the spectrum has darknet marketplaces that have hundreds of thousands of links to vendors and buyers, and at the other end has individual customers of a single marketplace, potential with only the one link.

A concluding observation is that both the SLM and DCE models provide a consistent picture of how legal and illegal users differ, this time in the context of their trade networks. Again, this suggests that the two different models tend to agree about the nature of the illegal activity in bitcoin.

5.8. Robustness tests

We conduct a number of different robustness tests. Perhaps the most rigorous robustness test of an empirical model is to compare its results with results from a completely different model/approach that makes different assumptions and draws on different information. Throughout the paper we put our two

[33] Formally, $Entropy = -\sum_d P(d)\log[P(d)]$, where $P(d)$ is the degree distribution (probability density of the degree for each user, where a user's degree, d, is the number of links the user has with other members of the same community).

empirical models through this test. The two models, one based on a network cluster analysis algorithm and the other on a structural latent variables model drawing on observable characteristics, provide highly consistent results. The two models tend to agree, within a reasonable margin of error, on the overall levels of illegal activity, as well as the differences between legal and illegal users in terms of characteristics and network structure.

We also subject each of the models to specific tests that vary key assumptions or modelling choices. Table 8 reports the estimated amount of illegal activity for the most notable of these tests. For the SLM, we re-estimate the model using transaction volumes as the measure of interaction between users rather than transaction counts (*SLM Alternative 1*). We also consider a modification of the SLM algorithm in which we impose a constraint that does not allow the sample of "observed" illegal users to be moved to the legal community (*SLM Alternative 2*). For the DCE model, one set of robustness tests involves examining the sensitivity to relaxing key exclusion restrictions. For example, in the baseline model, *Darknet Sites* (the number of operational darknet marketplaces at the time a user transacts) is included only as a determinant of illegal activity. As a robustness test (*DCE Alternative 1*), we include it in both equations, allowing it to also affect the probability of detection. Of all the determinants of illegal activity, *Darknet Sites* has the most plausible reasons for possibly also affecting detection—the existence of many darknet marketplaces might be a catalyst for increased surveillance and enforcement by law enforcement authorities. We also test sensitivity to the key exclusion restriction in the detection equation by including *Pre-Silk-Road User* in both equations (*DCE Alternative 1*), thereby allowing it to also affect the probability of illegal activity.

< Table 8 >

Table 8 shows that the estimated overall levels of illegal activity across the various activity measures are not overly sensitive to modifications of the baseline model. Similarly, the estimated characteristics of illegal users are not overly sensitive to these modifications (results not reported for conciseness). The Online Appendix Table A1 reports the coefficient estimates for the two DCE models described above in which we relax key exclusion restrictions, showing that the coefficients are also not particularly sensitive to these modifications.

We also examine the robustness of the DCE model to the initial parameter values used in estimating the model. We initialize the model with different starting values (-1, 0, +1, and randomly drawn starting values), and find that our results are not sensitive to the choice of starting values, suggesting convergence to a global rather than local maximum of the likelihood function.

Finally, we re-estimate the standard errors used in confidence bounds around the estimated illegal activity and significance tests. Instead of the bootstrapped standard errors that we use in the main results, we instead compute standard errors using analytic expressions. We find that the analytic standard errors are considerably smaller than the bootstrapped standard errors. This finding suggests that using bootstrapped standard errors in the main results is the more conservative of the two approaches.

Finally, the characteristics of illegal users could change through time (for example, in response to seizures by law enforcement agencies), which could lead to model mis-specification. To examine this possibility, we repeat the difference-in-means comparison of legal and illegal users, partitioning the sample into a pre-Silk-Road seizure period and a post-Silk-Road seizure period (pre/post October 2013). Tables A2 and A3 in the Online Appendix report these results for both SLM and DCE classifications of illegal users.[34] For most characteristics, the differences between legal and illegal users take the same sign in both the pre/post periods, typically with similar magnitudes. In cases where the pre and post periods are different, the difference is often driven by a change in the characteristics of legal rather than illegal users (the change in the legal user mean is larger than the change in the illegal user mean). This tendency suggests while some characteristics do change through time, the changes are more likely to reflect general trends rather than a response of illegal users to events such as darknet marketplaces seizures.

6. Discussion

6.1. Implications

Blockchain technology and the systems/protocols that can be implemented on a blockchain have the potential to revolutionize numerous industries. Possible benefits to securities markets include reducing equities settlement times and costs (Malinova and Park, 2016; Khapko and Zoican, 2016), increasing ownership transparency leading to improved governance (Yermack, 2017), and providing a payments system with the network externality benefits of a monopoly but the cost discipline imposed by free market competition (Huberman et al., 2017). The technology has even broader applications beyond securities markets, from national land registries, to tracking the provenance of diamonds, decentralized decision making, peer-to-peer insurance, prediction markets, online voting, distributed cloud storage, internet domain name management, conveyancing, medical record management, and many more.

This technology, however, is encountering considerable resistance, especially from regulators. Regulators are cautious due to their limited ability to regulate cryptocurrencies and the many potential but poorly understood risks associated with these innovations. The negative exposure generated by anecdotal accounts and salient examples of illegal activity no doubt contributes to regulatory concerns and risks

[34] The comparison excludes characteristics that have little or no variation with the pre or post periods, such as *Pre-Silk Road User* dummy variable, *Shadow Coins*, and *Darknet Sites*.

stunting the adoption of blockchain technology, limiting its realized benefits. In quantifying and characterizing this area of concern, we hope to reduce the uncertainty about the negative consequences of cryptocurrencies, allowing for more informed decisions by policymakers that assess both the costs and benefits. Hopefully, by shedding light on the dark side of cryptocurrencies, this research will help blockchain technologies reach their potential.

A second contribution of this paper is the development of new approaches to identifying illegal activity in bitcoin, drawing on network cluster analysis and detection controlled estimation techniques. These methods can be used by law enforcement authorities in surveillance activities. For example, our methods can be applied to blockchain data going forward as new blocks are created, allowing authorities to keep their finger on the pulse of illegal activity in bitcoin. Applied in this way, one could monitor trends in illegal activity such as its growth or decline, its response to various regulatory interventions such as seizures, and how its characteristics change through time. Such information could help make more effective use of scarce regulatory and enforcement resources.

Another surveillance application is in identifying individuals/entities of strategic importance, for example, major suppliers of illegal goods. Combining these empirical methods with other sources of information can "de-anonymize" the nameless entities identified in the data. This might be done, for example, by tracing the activity of particular individuals to the interface of bitcoin with either fiat currency or the regulated financial sector (many exchanges and brokers that convert cryptocurrencies to fiat currencies require personal identification of clients). The methods that we develop can also be used in analyzing many other blockchains.

Third, our finding that a substantial amount of illegal activity is facilitated with bitcoin suggests that bitcoin has contributed to the emergence of an online black market, which raises several welfare considerations. Should policymakers be concerned that people are buying and selling illegal goods such as drugs online and using the anonymity of cryptocurrencies to make the payments? This is an important question and the answer is not obvious. If the online market for illegal goods and services merely reflects a migration of activity that would have otherwise occurred "on the street" to the digital world of e-commerce, the illegal online activity facilitated via bitcoin might not be bad from a welfare perspective. In fact, there are many potential benefits to having illegal drugs and other goods bought and sold online rather than on the street. For example, it might be safer and lead to reduced violence (e.g., Barratt et al., 2016a). It could also increase the quality and safety of the drugs because darknet marketplaces rely heavily on user feedback and vendor online reputation, which can give a buyer access to more information about a seller's track record and product quality than when buying drugs on the street (e.g., Soska et al., 2015). There is also more choice in the goods offered, which has the potential to increase consumer welfare.

However, by making illegal goods more accessible, convenient, and reducing risk (due to anonymity), the darknet might encourage *more* consumption of illegal goods and increase reach, rather than simply migrating existing activity from the street to the online environment (Barratt et al., 2016b). Presuming illegal goods and services have negative net welfare consequences, then bitcoin and other cryptocurrencies could decrease welfare by enabling the online black market. Such negative consequences would have to be weighed up against welfare gains that also accompany cryptocurrencies.

Therefore, while our paper does not provide a definitive answer to the question of welfare effects, it does get us closer to an answer by having estimated both the trends and scale of illegal activity involving bitcoin (the most widely used cryptocurrency in darknet marketplaces). Future research might quantify the relation between drug trafficking on the street vs online (drawing on our methods or estimates) to understand to what extent we are experiencing a simple migration vs an expansion in the overall market. It might also quantify the benefits of moving to an online market and contrast them with the negative consequences of any expansion in the market as a result of it being more accessible / convenient / safe.

Our results also have implications for the intrinsic value of bitcoin. The rapid increase in the price of bitcoin in recent times has prompted much debate and divided opinions among market participants and even policymakers / central banks about whether cryptocurrency valuations are disconnected from fundamentals and whether their prices reflect a bubble. In part, the debate reflects the uncertainty about how to value cryptocurrencies and how to estimate a fundamental or intrinsic value. While we do not propose a valuation model, our results provide an input to an assessment of fundamental value in the following sense. One of the intrinsic uses of cryptocurrencies, giving them some fundamental value, is as a payment system. To make payments with bitcoin, one has to hold some bitcoin; the more widespread its use as a payment system, the greater the aggregate demand for holding bitcoin to make payments, which, given the fixed supply, implies a higher price. Our results suggest that currently, as a payment system, bitcoin is relatively widely used to facilitate trade in illegal goods and services and thus the illegal use of bitcoin is likely to be a meaningful contributor to bitcoin's fundamental value.

This observation—that a component of bitcoin's fundamental value derives from its use in illegal trade—raises a few issues. First, an ethical investor might not be comfortable investing in a security for which a meaningful component of the fundamental value derives from illegal use. Second, changes in the demand to use bitcoin in illegal trade are likely to impact its fundamental value. For example, increased attention from law enforcement agencies or increased adoption/substitution to more opaque alternative cryptocurrencies could materially decrease the fundamental value of bitcoin. Conversely, continued migration of the black market to online with continued use of bitcoin, could further increase bitcoin's fundamental value. Third, recent price appreciation of bitcoin greatly exceeds the growth in its use in

illegal activity, suggesting either a substantial change in other components of bitcoin's fundamental value or a dislocation of the bitcoin price from its fundamental value.

6.2. Relation to other literature

This paper contributes to three branches of literature. First, several recent papers analyze the economics of cryptocurrencies and applications of blockchain technology to securities markets (e.g., Malinova and Park, 2016; Khapko and Zoican, 2016; Yermack, 2017; Huberman et al., 2017; Easley et al., 2017). Our paper contributes to this literature by showing that one of the major uses of cryptocurrencies as a payment system is in settings in which anonymity is valued (e.g., illegal trade).

Another related, although small, branch of literature examines the degree of anonymity in bitcoin by quantifying the extent to which various algorithms can identify entities/users in bitcoin blockchain data and track their activity (e.g., Meiklejohn et al., 2013; Ron and Shamir, 2013; Androulaki et al., 2013; Tasca et al., 2016). In doing so, some of these papers also provide insights about the different types of activities that use bitcoin. Of these papers, one of the closest to ours is Meiklejohn et al. (2013), who explore the bitcoin blockchain up to April 2013, clustering addresses into entities/users and manually identifying some of those entities by physically transacting with them. They are able to identify the addresses of some miners, exchanges, gambling services, and vendors/marketplaces (including one darknet marketplace), suggesting bitcoin entities are not completely anonymous. Tasca et al. (2016) use a similar approach to explore the different types of activity in bitcoin, focusing only on the largest entities, so-called "super clusters", and within that set, only those with a known identity.

None of these papers attempt to categorize all of the activity in bitcoin, nor do they try and quantify or characterize the population of illegal bitcoin users, which is the focus of our paper. We exploit the lack of perfect anonymity that is documented in these studies and draw on some of the techniques from this literature to construct an initial sample of known illegal users. We add new methods to this literature, extending the empirical toolkit from making direct observations about individuals, to identification of communities and estimation of populations of users.

Finally, another related branch of literature is the recent studies of darknet marketplaces and the online drug trade, including papers from computer science and drug policy. For example, Soska and Christin (2015), use a web-crawler to scrape information from darknet marketplaces during 2013-2015, collecting a variety of data. Their paper provides valuable insights into these markets, including information about the types of goods and services traded (largely drugs), the number of goods listed, a lower bound on darknet turnover using posted feedback as a proxy (they do not have data on actual transactions/sales), the number of vendors, and the qualitative aspects of how these marketplaces operate (reputation, trust, feedback). The related drug policy studies often draw on other sources of information

such as surveys of drug users and contribute insights such as: (i) darknet marketplaces like the Silk Road facilitate initiation into drug use or a return to drug use after cessation (Barratt et al., 2016b) and can encourage drug use through the provision of drug samples (Ladegaard, 2017); (ii) darknet forums can promote harm minimization by providing inexperienced users with support and knowledge from vendors and more experienced users (Bancroft, 2017); (iii) darknet marketplaces tend to reduce systemic violence compared with in-person drug trading because no face-to-face contact is required (Barratt et al., 2016a; Martin, 2017; Morselli et al., 2017); (iv) about one-quarter of the drugs traded on the Silk Road occur at a wholesale scale, suggesting that such markets might also indirectly serve drug users "on the street" by impacting dealers (Aldridge and Décary-Hétu, 2016); and (v) there are interesting cross-country differences in the use of the darknet marketplace "Agora" (Van Buskirk et al., 2016).

We contribute to this literature by quantifying the amount of illegal activity undertaken using bitcoin. All of the illegal activity captured by the existing studies of one or several darknet marketplaces is also in our measures because one of the approaches we use to construct a sample of observed illegal activity involves measuring transactions with known darknet marketplaces. However, our estimates include much more than this activity—we use direct measures of transactions rather than a lower-bound measure such as feedback, consider all known darknet marketplaces (rather than one or a few), include two other methods of obtaining a sample of illegal activity, and most importantly, we estimate models that extrapolate from the *sample* of observed illegal activity to the estimated *population*. This yields vastly different and more comprehensive estimates. Empirically, we confirm that studies of darknet marketplaces only scratch the surface of the illegal activity involving bitcoin—the estimated population of illegal activity is several times larger than what can be "observed" through studying known darknet marketplaces. Furthermore, the studies of darknet marketplaces do not analyze how the characteristics of illegal and legal bitcoin users differ, or how recent developments such as increased mainstream interest in bitcoin and the emergence of new, more opaque cryptocurrencies impacts the use of bitcoin in illegal activity. These are further contributions of our paper.

7. Conclusion

As an emerging FinTech innovation, cryptocurrencies and the blockchain technology on which they are based could revolutionize many aspects of the financial system, ranging from smart contracts to settlement, interbank transfers to venture capital funds, as well as applications beyond the financial system. Like many innovations, cryptocurrencies also have their dark side. We shed light on that dark side by quantifying and characterizing their use in illegal activity.

We find that illegal activity accounts for a sizable proportion of the users and trading activity in bitcoin, as well as an economically meaningful amount in dollar terms. For example, approximately one-

quarter of all users and close to one-half of transactions are associated with illegal activity, equating to around 24 million market participants with illegal turnover of around $72 billion per year in recent times.

Illegal users of bitcoin tend to transact more, in smaller sized transactions, often repeatedly transacting with a given counterparty, and they tend hold less bitcoin. These features are consistent with their use of bitcoin as a payment system rather than for investment or speculation. Illegal users also make greater use of transaction techniques that obscure their activity, and their activity spikes following shocks to darknet marketplaces. The proportion of bitcoin activity associated with illegal trade declines with increasing mainstream interest and hype (Google search intensity), with the emergence of more opaque alternative cryptocurrencies, and with fewer darknet marketplaces in operation.

Our results have a number of implications. First, by shedding light on the dark side of cryptocurrencies, we hope this research will reduce some of the regulatory uncertainty about the negative consequences and risks of this innovation, thereby allowing more informed policy decisions that weigh up the benefits and costs. In turn, we hope this contributes to these technologies reaching their potential.

Second, the techniques developed in this paper can be used in cryptocurrency surveillance in a number of ways. The methods can be applied going forward as new blocks are added to the blockchain, allowing authorities to keep their finger on the pulse of illegal activity and monitor its trends, its responses to regulatory interventions, and how its characteristics change through time. Such information could help make more effective use of scarce regulatory and enforcement resources. The methods can also be used to identify individuals of strategic importance in illegal networks.

Third, our paper suggests that a significant component of the intrinsic value of bitcoin as a payment system derives from its use in facilitating illegal trade. This has ethical implications for those that view bitcoin as an investment, as well as valuation implications. For example, changes in the demand to use bitcoin in illegal trade (e.g., due to law enforcement crackdowns or increased adoption of more opaque cryptocurrencies in illegal trade) are likely to impact its fundamental value.

Finally, our paper moves the literature closer to answering the important question of the welfare consequences of the growth in illegal online trade. A crucial piece of this puzzle is understanding the extent to which the online illegal trade simply reflects migration of activity that would have otherwise occurred on the street, versus the alternative that by making illegal goods more accessible, convenient to buy, and less risky due to anonymity, the move online could lead to growth in the aggregate black market. Our estimates of the amount of illegal trade facilitated with bitcoin through time contribute to understanding this issue, but further research is required to relate these estimates to trends in the offline black market.

Appendix A: Bitcoin seizures and darknet sites

Table A1: Bitcoin seizures

This table reports major bitcoin seizures, the seizing authority, the owner of the seized bitcoin, the date of the seizure, and the amount (in bitcoin) seized.

Seizing authority	Seized entity	Owner of seized bitcoins	Date of seizure	Bitcoin seized
Australian Government	Individual	Richard Pollard	December 1, 2012	24,518
US government	Individual	Matthew Luke Gillum	July 23, 2013	1,294
ICE and HSI	Individual	Cornelius Jan Slomp	August 27, 2013	385,000
FBI	Individual	Ross William Ulbircht	October 1, 2013	144,000
FBI	Site	Silk Road escrow accounts (many users)	October 2, 2013	29,655

Table A2: Darknet sites accepting bitcoin, current and past

This table reports the 30 known darknet marketplaces with the longest operational history. For sites that remain operational (as at May 2017), the *End date* column states "Operational" and thus there is no *Closure reason*. *Days operational* is the number of days the site was operational before closure. Data are sourced from www.gwern.net.

Market	Launch date	End date	Closure reason	Days operational
Dream	November 15, 2013	Operational		>1,207
Outlaw	December 29, 2013	Operational		>1,163
Silk Road 1	January 31, 2011	October 2, 2013	Raided	975
Black Market Reloaded	June 30, 2011	December 2, 2013	Hacked	886
AlphaBay	December 22, 2014	Operational		>805
Tochka	January 30, 2015	Operational		>766
Crypto Market / Diabolus	February 14, 2015	Operational		>751
Real Deal	April 9, 2015	Operational		>697
Darknet Heroes	May 27, 2015	Operational		>649
Agora	December 3, 2013	September 6, 2015	Voluntary	642
Nucleus	October 24, 2014	April 13, 2016	Scam	537
Middle Earth	June 22, 2014	November 4, 2015	Scam	500
BlackBank	February 5, 2014	May 18, 2015	Scam	467
Evolution	January 14, 2014	March 14, 2015	Scam	424
Silk Road Reloaded	January 13, 2015	February 27, 2016	Unknown	410
Anarchia	May 7, 2015	May 9, 2016	Unknown	368
Silk Road 2	November 6, 2013	November 5, 2014	Raided	364
The Marketplace	November 28, 2013	November 9, 2014	Voluntary	346
Blue Sky Market	December 3, 2013	November 5, 2014	Raided	337
Abraxas	December 13, 2014	November 5, 2015	Scam	327
Pandora	October 21, 2013	August 19, 2014	Scam	302
BuyItNow	April 30, 2013	February 17, 2014	Voluntary	293
TorBazaar	January 26, 2014	November 5, 2014	Raided	283
Sheep	February 28, 2013	November 29, 2013	Scam	274
Cloud-Nine	February 11, 2014	November 5, 2014	Raided	267
Pirate Market	November 29, 2013	August 15, 2014	Scam	259
East India Company	April 28, 2015	January 1, 2016	Scam	248
Mr Nice Guy 2	February 21, 2015	October 14, 2015	Scam	235
Andromeda	April 5, 2014	November 18, 2014	Scam	227
Topix 2	March 25, 2014	November 5, 2014	Voluntary	225

Appendix B: Derivations for the DCE model

We define $I(.)$ and $D(.)$ to be monotonic link functions that map $x_{1i}\beta_1$ and $x_{2i}\beta_2$ to latent probabilities of a bitcoin user being involved predominantly in illegal activity, and detection of an illegal user, respectively.[35] That is,

$$I(x_{1i}\beta_1) = \Pr(L_{1i} = 1) \tag{B.1}$$

$$D(x_{2i}\beta_2) = \Pr(L_{2i} = 1 \mid L_{1i} = 1) \tag{B.2}$$

Table B1 reports the probabilities of various joint outcomes (represented by cells in the table). The joint outcomes are mutually exclusive and exhaustive, so the probabilities in Table B1 sum to one.

Table B1: Two-stage DCE model probability matrix

	Illegal user	Legal user
Detected	$I(x_{1i}\beta_1)D(x_{2i}\beta_2)$	0
Not detected	$I(x_{1i}\beta_1)[1 - D(x_{2i}\beta_2)]$	$1 - I(x_{1i}\beta_1)$

The log likelihood of the users that end up in the detected (seized) illegal users category (A) is the log of the sum (over users in A) of the probabilities of that joint outcome:

$$log\ L_A = \sum_{i\epsilon A} \log[I(x_{1i}\beta_1)D(x_{2i}\beta_2)] \tag{B.3}$$

Similarly, the log likelihood of the users that end up in the other category (A^C) is the log of the sum (over users in A^C) of the probabilities of that joint outcome (the probability that the user is a legal one plus the probability that an illegal user is not detected):

$$log\ L_{A^C} = \sum_{i\epsilon A^C} \log[I(x_{1i}\beta_1)[1 - D(x_{2i}\beta_2)] + 1 - I(x_{1i}\beta_1)] \tag{B.4}$$

$$log\ L_{A^C} = \sum_{i\epsilon A^C} \log[1 - I(x_{1i}\beta_1)D(x_{2i}\beta_2)] \tag{B.5}$$

Sets A and A^C constitute the universe of all bitcoin users. Therefore the full-sample log likelihood is:

$$log\ L = \sum_{i\epsilon A} \log[I(x_{1i}\beta_1)D(x_{2i}\beta_2)] + \sum_{i\epsilon A^C} \log[1 - I(x_{1i}\beta_1)D(x_{2i}\beta_2)] \tag{B.6}$$

Maximum likelihood estimation involves selecting parameter vectors β_1 and β_2 such that the function $log\ L$ is maximized.

[35] In our implementation, the link functions are cumulative logistic distribution functions, that is, $I(x_{1i}\beta_1) = \frac{1}{1+e^{-x_{1i}\beta_1}}$, $D(x_{2i}\beta_2) = \frac{1}{1+e^{-x_{2i}\beta_2}}$.

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Table 1: Variable definitions

This table defines the variables that we compute for each bitcoin user. The third column, *DCE equation*, specifies whether the variable is used in the first equation of the DCE model (the equation modelling whether the user is involved in illegal activity, *I*), the second equation of the DCE model (the equation modelling whether a user that is involved in illegal activity is "detected", e.g., seized by law enforcement agencies, *D*), both equations (*I* & *D*), or as an additional control variable in some specifications (*C*).

Variable	Definition	DCE equation
Transaction Count	The total number of bitcoin transactions involving the given user (where the user is a sender and/or recipient of bitcoin).	C
Transaction Size	Average USD value of the transactions involving the given user. The transaction size is converted from bitcoin to USD using end of day USD/BTC conversion rates. Exchange rates prior to July 18, 2010 are not available and are set to 0.09USD, being the exchange rate on that day.	I & D
Transaction Frequency	The number of bitcoin transactions made by the user per month. This is computed as *Transaction Count* divided by *Existence Time*.	I & D
Counterparties	The total number of other users with which the given user has transacted.	C
Holding Value	The average USD value of the user's bitcoin holdings. The average is computed from the holding balances recorded at the end of each of the user's bitcoin transactions. Holding values are converted from bitcoin to USD using end of day USD/BTC conversion rates. Exchange rates prior to July 18, 2010 are not available and are set to 0.09USD, being the exchange rate on that day.	C
Concentration	Concentration is a measure of the tendency for a user to transact with one or many counterparties. It ranges from 1 for a highly concentrated user who transacts with only one counterparty, to 0 for a user that has many transactions, each with a different counterparty. Formally, it is computed using an adaptation of a normalized Herfindahl–Hirschman Index: $$Concentration = \begin{cases} 1 - \left[\frac{\left[\left(\frac{C}{T}\right) - \left(\frac{1}{T}\right)\right]}{1 - \left(\frac{1}{T}\right)}\right] & \text{if} \quad T > 1 \\ 1 & \text{if} \quad T = 1 \end{cases}$$ where T is *Transaction Count* and C is *Counterparties* (the total number of other users with which the given user has transacted).	I & D
Existence Time	Number of months the bitcoin user is active in the bitcoin network. Measured as the number of months the user's first transaction until the user's last observed transaction, if that transaction results in the user having a bitcoin balance of zero. If the user's last transaction results in a bitcoin balance above zero, the user is regarded as active until the end of our sample in May 2017.	I & D
Darknet Sites	A transaction-weighted average of the number of operational illegal darknet marketplaces at the time a user transacts (the sum of number of operational darknet marketplaces at every transaction, divided by *Transaction Count*). The logic is that if a user transacts at a time when there is a lot of illegal darknet marketplace activity, they are more likely to be involved in illegal activity than if they are active when there is little or no illegal darknet activity.	I
Tumbling	Tumbling refers to techniques or services used to obscure a user's holdings or	I

	transaction history. Wash transactions (transactions where a user is both the sender and receiver of bitcoin in a transaction) are also sometimes used for such purpose. We compute *Tumbling* for each user by calculating the percentage of tumbling and wash transactions in their total number of transactions. We classify transactions involved in tumbling using three approaches, as follows. Approach 1: transactions with known tumbling service providers (such as Coin Fog). Approach 2: transactions where a user sends bitcoin to another user (potential tumbler) and that user sends the bitcoin back (less a tumbling fee of between 0 to 10 % (tumbler characteristic 1) within 10 blocks (tumbler characteristics 2). Approach 3: transactions with users that display the characteristics of tumbling service providers (a *Transaction Count* of 10 or above and displays the two tumbling characteristics above in at least 8% of transitions). The logic is that illegal users are likely to have greater incentives to obscure their activity than legal users.	
Shadow Coins	The transaction-weighted average of the number of opaque cryptocurrencies in existence (Dash, Monero, and ZCash) at the time the user participates in bitcoin. For each user, we calculate the number of major alternative "shadow coins" available (Dash, Monero, and ZCash, which provide more privacy than bitcoin) at the time of each user's transactions. We then compute the average across all of the user's transactions. The logic is that if illegal users make use of shadow coins, the likelihood of illegal activity in bitcoin will be lower when more shadow coins are in existence.	I
Darknet Shock Volume	The percentage of the user's transaction value that occurs immediately after shocks to darknet marketplaces, including one week after each seizure or "exit scam" of a darknet marketplace. Seizures by law enforcement officials and "exit scams" in which darknet sites close without warning are likely to result in increased activity from illegal users as they turn to alternative marketplaces or relocate their holdings. At the same time, shocks to darknet marketplaces are unlikely to materially affect the activity of legal users.	I
Bitcoin Hype	The transaction-weighted average of the Google Trends value for "bitcoin" (calculated from Jan 1, 2009 to May 1, 2017). For each user, we record the intensity of Google searches for the term "bitcoin" (scaled from 0-100) in the months of their transactions and then compute the average for each user across all of their transactions. The logic is that the more intensive is the search activity for bitcoin on Google, the more likely the user is transacting for speculative (as opposed to illegal) purposes.	I
Pre-Silk-Road User	Dummy variable that is equal to one if the user commenced transacting in bitcoin prior to the seizure of Silk Road 1 on October 1, 2013. The logic is that an illegal user that was using bitcoin prior to the first major darknet seizure by law enforcement authorities has a higher probability of having been detected than a user that started transacting in bitcoin after that seizure because such a user could not have been "detected" in the first seizure.	D

Table 2: Descriptive statistics for all users

This table reports descriptive statistics about bitcoin users. *Transaction Count* is the total number of bitcoin transactions involving the given user. *Transaction Size* (in USD) is the user's average transaction value. *Transaction Frequency* is the average rate at which the user transacts between their first and last transactions, annualized to transactions per year. *Counterparties* is the total number of other users with which the given user has transacted. *Holding Value* is the average value of the user's bitcoin holdings (in USD), where holdings are measured after each transaction. *Concentration* takes values between zero and one, with higher values indicating a tendency to repeatedly trade with a smaller number of counterparties. *Existence Time* is the number of months between the date of the user's first and last transaction. *Darknet Sites* is the average number of operational darknet sites at the time of each of the user's transactions. *Tumbling* is the percentage of the user's transactions that attempt to obscure the user's holdings (wash or tumbling trades). *Shadow Coins* is the average number of major opaque cryptocurrencies (Dash, Monero, ZCash) in existence at the time of each of the user's transactions. *Darknet Shock Volume* is the percentage of the user's total dollar volume that is transacted during the week after marketplace seizures or "exit scams". *Bitcoin Hype* is a measure of the intensity of Google searches for the term "bitcoin" around the time of the user's trades. *Pre-Silk-Road User* is a dummy variable taking the value one if the user's first bitcoin transaction is before the seizure of the Silk Road on October 2013. *StdDev* is the standard deviation, *P25* is the 25th percentile, and *P75* is the 75th percentile.

Variable	Mean	StdDev	Min	P25	Median	P75	Max
Panel A: Transactional characteristics							
Transaction Count	5.70	1,622.74	1.00	2.00	3.00	3.00	11,410,691
Transaction Size	5,207.61	56,939.00	1.00	22.06	111.91	668.44	92,504,688
Transaction Frequency	29.88	659.27	0.12	7.20	24.00	36.00	3,077,978
Counterparties	4.18	553.71	0.00	2.00	3.00	3.00	4,385,500
Holding Value	3,974.05	55,011.00	0.00	15.91	83.96	551.37	115,529,839
Concentration	0.10	0.28	0.00	0.00	0.00	0.00	1.00
Existence Time	6.61	11.91	1.00	1.00	1.00	5.00	101.00
Panel B: Characteristics associated with particular types of activity							
Darknet Sites	17.14	5.10	0.00	15.00	18.00	20.00	27.00
Tumbling	0.43	0.04	0.00	0.00	0.00	0.00	181.82
Shadow Coins	2.07	0.87	0.00	2.00	2.00	3.00	3.00
Darknet Shock Volume	16.51	0.36	0.00	0.00	0.00	0.00	100.00
Bitcoin Hype	28.29	15.44	0.00	19.00	24.00	38.00	100.00
Pre-Silk-Road User	0.07	0.26	0.00	0.00	0.00	0.00	1.00

Table 3: Size and activity of observed user groups

This table reports the size and activity of (1) all users, (2) observed illegal users, and (3) other users. The observed illegal user group includes three subgroups: users that had bitcoin seized by law enforcement agencies ("*Seized Users*"), illegal darknet marketplace escrow accounts (hot wallets) and users that have interacted (sent or received bitcoin) with those accounts ("*Black Market Users*"), and users whose bitcoin address(es) are mentioned in darknet forums ("*Forum Users*"). The measures of group size and activity are: the number of users (*Users*), the number of transactions (*Transaction Count*), the dollar value monthly average of bitcoin holdings (*Holding Value*), the number of bitcoin addresses (*Number Of Addresses*), and the dollar volume of transactions (*Volume*). The percentage of the total users/activity is reported in parentheses below each value.

Group / Subgroup	Users	Transaction Count (Mil)	Holding Value ($Mil)	Number Of Addresses (Mil)	Volume ($Bil)
1. All Users	106,244,432	605.69	2,964.66	221.71	1,862.51
	(100.00%)	(100.00%)	(100.00%)	(100.00%)	(100.00%)
2. Observed Illegal Users	6,223,337	196.11	1,342.43	58.38	241.46
	(5.86%)	(32.38%)	(45.28%)	(26.33%)	(12.96%)
2A. Seized Users	1,016	23.83	9.39	8.30	17.51
	(0.00%)	(3.93%)	(0.32%)	(3.74%)	(0.94%)
2B. Black Market Users (not in 2A)	6,221,873	157.30	1,324.32	49.71	220.91
	(5.86%)	(25.97%)	(44.67%)	(22.42%)	(11.86%)
2C. Forum Users (not in 2A or 2B)	448	14.98	8.72	0.38	3.03
	(0.00%)	(2.47%)	(0.29%)	(0.17%)	(0.16%)
3. Other Users	100,021,095	409.58	1,622.23	163.33	1,621.05
	(94.14%)	(67.62%)	(54.72%)	(73.67%)	(87.04%)

Table 4: Estimated size and activity of legal and illegal user groups

This table reports the size and activity of legal and illegal user groups. The measures of group size and activity are: the number of users (*Users*), the number of transactions (*Transaction Count*), the average dollar value of bitcoin holdings (*Holding Value*), the number of bitcoin addresses (*Number Of Addresses*), and the dollar volume of transactions (*Volume*). Panel A reports the values of these measures for the two user groups, while Panel B expresses the measures for each group as a percentage of the total. Different rows report different approaches to classifying the legal and illegal user groups. *SLM* provides estimates from the network cluster analysis approach to classification (a variant of the "Smart Local Moving" algorithm). *DCE* provides estimates from the detection controlled estimation (DCE) approach to classification, which exploits the characteristics of legal and illegal users. *Midpoint* is the average of the estimates from the SLM and DCE models. *Upper bound* and *Lower bound* provide a 99% confidence interval around the *Midpoint*, using a form of bootstrapped standard errors.

Group	Classification	Users (Mil)	Transaction Count (Mil)	Holding Value ($Mil)	Number Of Addresses (Mil)	Volume ($Bil)
Panel A: Values						
Illegal	SLM	30.94	276.63	1,394.76	87.95	436.78
	DCE	22.71	260.36	1,645.64	81.47	319.25
	Upper bound	30.55	283.78	1,831.89	91.39	447.52
	Midpoint	26.82	268.50	1,520.20	84.71	378.01
	Lower bound	23.09	253.21	1,208.51	78.03	308.50
Legal	SLM	75.31	329.06	1,569.90	133.76	1,425.73
	DCE	83.54	345.33	1,319.03	140.25	1,543.26
	Upper bound	83.16	352.48	1,756.15	143.69	1,554.00
	Midpoint	79.42	337.19	1,444.46	137.00	1,484.49
	Lower bound	75.69	321.91	1,132.77	130.32	1,414.98
Panel B: Percentages						
Illegal	SLM	29.12%	45.67%	47.05%	39.67%	23.45%
	DCE	21.37%	42.99%	55.51%	36.74%	17.14%
	Upper bound	28.76%	46.85%	61.79%	41.22%	24.03%
	Midpoint	25.24%	44.33%	51.28%	38.21%	20.30%
	Lower bound	21.73%	41.81%	40.76%	35.19%	16.56%
Legal	SLM	70.88%	54.33%	52.95%	60.33%	76.55%
	DCE	78.63%	57.01%	44.49%	63.26%	82.86%
	Upper bound	78.27%	58.19%	59.24%	64.81%	83.44%
	Midpoint	74.76%	55.67%	48.72%	61.79%	79.70%
	Lower bound	71.24%	53.15%	38.21%	58.78%	75.97%

Table 5: Differences in characteristics between illegal and legal users

This table reports differences in mean characteristics for illegal vs legal bitcoin users. The first three columns ("*Observed*") compare observed illegal users (those identified through law enforcement seizures, darknet marketplaces, and darknet forums) vs other users (including both legal and undetected illegal users). The second three columns ("*SLM*") compare illegal vs legal users, as classified by a network cluster analysis algorithm (SLM). The final three columns ("*DCE*") compare illegal vs legal users, as classified by a detection controlled estimation model (DCE). The characteristics are as follows. *Transaction Count* is the total number of bitcoin transactions involving the given user. *Transaction Size* (in USD) is the user's average transaction value. *Transaction Frequency* is the average rate at which the user transacts between their first and last transactions, annualized to transactions per year. *Counterparties* is the total number of other users with which the given user has transacted. *Holding Value* is the average value of the user's bitcoin holdings (in USD), where holdings are measured after each transaction. *Concentration* takes values between zero and one, with higher values indicating a tendency to repeatedly trade with a smaller number of counterparties. *Existence Time* is the number of months between the date of the user's first and last transaction. *Darknet Sites* is the average number of operational darknet sites at the time of each of the user's transactions. *Tumbling* is the percentage of the user's transactions that attempt to obscure the user's holdings (wash or tumbling trades). *Shadow Coins* is the average number of major opaque cryptocurrencies (Dash, Monero, ZCash) in existence at the time of each of the user's transactions. *Darknet Shock Volume* is the percentage of the user's total dollar volume that is transacted during the week after marketplace seizures or "exit scams". *Bitcoin Hype* is a measure of the intensity of Google searches for the term "bitcoin" around the time of the user's trades. *Pre-Silk-Road User* is a dummy variable taking the value one if the user's first bitcoin transaction is before the seizure of the Silk Road on October 2013. The significance of the difference in means is computed with t-tests. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels respectively.

Variable	Observed			SLM			DCE		
	Other (1)	Illegal (2)	Difference (2-1)	Legal (1)	Illegal (2)	Difference (2-1)	Legal (1)	Illegal (2)	Difference (2-1)
Transaction Count	4.09	31.51	27.42***	4.37	8.94	4.57***	4.13	11.47	7.33***
Transaction Size	5,346.87	2,969.38	-2377.49***	6,225.51	2,729.66	-3495.85***	5,955.68	2,455.41	-3500.28***
Transaction Frequency	28.91	45.46	16.54***	29.77	30.16	0.39**	31.44	24.15	-7.30***
Counterparties	3.53	14.61	11.08***	3.77	5.18	1.42***	3.71	5.91	2.20***
Holding Value	4,021.77	3,207.06	-814.71***	4,625.45	2,388.31	-2237.14***	4,487.67	2,084.42	-2403.25***
Concentration	0.09	0.20	0.11***	0.08	0.13	0.05***	0.06	0.23	0.17***
Existence Time	6.19	13.44	7.26***	5.91	8.31	2.40***	4.06	15.99	11.93***
Darknet Sites	17.17	16.67	-0.50***	17.13	17.17	0.04***	16.53	19.37	2.84***
Tumbling	0.38	1.15	0.77***	0.36	0.60	0.24***	0.24	1.11	0.87***
Shadow Coins	2.11	1.43	-0.69***	2.17	1.84	-0.33***	2.25	1.42	-0.83***
Darknet Shock Volume	15.84	27.25	11.40***	14.51	21.39	6.88***	10.34	39.21	28.87***
Bitcoin Hype	28.74	1.43	-27.31***	29.67	1.84	-27.82***	30.33	1.42	-28.9***
Pre-Silk-Road User	0.06	0.22	0.16***	0.06	0.12	0.07***	0.05	0.16	0.11***

Table 6: DCE model estimates

This table reports the coefficient estimates and marginal effects of two detection controlled estimation (DCE) models. Both models use the two-equation structure given by equations (1-4) of the paper. Model 1 is the baseline model used for the main results in the paper. Model 2 includes additional control variables. I() is the probability that a given user is predominantly using bitcoin for illegal activity. D() is the conditional probability of detection. Variables are defined in Table 1. Numbers not in brackets are the coefficient estimates. Numbers in brackets are the marginal effects (partial derivatives of the corresponding probability with respect to each of the variables, reported as a fraction of the estimated corresponding probability). Pseudo R^2 is McFadden's likelihood ratio index (one minus the ratio of the log-likelihood with all predictors and the log-likelihood with intercepts only). Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively, using bootstrapped standard errors.

	Model 1		Model 2	
Variable	I()	D()	I()	D()
Intercept	-1.127***	0.409***	-1.196***	0.564***
	(-0.744)	(0.194)	(-0.806)	(0.258)
Darknet Sites	0.659***		0.647***	
	(0.435)		(0.435)	
Tumbling	0.070***		0.078***	
	(0.046)		(0.052)	
Shadow Coins	-0.977***		-0.963***	
	(-0.645)		(-0.649)	
Bitcoin Hype	-0.512***		-0.505***	
	(-0.338)		(-0.340)	
Darknet Shock Volume	0.433***		0.429***	
	(0.286)		(0.289)	
Pre-Silk-Road User		0.862**		1.253***
		(0.410)		(0.573)
Transaction Frequency	0.328***	0.788***	0.153***	0.964***
	(0.217)	(0.375)	(0.103)	(0.441)
Transaction Size	-0.124***	-0.121*	-1.282***	0.274***
	(-0.082)	(-0.058)	(-0.863)	(0.126)
Concentration	0.292***	0.507***	0.291***	0.482***
	(0.193)	(0.241)	(0.196)	(0.220)
Existence Time	0.117***	2.322***	0.024**	2.362***
	(0.077)	(1.104)	(0.016)	(1.081)
Holding Value			1.831***	-0.909***
			(1.233)	(-0.416)
Transaction Count			4.967***	-1.085***
			(3.346)	(-0.497)
Pseudo R^2	19.90%		20.06%	

Table 7: Network characteristics of legal and illegal bitcoin user networks

This table reports metrics that characterize the trade networks of estimated legal and illegal bitcoin users. In the columns labelled "SLM" user classifications into legal and illegal communities are based on a network cluster analysis algorithm (SLM) and in the columns labelled "DCE" the classifications are from a detection controlled estimation (DCE) model. *Density* takes the range [0,1] and indicates how highly connected the users are within a community (versus how sparse the connections are between users); it is the actual number of links between users within the given community (a "link" between two users means that they have transacted with one another) divided by the total potential number of links. *Reciprocity* takes the range [0,1] and indicates the tendency for users to engage in two-way interactions (both sending and receiving bitcoin to and from one another); it is the number of two-way links between users within the given community divided by the total number of links within the given community (two-way and one-way). *Entropy* measures the amount of heterogeneity among users in their number of links. It takes its minimum value of zero when all users have the same number of links (same degree).

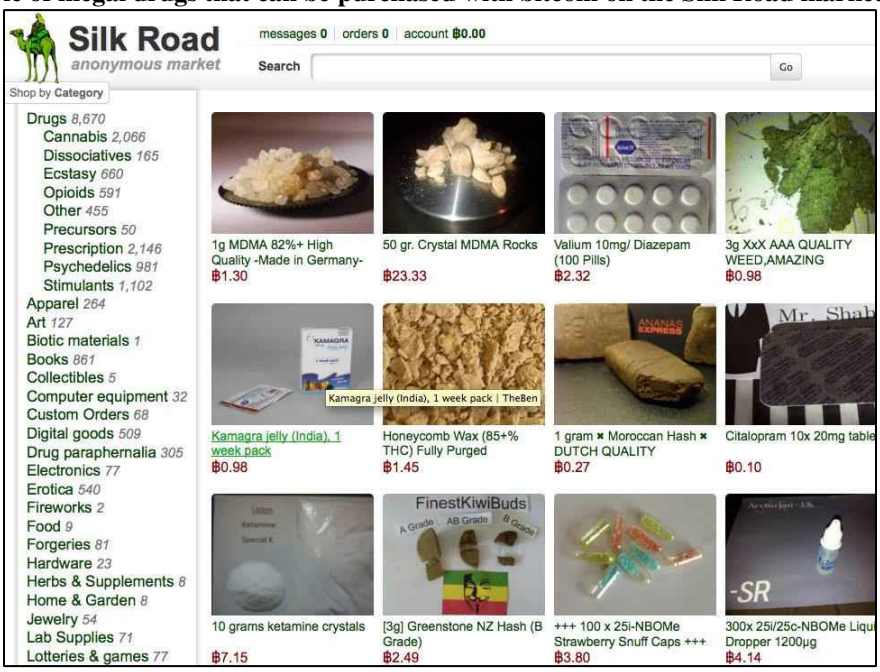
Metric	SLM		DCE	
	Legal	Illegal	Legal	Illegal
Density (10^{-6})	0.04	0.13	0.04	0.17
Reciprocity	0.01	0.03	0.01	0.03
Entropy	1.50	1.75	1.53	1.79

Table 8: Robustness tests

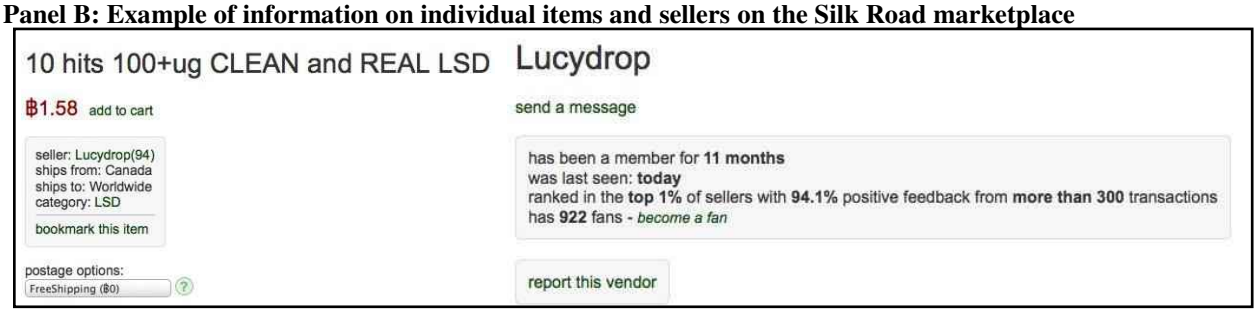
This table reports robustness tests for the sensitivity of the overall estimated amount of illegal activity in bitcoin to variations in the specification of the underlying empirical models. The rows reflect estimates from different models. *SLM Baseline* and *DCE Baseline* are the SLM and DCE models used to produce the main results, and are included for comparison. The models labelled "Alternative" are variations on the corresponding baseline model. *SLM Alternative 1* is an SLM model that considers the transaction volume (in bitcoins) rather than the transaction count as a measure of trading activity when applying the network cluster analysis algorithm. *SLM Alternative 2* is a variation of the baseline SLM model in which observed (known) illegal user are constrained from leaving the illegal community. *DCE Alternative 1* and *2* are variations of the baseline DCE model in which exclusion restrictions for the instrumental variables are relaxed one at a time (these models correspond to Models 1 and 2 of Table A1 in the internet appendix) respectively. The measures of group size and activity are: the number of users (*Users*), the number of transactions (*Transaction Count*), the average dollar value of bitcoin holdings (*Holding Value*), the number of bitcoin addresses (*Number Of Addresses*), and the dollar volume of transactions (*Volume*). Panel A reports the values of these measures for the two user groups, while Panel B expresses the measures for each group as a percentage of the total.

Group	Model	Users (Mil)	Transaction Count (Mil)	Holding Value ($Mil)	Number Of Addresses (Mil)	Volume ($Bil)
Panel A: Values						
Illegal	SLM Baseline	30.94	276.63	1,394.76	87.95	436.78
	SLM Alternative 1	28.95	270.69	1,418.42	85.10	400.29
	SLM Alternative 2	23.60	287.16	1,866.15	89.14	440.64
	DCE Baseline	22.71	260.36	1,645.64	81.47	319.25
	DCE Alternative 1	27.14	275.20	1,882.34	88.23	418.79
	DCE Alternative 2	21.14	254.79	1,722.23	78.77	309.96
Panel B: Percentages						
Illegal	SLM Baseline	29.12%	45.67%	47.05%	39.67%	23.45%
	SLM Alternative 1	27.25%	44.69%	47.84%	38.38%	21.49%
	SLM Alternative 2	22.21%	47.41%	62.95%	40.20%	23.66%
	DCE Baseline	21.37%	42.99%	55.51%	36.74%	17.14%
	DCE Alternative 1	25.55%	45.44%	63.49%	39.80%	22.49%
	DCE Alternative 2	19.90%	42.07%	58.09%	35.53%	16.64%

Panel A: Example of illegal drugs that can be purchased with bitcoin on the Silk Road marketplace



Panel B: Example of information on individual items and sellers on the Silk Road marketplace



Panel C: The escrow account and bitcoin payment interface for the Silk Road marketplace

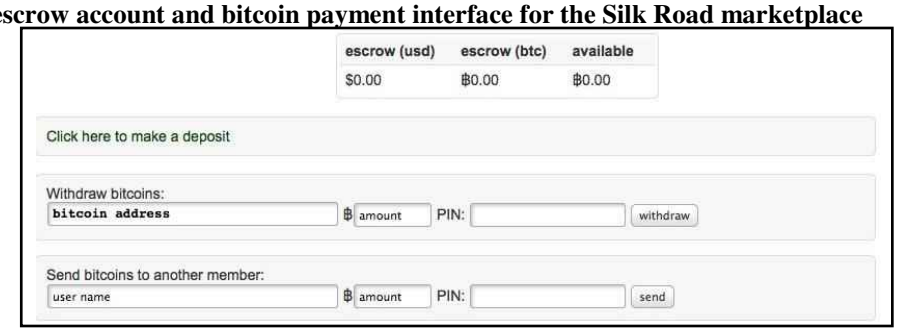


Figure 1
Screenshots from one of the first illegal darknet marketplaces, Silk Road 1
Panel A provides an example of the "Drugs" page from Silk Road. It illustrates the wide variety of illegal goods that can be purchased using bitcoin, including a vast array of illegal drugs, weapons, and forgeries. Panel B provides an example of information about individual items and sellers. Clicking on the appropriate headings, one can obtain further information about the item for sale (detailed product description, insurance/refunds, postage methods and locations, security and encryption, etc.) and about the seller (detailed feedback and ratings from buyers, history of sales, etc.). Panel C shows the interface for depositing bitcoin to Silk Road's escrow account, transferring bitcoins to a given seller, and withdrawing bitcoins from escrow. Screenshot source: www.businessinsider.com.au

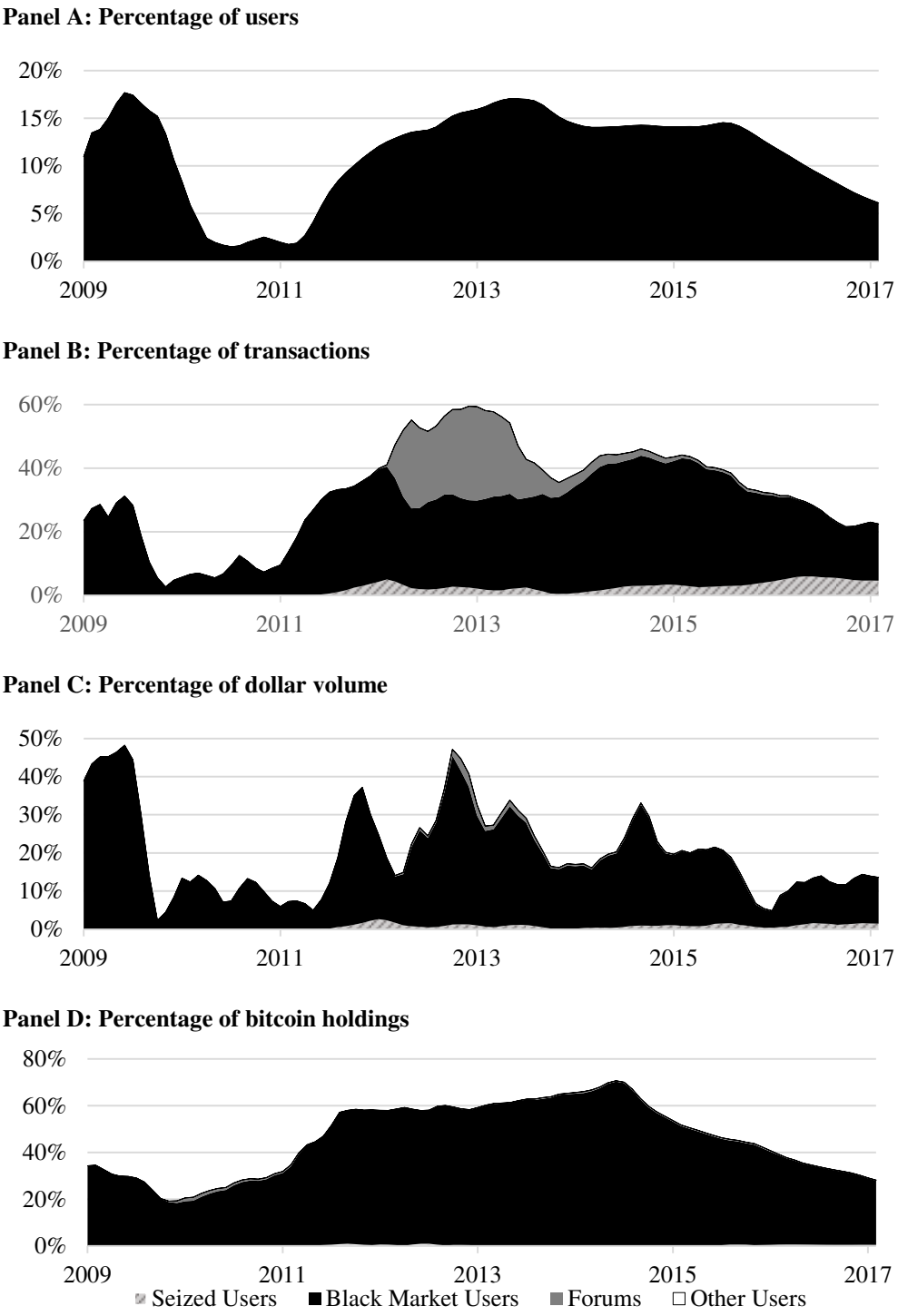


Figure 2
Size and activity of the sample of "observed" illegal bitcoin users
This figure illustrates the time-series of the three subgroups of observed illegal users as a percentage of total users (Panel A), their number of transactions as a percentage of all transaction (Panel B), the dollar value of their transactions as a percentage of the dollar value of all transactions (Panel C), and the dollar value of their bitcoin holdings as a percentage of the dollar value of all bitcoin holdings (Panel D). The observed illegal user group includes three subgroups: users that had bitcoin seized by law enforcement agencies ("*Seized Users*"), illegal darknet marketplace escrow accounts (hot wallets) and users that have sent or received bitcoin from those accounts ("*Black Market Users*"), and users whose bitcoin address(es) are mentioned in darknet forums ("*Forum Users*"). "*Other Users*" corresponds to all bitcoin users other than those in the sample of observed illegal users. The values are smoothed with a three-month moving average.

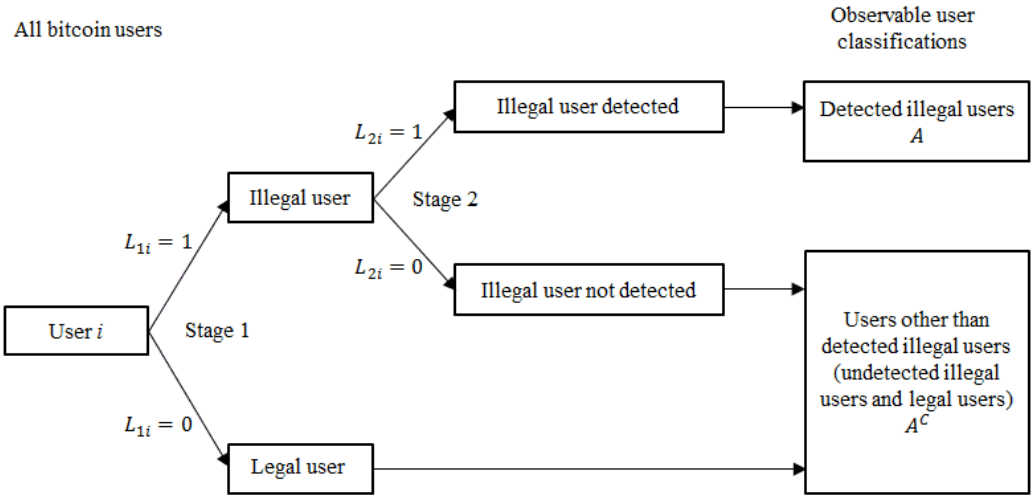
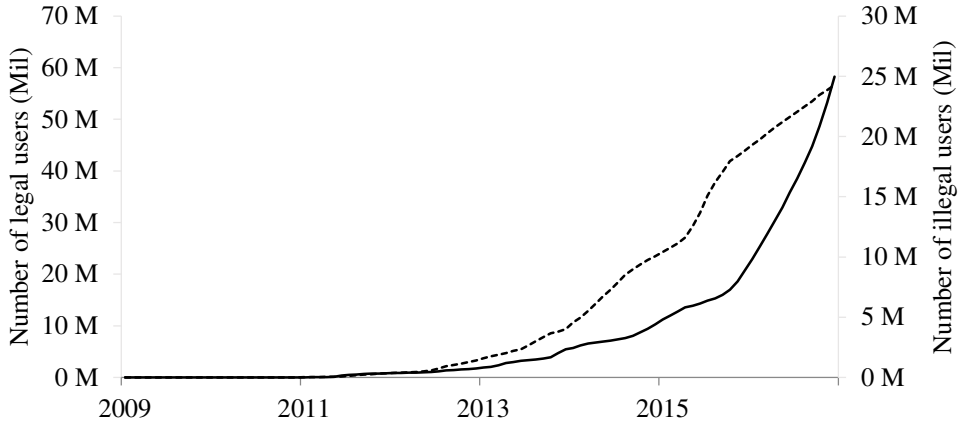


Figure 3
Two-stage detection controlled estimation (DCE) model
The figure illustrates the structure of the two-stage DCE model. Stage 1 models how legal and illegal users of bitcoin differ in characteristics. Stage 2 models the determinants of the probability that an illegal user was "detected" (had bitcoin seized by a law enforcement agency, was identified in darknet forums, or was observed in the blockchain data as having transacted with a known illegal darknet marketplace). Both stages are estimated simultaneously using maximum likelihood to select parameter values that maximize the likelihood of the observable user classifications, A and A^C.

Panel A: Estimated number of illegal and legal bitcoin users



Panel B: Estimated percentage of illegal bitcoin users with 99% confidence bounds

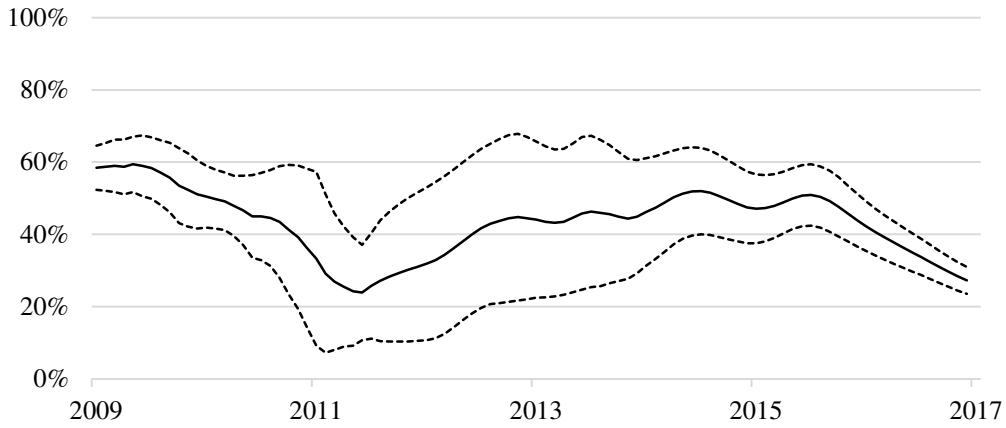
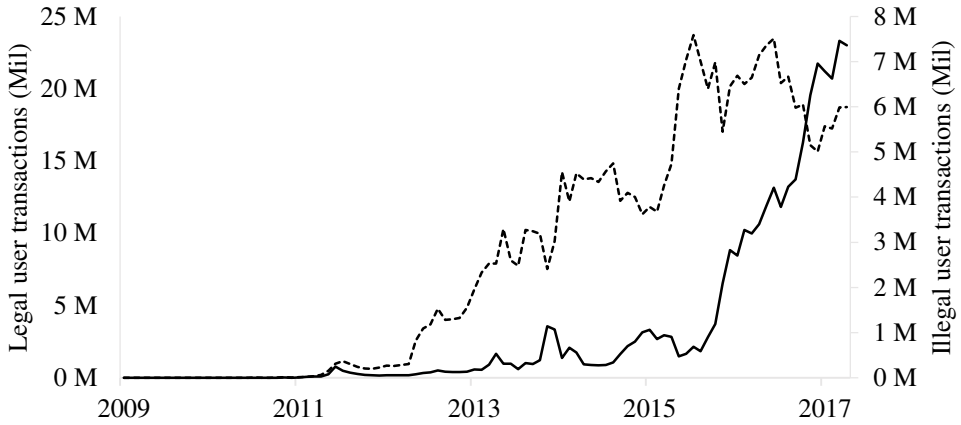


Figure 4
Estimated number and percentage of bitcoin users involved in illegal activity
This figure illustrates the time-series of the estimated number of illegal and legal bitcoin users (Panel A) and the percentage of illegal users (Panel B). In Panel A, the number of legal users is plotted with the solid line using the left-hand-side axis and the number of illegal users is plotted with the dashed line using the right-hand-side axis. In Panel B, the solid line is the point estimate of the percentage of illegal users and the dashed lines provide a 99% confidence interval using bootstrapped standard errors. The estimates come from a combination of two empirical models (the average of the estimates produced by the SLM and DCE models). All values are smoothed with a five-month moving average.

Panel A: Estimated number of illegal and legal bitcoin user transactions per month



Panel B: Estimated percentage illegal user transactions with 99% confidence bounds

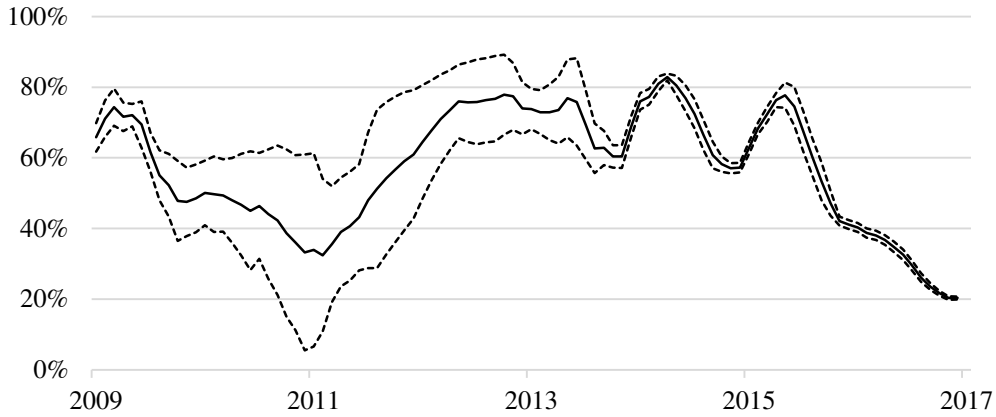
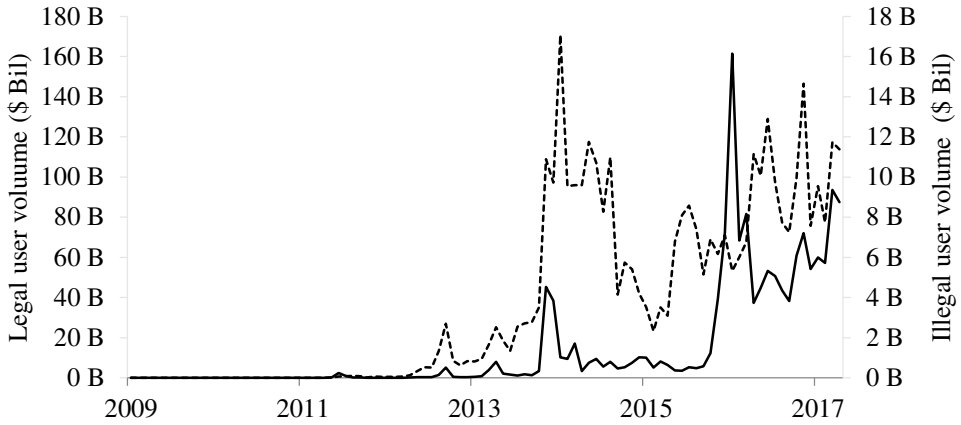


Figure 5
Estimated number and percentage of illegal bitcoin users transactions
This figure illustrates the time-series of the estimated number of illegal and legal bitcoin user transactions per month (Panel A) and the percentage of illegal user transactions (Panel B). In Panel A, the number of legal user transactions is plotted with the solid line using the left-hand-side axis and the number of illegal user transactions is plotted with the dashed line using the right-hand-side axis. In Panel B, the solid line is the point estimate of the percentage of illegal user transactions and the dashed lines provide a 99% confidence interval using bootstrapped standard errors. The estimates come from a combination of two empirical models (the average of the estimates produced by the SLM and DCE models). All values are smoothed with a five-month moving average.

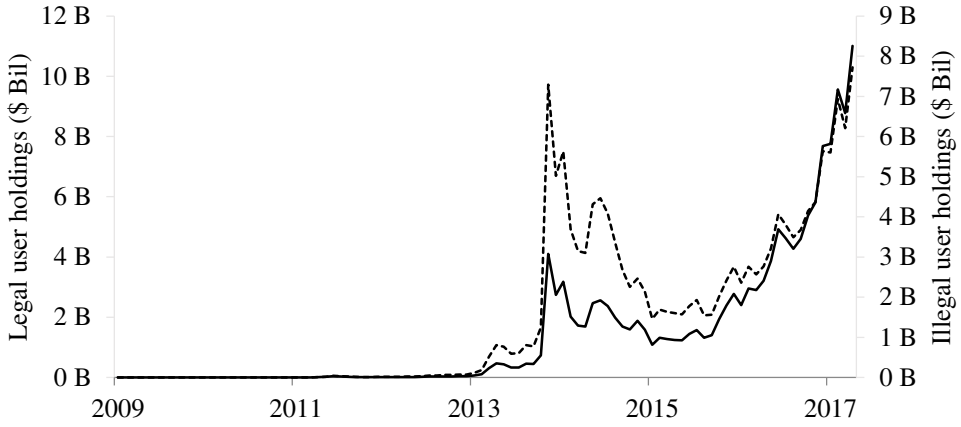
Panel A: Estimated dollar volume of illegal and legal bitcoin user transactions per month



Panel B: Estimated percentage illegal user dollar volume with 99% confidence bounds

Figure 6
Estimated dollar volume and percentage dollar volume of illegal bitcoin user transactions
This figure illustrates the time-series of the estimated dollar volume of illegal and legal bitcoin user transactions per month (Panel A) and illegal user dollar volume as a percentage of total dollar volume of bitcoin transactions (Panel B). In Panel A, the dollar volume of legal user transactions is plotted with the solid line using the left-hand-side axis and the dollar volume of illegal user transactions is plotted with the dashed line using the right-hand-side axis. In Panel B, the solid line is the point estimate of the illegal dollar volume as a percentage of total dollar volume and the dashed lines provide a 99% confidence interval using bootstrapped standard errors. The estimates come from a combination of two empirical models (the average of the estimates produced by the SLM and DCE models). All values are smoothed with a five-month moving average.

Panel A: Estimated dollar value of illegal and legal user bitcoin holdings



Panel B: Estimated percentage of illegal users bitcoin holdings with 99% confidence bounds

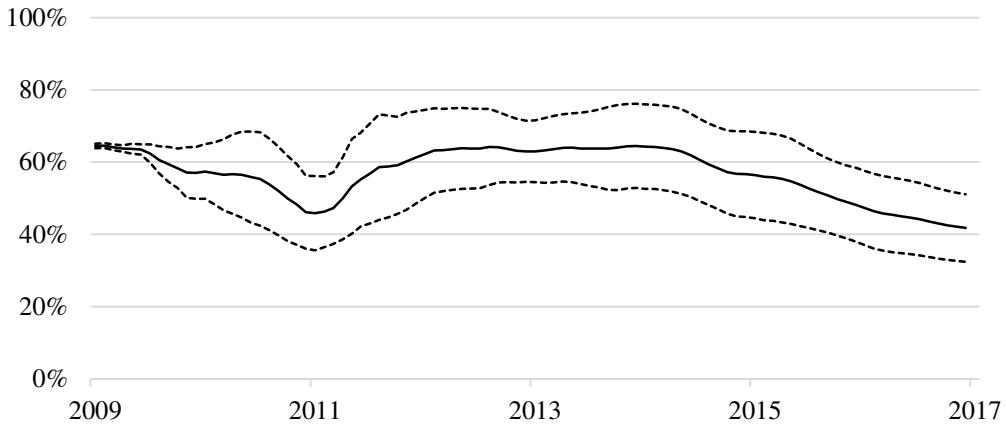


Figure 7
Estimated dollar value and percentage of illegal user bitcoin holdings
This figure illustrates the time-series of the estimated dollar value of illegal and legal user bitcoin holdings (Panel A) and illegal user holdings as a percentage of total bitcoin holdings (Panel B). In Panel A, the dollar value of legal user bitcoin holdings is plotted with the solid line using the left-hand-side axis and the dollar value of illegal user holdings is plotted with the dashed line using the right-hand-side axis. In Panel B, the solid line is the point estimate of the illegal user holdings as a percentage of total bitcoin holdings and the dashed lines provide a 99% confidence interval using bootstrapped standard errors. The estimates come from a combination of two empirical models (the average of the estimates produced by the SLM and DCE models). All values are smoothed with a five-month moving average.