From Darknets to Light

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A large majority of e-commerce happens on the "Surface Web", which consists of all the websites that can be accessed through search engines. However, there has recently been a rapid growth in the "Dark Web", consisting of websites which cannot be indexed by search engines. The Dark Web offers a high degree of anonymity and security to its users and has attracted illicit activity. Online marketplaces similar to eBay and Etsy on the Surface Web have also evolved on the Dark Web and are commonly known as "Darknet markets". These markets have attracted sellers and buyers of illegal products such as drugs, weapons, and counterfeits. Law enforcement agencies are interested in curbing the rise of these markets. In this research, we focus on a bust operation conducted by the FBI and Europol in November 2014 that shut down Silk Road 2.0, one of the biggest Darknet markets at the time. Using the bust as an exogenous shock, we investigate the causal effect of the bust on Evolution and Agora, the next two biggest Darknet markets that were not subject to the bust. We find that the bust had positive marketing consequences for the buyers and the administrators of Evolution and Agora. Specifically, the prices reduced, and the number of transactions per vendor increased following the bust. Our results also indicate that these benefits are not simply a product of the forces of supply and demand but that they occur despite them. Our findings demonstrate that there could be surprising and unintended consequences to such busts and recommend law enforcement agencies consider them into their enforcement strategies.

Key words: Two-sided markets; ecommerce; Dark Web

1. Introduction

The advent of the internet has led to an explosion in global retail e-commerce with its size estimated to be about $3.45 trillion in 2019 (eMarketer (2019)). A large majority of this e-commerce happens on what is known as the "Surface Web", which contains all the websites that can be indexed and hence be searched by search engines such as Google and Bing (Bergman (2001)). At the same time, there has also been a rapid growth in the "Dark Web" which consists of the part of the internet that can neither be indexed by search engines nor is accessible through regular web browsers due to the use of certain digital encryptions Brightplanet (2014). Two-sided marketplaces such as Amazon Marketplace or Etsy, where multiple vendors and buyers transact, have also evolved on the Dark Web and are commonly known as "Darknet" markets (Barratt and Aldridge (2016)).

Two key aspects differentiate Darknet markets from their Surface Web counterparts. First, the use of nonstandard software and protocols to access them has enabled a high level of anonymity and security to the identity of all its users. Second, the rise of cryptocurrency has enabled the possibility of conducting nearly untraceable transactions on these markets. Because of these features, Darknet markets have become hotbeds for buying and selling various illicit products such as drugs, weapons, counterfeits, and stolen credit cards (Foley et al. (2019)). Estimates of the amount of goods bought and sold in these markets range from $600 million to $700 million (Van Wirdum (2019)) with thousands of buyers and vendors frequenting these markets (EMCDDA and Europol (2017)). The first Darknet market that gained popularity and a big following was Silk Road, which began its operations in 2011 (Chen (2011)).

Not surprisingly, law enforcement authorities have been closely monitoring Darknet markets since their inception. The main difficulty they face in curbing these illegal sales is the high level of anonymity that is provided by the Dark Web infrastructure to all the players on these markets (i.e., vendors, buyers, and administrators of the market). Even so, there were early crackdowns by the Department of Justice in the US, which shut down Silk Road in 2013 (Crawford (2014)). Following this, Silk Road 2.0 (SR2) arose as the largest and most popular Darknet market. In November 2014, in a secret bust operation dubbed "Operation Onymous", the FBI and Europol together shut down the operation of Silk Road 2.0 along with several other Darknet markets. This operation involved shutting down servers that hosted the markets, arrests of its founders/administrators and seizures of computer servers, cash, and bitcoins involved with the markets (Europol (2014) and Department-Of-Justice (2014)). The anonymity of the Dark Web meant that they could only arrest the administrators but not any of the vendors or buyers on the busted markets who were free to migrate their future Darknet transactions to other markets.[1]

[1] For the rest of this article, we refer to the part of Operation Onymous that led to the closure of Silk Road 2.0 as simply "the bust".

From the perspective of law enforcement agencies, not only do such operations obviously curb illegal, criminal activity, they also potentially serve as a deterrent to the players in other current and future Darknet markets. Such strategic motivations were evident after the bust when Troels Oerting, the chief of the Interpol at the time, mentioned after the bust, “in the next wave we’re going to come after people using these sites. They might hear a knock at the door” (East-Bay-Times (2014)). Interestingly, during Operation Onymous, law enforcement agencies did not shut down either Evolution or Agora, which were the second and third largest Darknet markets at the time respectively. In response to a question regarding this, Oerting said, “We didn’t get Agora or Evolution, because there’s only so much we can do on one day” (East-Bay-Times (2014)). In other words, given the budget and personnel limitations of law enforcement agencies coupled with the increasing sophistication of each iteration of these markets, it is potentially impossible to completely eliminate all such markets. Law enforcement agencies have since conducted several such busts (See Table A1 of Foley et al. (2019)) but despite them, other Darknet markets continue to remain operational. This brings into focus the question of how such law enforcement busts affect other Darknet markets that are not subject to the bust.

We focus on Operation Onymous in our research and ask three questions from a marketing perspective regarding how the vendors and buyers operating in Evolution and Agora were affected by the bust. First, how did the vendors change their price after the bust with a looming threat of closure to their marketplace? Second, did the average vendor have fewer or more transactions after the bust? Third, from a policy perspective, was there an economic benefit to any of the players in Evolution or Agora as a result of the bust? We explore the answers to these questions by focusing on how the average price of products listed on these markets as well as the number of transactions per vendor evolved in Evolution and Agora as a result of the bust. This question is particularly interesting from a marketing perspective given not only the rich stream of research on two-sided markets (Sriram et al. (2015)), but also since it is unclear if law enforcement agencies consider the marketing consequences of the bust on other markets since they continue to conduct such bust operations (see Europol (2019) for the operation dated May 3, 2019).

We use data from a panel of 1,209 vendors selling 17,320 products on Evolution as well as a panel of 828 vendors selling 8,025 products on Agora. As the occurrence and the timing of the bust was unexpected, we causally identify the effect of the bust on Evolution and

Agora by focusing on a narrow time window around the bust. Our results are robust and suggest that there was a significant drop in the price of products across the two markets following the bust. The price of the average product fell by 8.80% in Evolution and 4.18% in Agora in the one month period after the bust. We also find that the average number of transactions by a vendor in Evolution significantly increased after the bust.[2] The first result suggests economic benefit to buyers since these products became cheaper after the bust. The second result suggests economic benefit to the administrators of the markets since their revenue, which is obtained by charging vendors a commission on each sale, increased after the bust. Our results suggest that the outcome is less clear for vendors.

One obvious explanation of our results is that following the bust, there was a demand shock in Evolution and Agora due to buyers who migrated from SR2 and a competitive shock on the supply side due to the corresponding vendor migration. As a result of this, the new equilibrium prices decreased. While our finding about the number of transactions is consistent with an increase in demand, our data surprisingly suggests that there was no significant increase in the number of vendors in either Evolution or Agora after the bust. Taken together, this seems to contradict microeconomic theory that suggests that when demand increases while supply remains relatively unchanged, price should increase in the market. We conduct two additional analyses to further investigate the effects of the demand shock.

First, we investigate if there was a buyer migration from SR2 by focusing on multihomers, who are vendors who sell simultaneously on multiple markets. In particular, we look at the price and the number of transactions of vendors who sold at SR2 before the bust and also at either Evolution or Agora. Our results suggest that multihoming vendors significantly decreased their price after the bust compared to the average non-multihoming vendor at Evolution and Agora. Further, they also had significantly more transactions after the bust compared to the average non-multihoming vendor. These findings are consistent with the hypothesis that buyers from SR2 migrated to Evolution and Agora and perhaps continued buying from vendors they knew in SR2.

Second, we recategorize the various products sold on these markets by whether they were physical (e.g., drugs, weapons, etc.) or digital products (e.g., pirated software, hacked

[2] Agora did not display the exact number of transactions during our data duration but only presented the data in irregular intervals. We therefore limit this analysis to Evolution.

passwords, etc.). We repeat our price analyses separately for these two product categories. Our results suggest that the price drop was steeper for digital products compared to physical products. Given the higher marginal cost of physical products compared to digital products, this suggests that vendors responded to the bust with a flash sale/promotion by decreasing their price in an effort to retain their customers.

In sum, our results suggest that while the outcome is less obvious for vendors, both buyers and the administrators of Evolution and Agora benefited from the Silk Road 2.0 bust. Curbing illegal activity is important and shutting down SR2 through the bust halted criminal activities of thousands of its buyers and sellers. At the same time, as a consequence of the bust, and especially because it did not affect the other markets that were operational at the time, our results suggest that it resulted in beneficial outcomes for the buyers and administrators in these markets. While we do not advocate one way or another in this research on whether law enforcement agencies should conduct busts similar to Operation Onymous, we highlight how the marketing environment in these markets could change as a consequence of such busts. This could lead to outcomes that perhaps run counter to the goals of law enforcement agencies. We hence recommend law enforcement agencies consider the marketing consequences of busts into their enforcement strategies.

Our work contributes to three streams of research. First, we add to the growing literature on two-sided markets (for a review of this literature, see Rysman (2009) and Sriram et al. (2015)). Since the theoretical framework for the pricing decisions of a platform were first laid out by Rochet and Tirole (2003) , this literature has focused on various aspects of the markets such as the pricing decisions of the agents involved (Rochet and Tirole (2006) ; Kaiser and Wright (2006)), network effects (Chu and Manchanda (2016)), competition (Armstrong (2006)), reputation (Yoganarasimhan (2013)), the role of algorithms (Fradkin (2015)), and the effects of advertisement (Tucker and Zhang (2010)) using a wide variety of offline markets such as newspapers (Seamans and Zhu (2013)), television advertising (Wilbur (2008)), video games (Landsman and Stremersch (2011) ; Liu (2010)) and online markets on the Surface Web such as eBay (Resnick et al. (2006)) and Airbnb (Fradkin (2015)). We add Darknet markets to the empirical context of this literature. Our key contribution to this literature is to demonstrate that when two-sided markets operate illegally, apart from the regular economic forces of supply and demand noted in the above literature, there is also the threat of a bust that can affect the pricing behavior among the sellers of the markets.

Second, since their inception, there has been a burgeoning literature on the various aspects of Darknet markets. The early descriptive studies documented that these markets operate on a global scale (Van Buskirk et al. (2017)) and that over time, there was an evolution in the product listings and their diversity in the overall economy of Darknet markets (Broséus et al. (2016)). The critical role that reputation plays in these markets (Espinosa (2019); Hardy and Norgaard (2016)) and how law enforcement agencies could use them strategically has also been explored (Markopoulos et al. (2015)). Closer to our setting, a few studies have focused in particular on Operation Onymous. Décary-Hétu and Giommoni (2017) shows, contradictory to our results, that prices did not decrease after the bust, perhaps since they report marketwide average prices, unlike the panel of vendor-products that we analyze in our research. Similarly, Van Buskirk et al. (2017) report that the rate at which vendors enter the markets remains unaffected by the bust, a finding consistent with our analysis. We contribute to this literature by identifying the causal effect of the bust on various marketing outcomes.

Third, we add to the literature on how law enforcement/governmental interventions affect marketing outcomes. This stream of literature has reported that both imposing as well as removing regulatory actions can lead to positive outcomes. Jin and Leslie (2003) show that a policy requiring restaurants to display hygiene grade cards on their windows leads to several positive health outcomes. Dhar and Baylis (2011) show that a ban on advertising to children leads to better food consumption. Similarly, Rao and Wang (2017) show that when firms are caught making false claims, it leads to reduced demand for their products. Finally, Rao (2018) shows that when the FTC shut down several fake news websites, the interest for consumption of such news decreased. On the other hand, Ippolito and Mathios (1990) show that after a regulatory ban on advertising health benefits was removed, it lead to people buying healthier products. We show that law enforcement actions on illegal markets can also affect marketing outcomes.

The rest of this paper is organized as follows. In the next section, we layout in detail what Darknet markets are and how they function. Following that, we explain in detail our data and how it helps us with the identification in our empirical context. In Section 3, we present the models and results we use for our analyses regarding price and the number of transactions. We next show the robustness of these results and focus on the mechanism in Section 4. Finally, Section 5 concludes our research with a discussion on the implications of our findings.

2. Empirical Context and Data

2.1. Darknet Markets

The Internet (or the Web) can be classified into the "Surface Web" and the "Deep Web". The Surface Web contains all the websites that can be indexed and hence be searched by regular search engines such as Google and Bing. In contrast, the Deep Web consists of all the webpages that cannot be indexed or searched by search engines. The Deep Web is estimated to be about 500 times larger than the Surface Web (Bergman (2001)) and growing rapidly in size and content diversity (He et al. (2007)). It contains webpages protected by logins and passwords, content behind paywalls, proprietary databases, protected content on social media, as well as the Dark Web. The Dark Web is part of the Deep Web and consists of websites that use nonstandard encryption software and protocols for their access.

The most popular encryption software used to access the Dark Web is The Onion Router (TOR). Its name is derived from the mechanism it uses to anonymize a user's identity. When a user's request to access a website is routed directly to that website's server, it leaves open the possibility that a third-party can compromise the user's identity by surveiling on this communication. To prevent this, TOR is operationalized by routing a user's request through a randomly generated path among multiple layers (like an onion) of a network of servers hosted by thousands of volunteers across the world. Since a new random path among the servers is generated each time a user requests a website, it is probablistically impossible for a third-party listener to obtain the information regarding which user accesses which website.

An early prototype of TOR was first developed at the US Naval Research Lab as a tool to provide anonymity and security to users on the Surface Web (Tor (2019)). However, since its inception, TOR's features of anonymity and security have attracted usage past the Surface Web to access content on the Dark Web. These are websites that require the usage of TOR (or other similar anonymizing software) to access them. Access to the Dark Web has been made easy with the TOR browser extension, which users can download on their web browser. When the extension is activated, users can access the Dark Web by just typing in the address of the website in the browser's address bar.

As of 2019, about 2.5 million users worldwide access about 75,000 websites available on the Dark Web through TOR's encryption. The Dark Web has been used as a communication medium for journalists and whistleblowers, particularly in authoritarian regimes, with the New York Times, the CIA, and Facebook having official websites on the Dark Web.[3] However, the Dark Web has also attracted illicit activity. Chief among them are Darknet marketplaces that allow vendors and buyers of illegal products such as drugs, weapons, and counterfeits to transact.

Darknet markets work similar to online marketplaces on the surface web such as Amazon Marketplace or Etsy. That is, they are two-sided markets where multiple vendors and buyers transact. However, a critical difference is that in Darknet markets, the identities of the buyers, vendors and the administrators remain anonymous. All transactions are paid for using cryptocurrencies, ensuring anonymity of all players. The administrators of the markets typically earn their revenue by charging vendors a commission per transaction. Since all the players in the market are anonymous, Darknet markets have developed an escrow model. When a transaction occurs, the buyer first pays the administrator of the market, which is held in escrow until the vendor ships the product and the buyer confirms receiving it. The administrator then keeps their commission and transfers the remaining money to the vendor.

We focus our empirical context around Operation Onymous, which was a law enforcement operation conducted jointly by the FBI and Europol on November 6, 2014 (Europol (2014)). This was a secret bust operation that arrested 17 individuals across many countries and shut down hundreds of websites on the Dark Web. The arrests were of the administrators of different Darknet markets. The agencies did not reveal how they were able to identify the administrators of the markets despite the anonymizing mechanism of TOR. The prime target of the bust included the administrator of Silk Road 2.0, the biggest Darknet market at the time (Economist (2016)). As law enforcement agents seized all the money that was held in escrow by the administrators of SR2, its buyers and vendors lost that

[3] See https://open.nytimes.com/https-open-nytimes-com-the-new-york-times-as-a-tor-onion-service-e0d0b67b7482, https://www.wired.com/story/cia-sets-up-shop-on-tor/, and https://www.facebook.com/notes/protect-the-graph/making-connections-to-facebook-more-secure/1526085754298237 for more details.

money. A message indicating that the FBI and Europol had seized that website displayed to anyone who tried to access the market after the bust.

Evolution and Agora were the second and third biggest markets by total number of product listings on the Dark Web at the time of the bust. The buyers and vendors of Evolution and Agora were able to conduct their business as usual after the bust since these markets were not bust. However, as the information regarding the bust was widespread in the media[4], the threat of closure of these markets loomed large. We exploit the secrecy of the occurrence and timing of the bust to causally identify the effect of the bust on Evolution and Agora. We focus on a narrow time window around the bust and argue that the difference in price and number of transactions observed after the bust is caused by the bust.

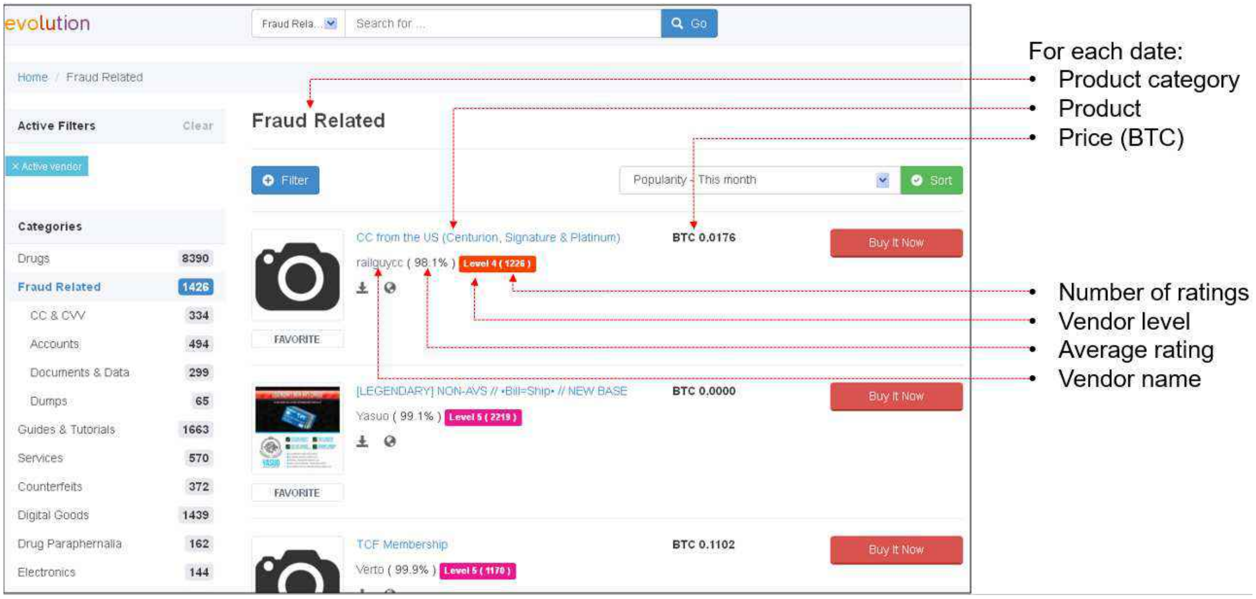
2.2. Data

The data for this study was obtained from Gwern Branwen (2015), who collected the data by scraping all the webpages associated with several Darknet markets on multiple dates during the period of 2013 to 2015. We use data that was collected by scraping the product listing pages of Evolution and Agora markets. Figure 1 shows an example of a product listing page on Evolution and Figure 2 shows a listing page on Agora. As can be seen, we only have data on the products that were listed for sale on the market on a given date but not actual sales data. The data includes the vendor's name, product category, product (description), price (in Bitcoins), and data on the vendor's reputation (percentage of positive reviews or average rating as well as the total number of reviews). Table A1 shows the dates and number of listings for Evolution and Table A2 shows the same information for Agora.

Vendors often list an assortment of multiple products that can change over time. Additionally, vendors often enter and exit or delist products on the market. In order to causally identify the effect of the bust on Evolution and Agora, we create a panel for each market consisting of only those vendor-products that were listed in the market both before and after the bust. Consequently, the unit of analysis in our data is vendor-product-date. We use three different methods of including vendor-products in the panels. First, as the most

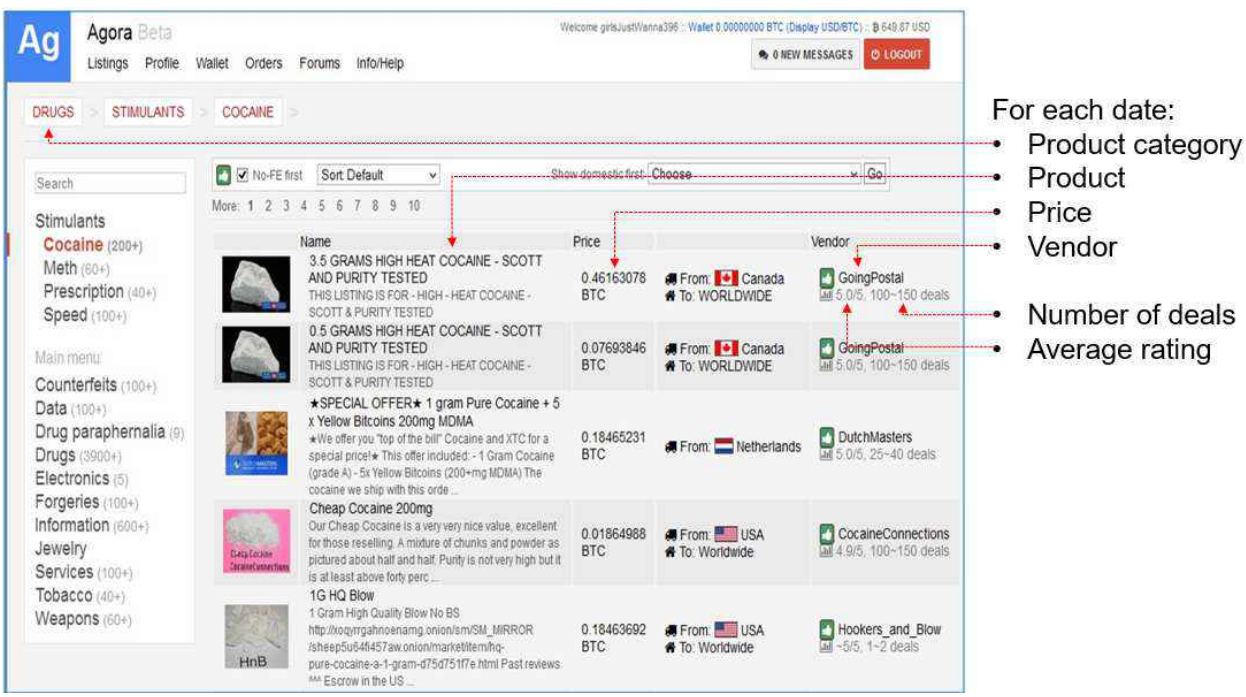
[4] For example, see https://www.bbc.com/news/technology-29950946, https://www.nytimes.com/2014/11/08/world/europe/dark-market-websites-operation-onymous.html, and https://www.washingtonpost.com/news/wonk/wp/2014/11/06/the-fbi-promises-a-perpetual-futile-drug-war-as-it-shuts-down-silk-road-2-0/

Figure 1 Listing Page on Evolution



Source: https://www.dailydot.com/crime/evolution-biggest-dark-net-market-of-all-time/

Figure 2 Listing Page on Agora



Source: https://www.dailydot.com/crime/evolution-biggest-dark-net-market-of-all-time/

general way, we include vendor-products that had at least one observation each before and after the bust during our data duration. Second, we limit our analysis to only dates that are within the 30-day window before and after the bust and include those vendor-products

Table 1 Evolution Data Descriptives

Variable	Vendor-products that have at least one observation each before and after the bust			Vendor-products that have at least one observation each in the one month before and after the bust			Vendor-products that have at least one observation in each of the three months before and after the bust		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Price (USD)	186.473	442.915	45.739	188.202	436.124	49.391	153.890	369.443	39.738
Bust flag	0.566	0.496	1.000	0.497	0.500	0.000	0.491	0.500	0.000
Percent positive rating	98.542	4.494	99.700	98.612	4.575	99.800	98.234	5.754	99.600
Number of ratings	916.333	1602.779	235.000	641.743	1071.863	193.000	961.680	1541.802	247.000
Vendor concentration	10.392	26.556	4.000	5.069	4.515	4.000	9.029	25.270	4.000
Vendor level number	2.917	1.288	3.000	2.784	1.253	3.000	2.952	1.296	3.000
Number of observations	1,597,106			685,893			677,127		

that have at least one observation each in both the intervals. Finally, as the most restrictive way of constructing the panel, we include only those vendor-products that have at least one observation in each of the three months before the bust and similarly at least one observation in each of the three months after the bust.

In order to interpret the data better, we convert the prices to US Dollars by using the conversion rate on that day.[5] Additionally, in order to not bias the results in the panels with very expensive products, we remove 1.72% of observations in Evolution and 0.62% of observations in Agora which listed products costing more than $5000.

The most frequently listed product category in both the markets is drugs, with 45.3% of the listings in Evolution and 79.8% of the listings in Agora from this category. Table A3 and Table A4 report the breakdown of the listings by product category in the markets. The data in the three panels in Evolution and Agora are summarized in Table 1 and Table 2. The average product in the Evolution panel costs $186.43 but the distribution of price is skewed to the right with the median price at only $45.74. There is evidence of potential survivor bias among vendors in the data since the average vendor in the data has about 916 ratings with an overwhelming 98.5% positive ratings.

Note that there are two differences in the Agora data compared to Evolution. First, vendor rating is displayed as a star-rating out of 5 stars. Second, the number of reviews for a vendor is not displayed in the product listings. Instead, as shown in Figure 2, a range of the number of deals made by the vendor is displayed. Table A5 in the Appendix shows the distribution of the number of deals. Price data from Agora market is similar to Evolution, with the average price of a product at $225.73, but is slightly less skewed compared to

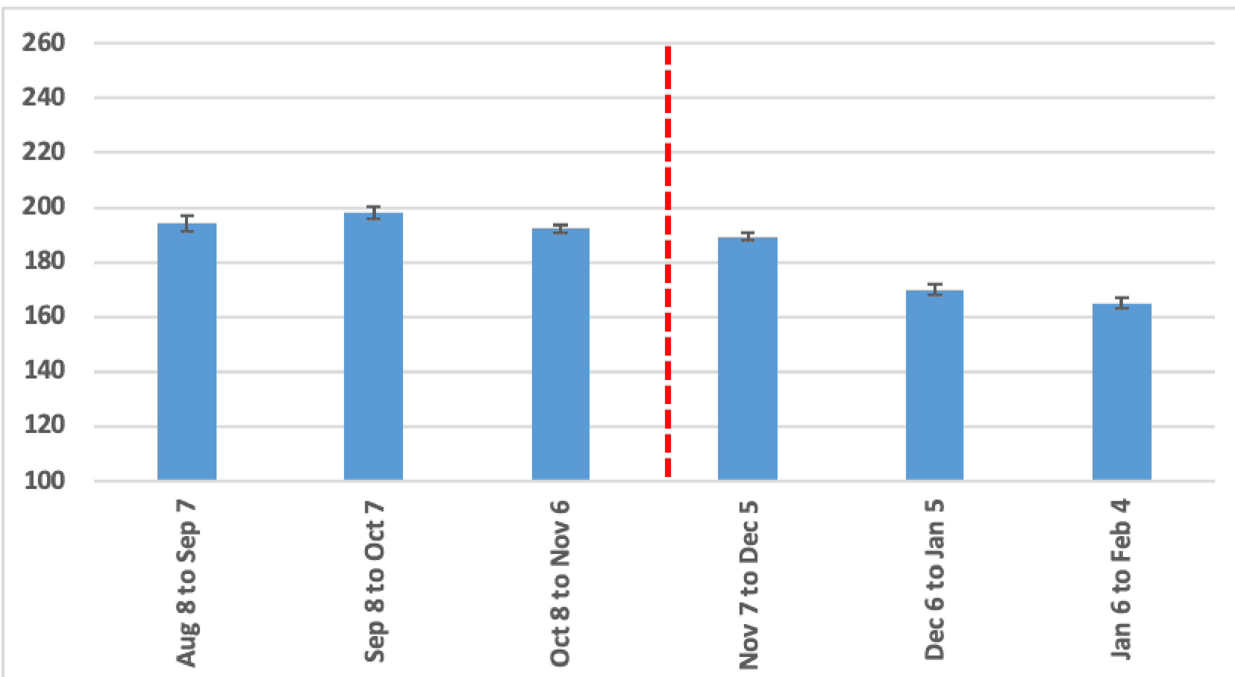
[5] Data collected from https://www.investing.com/crypto/bitcoin/btc-usd-historical-data

Table 2 Agora Data Descriptives

Variable	Vendor-products that have at least one observation each before and after the bust			Vendor-products that have at least one observation each in the one month before and after the bust			Vendor-products that have at least one observation in each of the three months before and after the bust		
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Price (USD)	225.726	486.433	69.746	237.990	503.377	74.791	213.995	477.695	59.296
Bust flag	0.736	0.441	1.000	0.588	0.492	1.000	0.687	0.464	1.000
Average rating (out of 5)	4.902	0.162	4.954	4.909	0.165	4.966	4.908	0.133	4.953
Vendor concentration	274.437	172.186	342.000	301.318	174.666	355.000	249.702	183.704	337.000
Number of observations		510,841			137,982			154,826	

Evolution with a median price of $69.75. The ratings pattern are similar to Evolution as well, with the average product having a rating of 4.90 out of 5.

Figure 3 Average Price of Product Listings on Evolution (US Dollars)



We demonstrate model-free evidence for how the bust affects the price and number of transactions in the markets. Figure 3 shows the average price of the vendor-products on Evolution (with 95% confidence intervals) in the three months before and after the bust. As can be seen, there was a sharp drop in the average price in the months immediately following the bust. Figure 4 shows similar patterns for the vendor-products in Agora.

We use the number of ratings added to a vendor's account during a given time interval as a proxy for the number of transactions that that vendor had during that interval. A similar

Figure 4 **Average Price of Product Listings on Agora (US Dollars)**

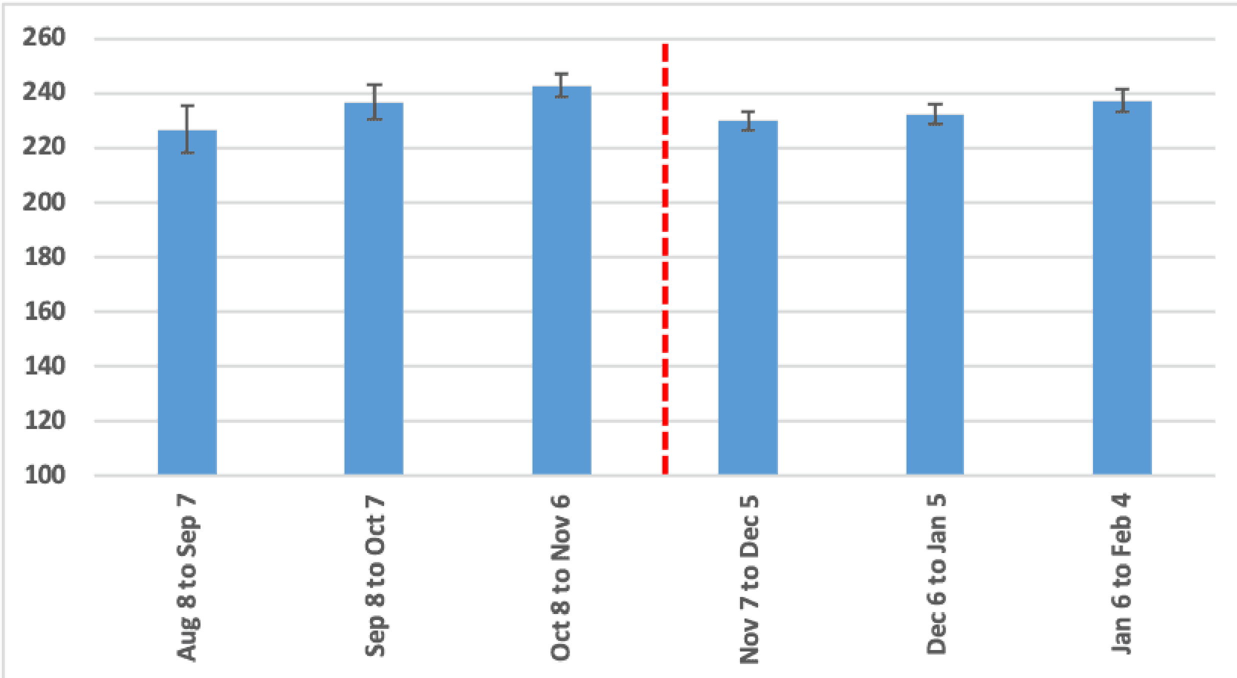
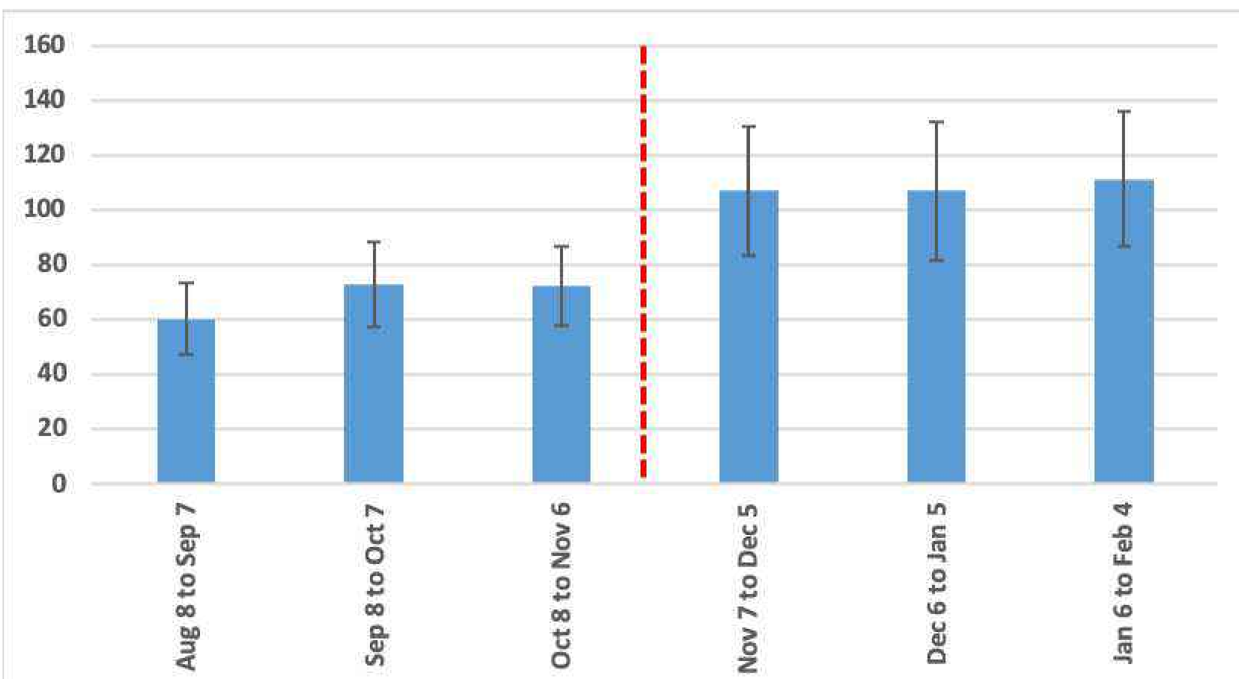


Figure 5 **Average Number of Reviews Added per Vendor in a Month on Evolution**



approach has also been used by Deng et al. (2019), Kummer and Schulte (2019) and Liu and Ishihara (2017). It is important to take note of two points before this analysis. First, while the exact number of reviews accrued by a vendor are displayed in Evolution, Agora only displays this information in broad intervals (as shown in Table A6). Consequently, we conduct this analysis for Evolution alone. Second, as can be seen from Table A1, we do not have snapshots of the markets at regular intervals. We therefore use best possible 30-day intervals as highlighted in Table A7 to compute the number of reviews added in each 30-day interval. Figure 5 shows the average number reviews added per vendor (with 95% confidence intervals) in the three month period before and after the bust. As can be seen, the number of reviews added per vendor increased significantly after the bust. Of course, this analysis does not control for other covariates that may vary during this time period and we account for them in our model.

3. Model

3.1. Price

We estimate a fixed-effects panel regression model to capture the effect of the bust on the price of a product in Evolution as follows:

$$\begin{aligned} Price_{\mathrm{vjt}} = \alpha + Bust_t + PosRatings_{\mathrm{vjt}} + NumRatings_{\mathrm{vjt}} + NumVendors_{\mathrm{jt}} + \\ \beta_{\mathrm{vj}} + Time_t + Category_j + \epsilon_{\mathrm{vjt}} \end{aligned} \tag{1}$$

The dependent variable is $Price_{\mathrm{vjt}}$, the price of product j sold by vendor v at time t. The main independent variable of interest is $Bust_t$ which is a dummy variable with a value of 1 after the bust and 0 before the bust. We control for the vendor's reputation using the average positive rating of vendor v at time t, $PosRatings_{\mathrm{vjt}}$, and the number of ratings received by vendor v until time t, $NumRatings_{\mathrm{vjt}}$. We control for competition among vendors by including the number of vendors in that product category at time t, $NumVendors_t$. We use vendor-product specific fixed-effects β_{vj} to control for any unobservables that may be specific to a vendor as well as the product. In addition, to control for any particular date-specific variations, we include date-specific fixed effects $Time_t$. Finally, since pricing decisions of products in a category such as drugs may be systematically different from pricing in category such as weapons, we also include product category fixed effects $Category_j$.

Table 3 The Effect of the Bust on Price of Products in Evolution

Dependent variable: Price of a product (US Dollars)	(I) At least one vendor-product obs. before and after the bust		(II) At least one vendor-product obs. one month before and after the bust		(III) At least one vendor-product obs. each of 3 months before and after the bust	
	Estimate	SE	Estimate	SE	Estimate	SE
Post FBI/Europol bust	-13.252	1.496***	-16.570	1.055***	-8.880	2.738***
Average positive rating (out of 100)	0.176	0.049***	0.135	0.058**	0.099	0.039**
Number of ratings	0.000	0.000	-0.001	0.001	0.000	0.001
Number of vendors in the marketplace	0.035	0.004***	0.023	0.024	0.069	0.005***
Vendor level fixed effects	Yes		Yes		Yes	
Date fixed effects	Yes		Yes		Yes	
Product category fixed effects	Yes		Yes		Yes	
Vendor-product fixed effects	Yes		Yes		Yes	
N	1,597,106		685,893		677,127	
Vendor-products	15,789		13,063		4,863	
R^2	0.023		0.016		0.040	

*= p<0.10, **= p<0.05, ***= p<0.01

We first use the data from Evolution and report in Column (I) of Table 3 the results using the panel that includes vendor-products with at least one observation each before and after the bust. As can be seen, the price of an average product dropped significantly by $13.25 after the bust. This is a substantial drop since at the average price of a product in the data, this is a 7.11% decrease while this constitutes a 28.97% drop at the median price. Our results from including other control variables indicates, not surprisingly, that the percentage of positive reviews is positively associated with price but interestingly that the number of vendors in a product category is also positively associated with price.

In Column (II), we report the results when we limit our analysis to only dates that are within the 30-day window before and after the bust and include only those vendor-products that have at least one observation each in both the intervals. We find once again that there is a significant price drop, on average by $16.57 after the bust. This similarly translates to 8.89% at the average and 36.23% at the median. Finally, in Column (III), we show the results when we include only those vendor-products in the data that have at least one observation in each of the three months before the bust and similarly at least one observation in each of the three months after the bust. Once again, our results are consistent.

We shift our focus next to Agora. Note that two covariates are operationalized differently in Agora as compared to Evolution. The average rating of vendors is displayed as a star-rating out of 5 stars and rather than displaying the number of reviews received by a vendor,

Table 4 The Effect of the Bust on Price of Products in Agora

Dependent variable: Price of a product (US Dollars)	(I) At least one vendor-product obs. before and after the bust		(II) At least one vendor-product obs. one month before and after the bust		(III) At least one vendor-product obs. each of 3 months before and after the bust	
	Estimate	SE	Estimate	SE	Estimate	SE
Post FBI/Europol bust	-56.804	11.448***	-9.939	3.582***	-7.453	1.968***
Average rating of the vendor (out of 5)	6.289	1.970***	10.326	4.433**	7.521	2.474***
Number of vendors in the marketplace	-0.005	0.002 ***	-0.006	0.002***	-0.003	0.003
Date fixed effects	Yes		Yes		Yes	
Number of deals controls	Yes		Yes		Yes	
Product category fixed effects	Yes		Yes		Yes	
Vendor-product fixed effects	Yes		Yes		Yes	
N	510,842		154,826		137,982	
Vendor-products	8,106		2,632		6,814	
R^2	0.033		0.059		0.026	

*= p<0.10, **= p<0.05, ***= p<0.01

the number of deals (transactions) by a vendor is displayed as a range. Since these ranges are of varying lengths, we use dummy variables to capture the effect of each category. The results are shown in Table 4. The results echo those of Evolution.

3.2. Number of Transactions

We turn to how the bust affected the number of transactions by a vendor. As noted in Section 2.2, we use the number of reviews added to a vendor's account in a 30-day window as a proxy for the number of transactions by the vendor during that time. Table A6 reports the dates we use for this analysis. We use a panel that consists of 718 vendors. We estimate a fixed-effects panel regression model for Evolution as follows:

$$\begin{aligned}\Delta NumReviews_{\mathrm{vm}} = \alpha + Bust_m + NumRatings_{\mathrm{vm}} + NumVendors_{\mathrm{m}} + \\ \beta_{\mathrm{v}} + Time_m + \epsilon_{\mathrm{vjt}}\end{aligned} \tag{2}$$

The dependent variable is $\Delta NumReviews_{\mathrm{vm}}$, the number of reviews added to vendor v's account during month m. The main independent variable of interest is $Bust_m$. We include the average positive rating of vendor v at the end of month m, $PosRatings_{\mathrm{vm}}$, and the number of ratings received by vendor v until month m, $NumRatings_{\mathrm{vm}}$. We control for competition among vendors by including the number of vendors in Evolution at the end of month m, $NumVendors_m$. Finally, to account for any unobserved covariates that relate to a vendor, we include vendor-specific fixed-effects β_{v}, and date-specific fixed effects $Time_m$.

We use three panels for this estimation which are created in similar fashion as in Section 2.2 above but include vendors here who have at least one observation in each of one, two

Table 5 The Effect of the Bust on Number of Transactions per Vendor in Evolution

Dependent variable: Number of reviews added in a month	(I) At least one vendor-product obs. before and after the bust		(II) At least one vendor-product obs. one month before and after the bust		(III) At least one vendor-product obs. each of 3 months before and after the bust	
	Estimate	SE	Estimate	SE	Estimate	SE
Post FBI/Europol bust	30.314	5.928***	28.587	5.540***	26.959	5.865***
Number of vendors	0.267	1.124	0.663	0.502	-0.079	0.088
Vendor level fixed effects	Yes		Yes		Yes	
Vendor fixed effects	Yes		Yes		Yes	
Date fixed effects	Yes		Yes		Yes	
N	1,386		2,048		2,172	
Vendors	718		535		379	
R^2	0.886		0.844		0.835	

*= p<0.10, **= p<0.05, ***= p<0.01

and three months before and after the bust. Column (I) of Table 5 shows the result when using the panel that includes vendors with at least one observation each one month before and after the bust. Vendors have significantly more reviews added per month after the bust compared to before. We use the other two panel specifications in Column (II) and Column (III) and find similar results.

3.3. Robustness Checks

We conduct two robustness checks of our results about how the bust affected the price of products. First check relates to our identification assumption. Note that our identification strategy is similar to an event study. That is, we focus on a narrow time-window around the bust and claim that the difference in the outcomes after the bust as compared to before is caused by the bust. A key assumption here is that temporal trends (and other variables not accounted for in our model) remain unchanged during the time-window of analysis. As an alternative to this, we estimate a difference-in-differences model using the two months prior to the bust as placebo controls. That is, we assign vendor-product observations from the one month period before and after the bust to treatment group. We similarly assign the vendor-products from the two month period before the treatment group to placebo control group. Within each group, we then assign the later month to the "after" group and the earlier month to the "before" group. The interaction variable of "after" and "treatment" gives the difference-in-difference estimate of the effect of the treatment (i.e., the bust) minus the effect of any time trend captured by the "after" variable.

In order to estimate this, we design a new cut of data. We include in our analyses only those vendor-products which have at least one observation in each of the four months

Table 6 Robustness Check Using Placebo Control

Dependent variable: Price of a product (US Dollars)	(I) Evolution: At least one vendor-product obs. each of the 4 months in the analysis		(II) Agora: At least one vendor-product obs. each of the 4 months in the analysis	
	Estimate	SE	Estimate	SE
Treatment group	-4.236	0.747***	9.884	2.391***
After bust	2.240	0.749***	16.617	2.153***
Difference-in-difference estimate	-4.756	0.795***	-32.726	2.533***
Average positive rating	0.074	0.066		
Average rating			1.872	3.040
Number of ratings	0.000	0.000		
Number of vendors in the marketplace	0.067	0.004***	-0.008	0.002***
Vendor level fixed effects	Yes			
Number of deals (levels)			Yes	
Date fixed effects	Yes		Yes	
Product category fixed effects	Yes		Yes	
Vendor-product fixed effects	Yes		Yes	
N	645,691		481,103	
Vendor-products	6,791		5,419	
R^2	0.040		0.012	

*= p<0.10, **= p<0.05, ***= p<0.01

that are part of the difference-in-difference analysis. The results of our estimation from the Evolution data are shown in Column (I) of Table 6. As can be seen, we continue to find that the average price of a product dropped in Evolution due to the bust, even after controlling for temporal trends. We conduct a similar analysis using the Agora data. The results of this analysis are presented in Column (II). Once again, we continue to find that the average price of products dropped after the bust.

The second robustness check for price concerns how we define the bust variable. In all the results presented above, the bust dummy variable has a value of 1 for vendor-product observations starting November 7, 2014, the day after the bust. However, since we also have observations from November 6, 2014, the day of the bust, we check if our results change if we specify the bust dummy value to be 1 for these observations. Note that this changes the vendor-products that will be included in each of the three data cuts. We replicate the estimations of Table 3 and Table 4 using this alternative specification of the bust variable. The results are reported in Table 7 and Table 8 and are consistent with the previous results.

We next check the robustness of our analysis about how the bust affected the number of transactions per vendor. Note that our dependent variable is the number of reviews added to a vendor's account in a 30-day period. An issue with this dependent variable, is

Table 7 Robustness Check for the Date of the Bust: Evolution

Dependent variable: Price of a product (US Dollars)	(I) At least one vendor-product obs. before and after the bust		(II) At least one vendor-product obs. one month before and after the bust		(III) At least one vendor-product obs. each of 3 months before and after the bust	
	Estimate	SE	Estimate	SE	Estimate	SE
Post FBI/Europol bust	-13.504	1.489***	-16.917	1.047***	-9.187	2.739***
Average positive rating	0.173	0.048***	0.136	0.057**	0.112	0.040***
Number of ratings	0.000	0.000	-0.001	0.001	0.000	0.001
Number of vendors in the marketplace	0.036	0.004***	0.021	0.024	0.070	0.005***
Vendor level fixed effects	Yes		Yes		Yes	
Date fixed effects	Yes		Yes		Yes	
Product category fixed effects	Yes		Yes		Yes	
Vendor-product fixed effects	Yes		Yes		Yes	
N	1,635,404		712,702		701,906	
Vendor-products	17,462		14,901		5,159	
R^2	0.024		0.016		0.041	

*= p<0.10, **= p<0.05, ***= p<0.01

Table 8 Robustness Check for the Date of the Bust: Agora

Dependent variable: Price of a product (US Dollars)	(I) At least one vendor-product obs. before and after the bust		(II) At least one vendor-product obs. one month before and after the bust		(III) At least one vendor-product obs. each of 3 months before and after the bust	
	Estimate	SE	Estimate	SE	Estimate	SE
Post FBI/Europol bust	-56.849	11.454***	-9.870	3.599***	-7.535	1.976***
Average rating of the vendor (out of 5)	6.310	1.975***	10.342	4.432**	7.459	2.536***
Number of vendors in the marketplace	-0.005	0.002***	-0.006	0.002***	-0.003	0.003
Date fixed effects	Yes		Yes		Yes	
Number of deals controls	Yes		Yes		Yes	
Product category fixed effects	Yes		Yes		Yes	
Vendor-product fixed effects	Yes		Yes		Yes	
N	505,219		154,137		136,396	
Vendor-products	8,053		2,614		6,728	
R^2	0.033		0.058		0.026	

*= p<0.10, **= p<0.05, ***= p<0.01

a significant proportion of zeros in the data. In our data, 18.33%, 21.48%, and 25.28% of the vendor-month observations in the three data cuts used in Columns (I) through (III) of Table 5 have no new reviews added in the month. To check if the presence of zeros biases our results, we estimate our specification from Table 5 using a Tobit Type I model in place of a linear model. Our results are presented in Table 9. As can be seen, our main result holds.

4. Mechanism

Our results show that the price of products dropped and the number of transactions per vendor increased in Evolution and Agora as a result of the bust. One possible explanation

Table 9 Robustness Check for the Number of Transactions per Vendor

Dependent variable: Number of reviews added in a month	(I) At least one vendor-product obs. before and after the bust		(II) At least one vendor-product obs. one month before and after the bust		(III) At least one vendor-product obs. each of 3 months before and after the bust	
	Estimate	SE	Estimate	SE	Estimate	SE
Post FBI/Europol bust	38.564	3.479***	33.892	3.450***	31.471	3.494***
Number of vendors	0.768	0.614	0.756	0.461	-0.069	0.085
Vendor level fixed effects	Yes		Yes		Yes	
Vendor fixed effects	Yes		Yes		Yes	
Date fixed effects	Yes		Yes		Yes	
N	1,386		2,048		2,172	
Vendors	718		535		379	
R^2	0.191		0.167		0.166	
Log likelihood	-6168.700		-9166.361		-9306.914	

*= p<0.10, **= p<0.05, ***= p<0.01

for these results is that they were due to demand and supply shifts in Evolution and Agora as a result of the bust. This is a particularly plausible scenario since at the time of the bust, Evolution and Agora were the next biggest Darknet markets, making them the likely destinations for buyers and vendors of SR2. We use two additional analyses to check if this explanation is supported.

4.1. Multihomers

Multihomers are agents in a two-sided network who choose to use more than one platform (Landsman and Stremersch (2011)). In our context, multihomers are vendors who sell simultaneously on multiple Darknet markets. We focus here on multihomers who sell on both Silk Road 2.0 (before it was bust) as well as either Evolution or Agora. If there indeed was a migration of buyers from SR2 to either Evolution or Agora, it is likely that these buyers continue their transactions with the multihoming vendors from SR2 that they are already familiar with. In fact, we do see some anecdotal evidence of this. For example, in a review for vendor DankBoss101 on Evolution, one reviewer writes: "Simply great buds quick service, absolutely coming back for more. Good stealth, good speed, good quality, good s***..This vendor is awesome. Bought from them on SR2 and glad they are here." After the bust, compared to other vendors in Evolution and Agora, multihoming vendors would have experienced firsthand the loss of buyers due to closure of SR2. Therefore they are likely to have a greater inclination to attract the migrating buyers from SR2. We therefore hypothesize that if there was a migration of buyers from SR2, multihoming

Table 10 The Effect of the Bust on Price for Multihomers in Evolution

Dependent variable: Price of a product (US Dollars)	(I) At least one vendor-product obs. before and after the bust		(II) At least one vendor-product obs. one month before and after the bust		(III) At least one vendor-product obs. each of 3 months before and after the bust	
	Estimate	SE	Estimate	SE	Estimate	SE
Post FBI/Europol bust	-12.973	1.504***	-15.864	1.158***	-8.612	2.817***
Post FBI/Europol bust X Silk Road 2.0 vendor	-3.740	1.233***	-4.130	1.089***	-4.738	2.017*
Average positive rating	0.222	0.050***	0.182	0.060***	0.177	0.047***
Number of ratings	0.000	0.000	-0.001	0.001	0.000	0.001
Number of vendors in the marketplace	0.035	0.004***	0.023	0.024	0.069	0.005***
Vendor level fixed effects	Yes		Yes		Yes	
Date fixed effects	Yes		Yes		Yes	
Product category fixed effects	Yes		Yes		Yes	
Vendor-product fixed effects	Yes		Yes		Yes	
N	1,597,106		685,893		677,127	
Vendor-products	15,789		13,063		4,863	
R^2	0.024		0.016		0.040	

*= p<0.10, **= p<0.05, ***= p<0.01

vendors would offer significantly lower prices comapred to non-multihoming vendors and likewise experience significantly higher number of transactions after the bust.

We identify multihomers in our data by matching vendor names from Silk Road 2.0 to those on Evolution as well as Agora. Where we find an exact match (i.e., same spelling and case of vendor name), we assume the vendor to be a multihomer. In our data, we find 135 of the 1,209 vendors in Evolution to be multihomers between SR2 and Evolution and similarly 102 multihomers between SR2 and Agora among 828 vendors. To identify the effect of the bust on multihomers, we estimate equations (1) and (2) with an additional covariate capturing the interaction of the bust variable with whether a vendor was a multihomer or not. The results of the price regressions are shown in Table 10 for Evolution and Table 11 for Agora. As can be seen, compared to non-multihoming vendors, multihoming vendors further decreased their prices on both Evolution and Agora.

The regressions for number of transactions are shown in Table 12. Once again, we find evidence consistent with our hypothesis as multihomers had significantly higher number of reviews added after the bust compared to non-multihomers. Taken together, these results are consistent with a buyer migration from SR2 after the bust. Interestingly, we do not find a similar migration of non-multihomer vendors from SR2 to Evolution or Agora. Table A7 and Table A8 show the total number of vendors in our Evolution and Agora data. As can be seen there was no increase in the vendors after the bust.[6]

[6] We also confirm these results through a regression analysis. The results are available upon request.

Table 11 The Effect of the Bust on Price for Multihomers in Agora

Dependent variable: Price of a product (US Dollars)	(I) At least one vendor-product obs. before and after the bust		(II) At least one vendor-product obs. one month before and after the bust		(III) At least one vendor-product obs. each of 3 months before and after the bust	
	Estimate	SE	Estimate	SE	Estimate	SE
Post FBI/Europol bust	-55.943	11.547***	-8.280	4.085**	-6.658	2.145***
Post FBI/Europol bust X Silk Road 2.0 vendor	-2.770	1.642*	-2.380	1.251*	-1.757	1.304
Average rating of the vendor (out of 5)	6.220	1.972***	10.316	4.424**	7.539	2.483***
Number of vendors in the marketplace	-0.005	0.002***	-0.006	0.002***	-0.003	0.003
Date fixed effects	Yes		Yes		Yes	
Number of deals controls	Yes		Yes		Yes	
Product category fixed effects	Yes		Yes		Yes	
Vendor-product fixed effects	Yes		Yes		Yes	
N	510,842		154,826		137,982	
Vendor-products	8,106		2,632		6,814	
R^2	0.033		0.059		0.026	

*= p<0.10, **= p<0.05, ***= p<0.01

Table 12 The Effect of the Bust on Number of Transactions per Vendor for Multihomers in Evolution

Dependent variable: Number of reviews added in a month	(I) At least one vendor-product obs. before and after the bust		(II) At least one vendor-product obs. one month before and after the bust		(III) At least one vendor-product obs. each of 3 months before and after the bust	
	Estimate	SE	Estimate	SE	Estimate	SE
Post FBI/Europol bust	19.231	5.037***	17.670	4.706***	17.520	4.795***
Post FBI/Europol bust X Silk Road 2.0 vendor	71.441	26.294***	76.567	27.106***	75.890	33.124***
Number of vendors	-0.121	1.064	0.571	0.473	-0.059	0.091
Vendor level fixed effects	Yes		Yes		Yes	
Vendor fixed effects	Yes		Yes		Yes	
Date fixed effects	Yes		Yes		Yes	
N	1,430		2,120		2,258	
Vendors	721		535		379	
R^2	0.891		0.848		0.838	

*= p<0.10, **= p<0.05, ***= p<0.01

In summary, our analysis suggests that there was a buyer migration from SR2 after the bust while a corresponding vendor migration seems absent. Consequently, these markets experienced a demand shock from the buyer migration without a similar supply shock. This indicates that prices should have gone up in these markets after the bust. We investigate this further by conducting one more analysis.

4.2. Category Analysis

Table A3 and Table A4 show the various categories of products sold on Evolution and Agora. Since our main results indicate that prices decreased after the bust, we further investigate how this effect varies by product category. We recategorize the different product categories based on whether the products sold are physical or digital in nature. Physical products typically need to be shipped out from the vendor to the buyer and likely involve

Table 13 Breakdown of the Effect of the Bust on the Price of Physical and Digital Products in Evolution

	(I)		(II)		(III)		(IV)		(V)		(VI)	
Dependent variable:	At least one vendor-product obs.				At least one vendor-product obs.				At least one vendor-product obs.			
Price of a product	before and after the bust				one month before and after the bust				each of 3 months before and after the bust			
(US Dollars)	Physical products		Digital products		Physical products		Digital products		(Physical products)		Digital products	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Post FBI/Europol bust	-14.877	2.018***	-10.063	2.013***	-18.371	1.289***	-11.001	1.508***	-7.718	4.090*	-10.723	2.379***
Average positive rating	0.262	0.072***	0.061	0.067	0.165	0.064**	0.110	0.126	0.137	0.063**	0.070	0.043*
Number of ratings	0.000	0.000	0.000	0.000	-0.005	0.002	0.002	0.001**	-0.001	0.001*	0.000	0.001
Number of vendors in the marketplace	0.047	0.005***	0.027	0.007***	-0.038	0.027**	0.255	0.068***	0.078	0.006***	0.097	0.016***
Vendor level fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Date fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Product category fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Vendor-product fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
N	1,116,003		481,103		505,576		180,317		440,909		236,218	
Vendor-products	11,797		5,419		10,005		4,369		3,388		2,340	
R^2	0.031		0.012		0.022		0.009		0.045		0.042	
Mean price ($)	232.016		80.826		225.282		84.236		186.381		93.245	
% price decrease at the mean after bust	-6.41%		-12.45%		-8.15%		-13.06%		-4.14%		-11.50%	

*= p<0.10, **= p<0.05, ***= p<0.01

Table 14 Breakdown of the Effect of the Bust on the Price of Physical and Digital Products in Agora

	(I)		(II)		(III)		(IV)		(V)		(VI)	
Dependent variable:	At least one vendor-product obs.				At least one vendor-product obs.				At least one vendor-product obs.			
Price of a product	before and after the bust				one month before and after the bust				each of 3 months before and after the bust			
(US Dollars)	Physical products		Digital products		Physical products		Digital products		(Physical products)		Digital products	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Post FBI/Europol bust	-75.372	15.687***	-7.918	7.956	-13.595	4.006***	1.027	1.128	-10.512	1.532***	-4.606	1.955**
Average rating of the vendor (out of 5)	4.927	1.980**	3.988	5.350	5.645	3.812	46.611	17.683***	7.607	2.538***	9.692	3.221***
Number of vendors in the marketplace	-0.008	0.003***	0.002	0.054	-0.007	0.002***	-0.031	0.046	0.000	0.003	-0.032	0.042
Date fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Number of deals controls	Yes		Yes		Yes		Yes		Yes		Yes	
Product category fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
Vendor-product fixed effects	Yes		Yes		Yes		Yes		Yes		Yes	
N	415,431		95,411		116,446		38,380		114,943		23,039	
Vendor-products	7,190		959		2,081		560		5,928		914	
R^2	0.039		0.012		0.071		0.100		0.031		0.005	
Mean price ($)	265.922		50.755		271.231		40.339		274.295		56.862	
% price decrease at the mean after bust	-28.34%		-		-5.01%		-		-3.83%		-8.10%	

*= p<0.10, **= p<0.05, ***= p<0.01

some cost to the vendor to produce the good. In contrast, digital goods have near zero marginal cost of production (Lambrecht et al. (2014)). Consequently, we hypothesize that vendors would be willing to offer deeper discounts on digital goods compared to physical goods in order to still remain profitable.

We estimate the price regressions of Equation (1) and (2) separately for digital and physical categories in the data using the three definitions of data. Our results for Evolution are shown in Table 13. As can be seen, prices decreased for both digital and physical goods after the bust. The results support our hypothesis with deeper discounts offered for digital goods compared to physical goods as shown in the final row of the table. Table 14 shows the results for Agora. Note that unlike Evolution, about 80% of the products sold in Agora are related to drugs and are hence physical. Therefore, our data lacks statistical power to estimate the effect of the bust on digital goods in two out of the three methods of creating the data. As can be seen, our results are consistent with our hypothesis when our data includes those vendor-products that have at least one observation in each of the three months before and after the bust.

It is interesting to note that prices decreased in these markets after the bust despite an increase in demand. This is likely the case because vendors were responding to the bust of SR2 and the threat of a future bust in these markets through either a flash sale to attract/retain customers or clearing their inventory to exit Darknet markets.

5. Discussion and Conclusion

The changing landscape of the Web has brought forth many new technological advances. One such recent technology that was designed with the intention of promoting user anonymity is the Dark Web but it has also unintentionally facilitated illicit activity in the form of Darknet markets. Law enforcement agencies continue to remain interested in busting these markets. The most recent bust operation occurred in May 2019 and involved the bust of the second largest Darknet market at the time that had 1.15 million buyers and over 7,500 vendors (Europol (2019)).

In this research we ask how such law enforcement busts affect the marketing outcomes of markets that are not subject to the bust. This is important because Darknet markets operate like a whack-a-mole game. When one market gets shut down, another is born. Our results suggest that shutting one market may lead to beneficial outcomes for some agents of other markets not subject to the bust. Our results also indicate that these benefits are not simply a product of the forces of supply and demand but that they occur despite them. In particular, our results suggest that vendors decrease prices after the bust which benefits buyers who can now buy the same products at a cheaper price. Similarly, our results also show that the total number of transactions of an average vendor increased after the bust. Since the administrators of the markets obtain their revenue by charging a commission for each sale, this indicates that administrators of Evolution and Agora generated more revenue directly as a result of the bust.

These outcomes perhaps run counter to the goals of law enforcement agencies as they further encourage buyers to continue transacting as well as administrators to continue operating these markets. We recommend these agencies to hence consider these perhaps unintended marketing outcomes of the bust while conducting similar operations in the future.

Our research has two limitations that future studies can address. First, there is of course benefits to conducting busts and curbing illegal sales. Future studies can incorporate not just the effect on other markets as we do in our study but an economic analysis of the entire system of all markets to determine the effect of conducting busts in totality. Our goal in this study is simply to highlight the consequences of busts on other markets that are not subject to the bust. Second, future studies could obtain user level data from these markets to study choice behavior under anonymity.

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Appendix.

Table A1 Date and Number of Listings on Evolution

Date	Listings	Percent	Date	Listings	Percent	Date	Listings	Percent
10-Aug-14	8,866	0.56	01-Nov-14	36,702	2.30	06-Jan-15	17,648	1.10
15-Aug-14	30,580	1.91	03-Nov-14	30,299	1.90	08-Jan-15	12,040	0.75
22-Aug-14	23,056	1.44	06-Nov-14	36,964	2.31	09-Jan-15	8,428	0.53
25-Aug-14	14,916	0.93	07-Nov-14	4,730	0.30	10-Jan-15	4,600	0.29
27-Aug-14	25,617	1.60	09-Nov-14	28	0.00	11-Jan-15	3,188	0.20
02-Sep-14	15,784	0.99	11-Nov-14	20,480	1.28	14-Jan-15	8,654	0.54
10-Sep-14	36,480	2.28	14-Nov-14	33,986	2.13	16-Jan-15	17,539	1.10
15-Sep-14	25,215	1.58	15-Nov-14	33,484	2.10	21-Jan-15	20,343	1.27
19-Sep-14	39,642	2.48	16-Nov-14	26,123	1.64	24-Jan-15	21,217	1.33
23-Sep-14	22,602	1.42	18-Nov-14	33,438	2.09	29-Jan-15	23,259	1.46
26-Sep-14	18,224	1.14	19-Nov-14	21,023	1.32	01-Feb-15	14,052	0.88
30-Sep-14	27,024	1.69	21-Nov-14	20,856	1.31	02-Feb-15	13,656	0.86
04-Oct-14	30,020	1.88	22-Nov-14	31,133	1.95	03-Feb-15	12,295	0.77
05-Oct-14	213	0.01	23-Nov-14	21,243	1.33	05-Feb-15	13,079	0.82
06-Oct-14	14,652	0.92	24-Nov-14	25,404	1.59	09-Feb-15	17,902	1.12
08-Oct-14	32,000	2.00	25-Nov-14	20,465	1.28	11-Feb-15	14,234	0.89
11-Oct-14	29,237	1.83	29-Nov-14	29,622	1.85	17-Feb-15	17,569	1.10
12-Oct-14	13,864	0.87	04-Dec-14	21,538	1.35	19-Feb-15	13,541	0.85
13-Oct-14	13,169	0.82	06-Dec-14	20,542	1.29	21-Feb-15	16,489	1.03
15-Oct-14	32,783	2.05	07-Dec-14	13,941	0.87	24-Feb-15	7,756	0.49
17-Oct-14	3,647	0.23	14-Dec-14	29,860	1.87	26-Feb-15	15,947	1.00
20-Oct-14	24,510	1.53	20-Dec-14	28,321	1.77	28-Feb-15	9,990	0.63
22-Oct-14	29,333	1.84	21-Dec-14	15,088	0.94	03-Mar-15	19,056	1.19
23-Oct-14	6,358	0.40	24-Dec-14	18,936	1.19	07-Mar-15	21,180	1.33
26-Oct-14	35,779	2.24	26-Dec-14	9,566	0.60	16-Mar-15	31,611	1.98
27-Oct-14	14,950	0.94	28-Dec-14	18,600	1.16	17-Mar-15	12,262	0.77
29-Oct-14	20,843	1.31	02-Jan-15	17,835	1.12	Total	1,597,106	100.00

Table A2 No. of Listings on Agora

Date	Listings	Percent	Date	Listings	Percent	Date	Listings	Percent	Date	Listings	Percent	Date	Listings	Percent
1-Jan-14	48	0.01	3-Aug-14	2,159	0.42	14-Nov-14	4,227	0.83	21-Jan-15	3,873	0.76	13-Apr-15	3,054	0.60
9-Jan-14	88	0.02	9-Aug-14	179	0.04	15-Nov-14	4,990	0.98	23-Jan-15	3,626	0.71	14-Apr-15	2,198	0.43
16-Jan-14	151	0.03	14-Aug-14	3,369	0.66	16-Nov-14	5,542	1.08	24-Jan-15	3,765	0.74	20-Apr-15	1,238	0.24
26-Jan-14	211	0.04	18-Aug-14	720	0.14	18-Nov-14	5,601	1.10	26-Jan-15	3,785	0.74	22-Apr-15	1,364	0.27
2-Feb-14	260	0.05	20-Aug-14	1,258	0.25	19-Nov-14	3,841	0.75	28-Jan-15	3,571	0.70	23-Apr-15	1,477	0.29
5-Feb-14	255	0.05	27-Aug-14	3,409	0.67	21-Nov-14	3,486	0.68	29-Jan-15	3,608	0.71	25-Apr-15	2,598	0.51
10-Feb-14	170	0.03	30-Aug-14	2,258	0.44	22-Nov-14	4,975	0.97	1-Feb-15	3,885	0.76	27-Apr-15	2,243	0.44
15-Feb-14	81	0.02	5-Sep-14	2,524	0.49	23-Nov-14	4,078	0.80	2-Feb-15	3,590	0.70	30-Apr-15	1,742	0.34
18-Feb-14	250	0.05	8-Sep-14	346	0.07	24-Nov-14	4,517	0.88	3-Feb-15	3,532	0.69	3-May-15	1,306	0.26
23-Feb-14	820	0.16	15-Sep-14	3,615	0.71	25-Nov-14	3,597	0.70	5-Feb-15	3,327	0.65	4-May-15	2,504	0.49
24-Feb-14	728	0.14	20-Sep-14	2,887	0.57	27-Nov-14	703	0.14	9-Feb-15	3,583	0.70	5-May-15	2,260	0.44
28-Feb-14	1,044	0.20	22-Sep-14	3,653	0.72	28-Nov-14	844	0.17	11-Feb-15	3,457	0.68	6-May-15	2,343	0.46
1-Mar-14	614	0.12	26-Sep-14	1,823	0.36	1-Dec-14	4,476	0.88	13-Feb-15	3,392	0.66	10-May-15	2,950	0.58
3-Mar-14	1,052	0.21	29-Sep-14	2,875	0.56	3-Dec-14	4,839	0.95	16-Feb-15	3,459	0.68	11-May-15	1,758	0.34
6-Mar-14	1,008	0.20	30-Sep-14	136	0.03	4-Dec-14	684	0.13	17-Feb-15	3,172	0.62	13-May-15	2,269	0.44
18-Mar-14	238	0.05	3-Oct-14	450	0.09	6-Dec-14	4,546	0.89	19-Feb-15	3,391	0.66	15-May-15	1,122	0.22
6-Apr-14	1,481	0.29	4-Oct-14	3,188	0.62	7-Dec-14	3,229	0.63	21-Feb-15	1,990	0.39	16-May-15	988	0.19
21-Apr-14	181	0.04	5-Oct-14	454	0.09	10-Dec-14	4,612	0.90	24-Feb-15	3,432	0.67	17-May-15	969	0.19
24-Apr-14	986	0.19	6-Oct-14	3,819	0.75	12-Dec-14	4,103	0.80	26-Feb-15	3,197	0.63	21-May-15	1,690	0.33
25-Apr-14	211	0.04	7-Oct-14	321	0.06	15-Dec-14	4,493	0.88	28-Feb-15	3,353	0.66	28-May-15	820	0.16
26-Apr-14	1,137	0.22	9-Oct-14	4,031	0.79	17-Dec-14	4,118	0.81	3-Mar-15	3,372	0.66	29-May-15	1,159	0.23
3-May-14	979	0.19	12-Oct-14	469	0.09	18-Dec-14	2,056	0.40	5-Mar-15	3,049	0.60	31-May-15	1,851	0.36
5-May-14	782	0.15	14-Oct-14	1,431	0.28	20-Dec-14	4,130	0.81	7-Mar-15	3,492	0.68	1-Jun-15	2,039	0.40
6-May-14	1,107	0.22	17-Oct-14	3,625	0.71	21-Dec-14	3,136	0.61	10-Mar-15	3,492	0.68	2-Jun-15	2,037	0.40
10-May-14	570	0.11	19-Oct-14	3,686	0.72	23-Dec-14	4,272	0.84	13-Mar-15	3,265	0.64	4-Jun-15	2,703	0.53
16-May-14	1,730	0.34	20-Oct-14	804	0.16	24-Dec-14	3,672	0.72	15-Mar-15	3,208	0.63	7-Jun-15	2,753	0.54
24-May-14	1,934	0.38	22-Oct-14	4,537	0.89	26-Dec-14	3,480	0.68	16-Mar-15	2,766	0.54	11-Jun-15	2,615	0.51
31-May-14	1,641	0.32	23-Oct-14	1,239	0.24	28-Dec-14	3,939	0.77	19-Mar-15	3,116	0.61	12-Jun-15	1,894	0.37
1-Jun-14	2,129	0.42	25-Oct-14	5,420	1.06	30-Dec-14	3,978	0.78	22-Mar-15	3,348	0.66	13-Jun-15	2,056	0.40
3-Jun-14	620	0.12	27-Oct-14	4,690	0.92	1-Jan-15	3,601	0.70	25-Mar-15	2,464	0.48	15-Jun-15	2,282	0.45
11-Jun-14	1,368	0.27	29-Oct-14	5,425	1.06	2-Jan-15	3,416	0.67	27-Mar-15	1,676	0.33	20-Jun-15	2,670	0.52
16-Jun-14	981	0.19	31-Oct-14	5,635	1.10	4-Jan-15	3,662	0.72	29-Mar-15	2,996	0.59	22-Jun-15	2,178	0.43
19-Jun-14	2,161	0.42	1-Nov-14	5,771	1.13	6-Jan-15	3,607	0.71	30-Mar-15	3,029	0.59	26-Jun-15	2,541	0.50
22-Jun-14	200	0.04	3-Nov-14	5,790	1.13	7-Jan-15	933	0.18	2-Apr-15	2,853	0.56	28-Jun-15	1,897	0.37
5-Jul-14	349	0.07	6-Nov-14	5,940	1.16	8-Jan-15	4,098	0.80	3-Apr-15	2,928	0.57	30-Jun-15	2,221	0.43
18-Jul-14	2,296	0.45	7-Nov-14	5,730	1.12	9-Jan-15	4,048	0.79	4-Apr-15	1,506	0.29	1-Jul-15	469	0.09
21-Jul-14	2,668	0.52	8-Nov-14	5,676	1.11	10-Jan-15	2,658	0.52	7-Apr-15	3,095	0.61	4-Jul-15	1,879	0.37
26-Jul-14	2,419	0.47	10-Nov-14	5,751	1.13	15-Jan-15	4,124	0.81	9-Apr-15	2,641	0.52	7-Jul-15	2,181	0.43
29-Jul-14	1,598	0.31	11-Nov-14	4,436	0.87	16-Jan-15	3,515	0.69	10-Apr-15	2,558	0.50	Total	5,10,841	100.00
30-Jul-14	293	0.06	13-Nov-14	5,783	1.13	18-Jan-15	3,655	0.72	12-Apr-15	3,049	0.60			

Table A3 Category of Product Listings on Evolution

Category	Listings	Percent
Drugs	723,742	45.32%
Other	227,233	14.23%
Fraud	200,142	12.53%
Pirated goods	174,439	10.92%
Hacking	75,999	4.76%
Drug equipment	50,110	3.14%
Guides and Tutorials	27,988	1.75%
Weapons	17,848	1.12%
Electronics	13,707	0.86%
Jewelry	8,308	0.52%
Apparel	7,776	0.49%
Health	69,814	4.37%
Total	1,597,106	100.00%

Table A4 Category of Product Listings on Agora

Category	Listings	Percent
Drugs	407,865	79.84%
Pirated goods	68,225	13.36%
Other	14,138	2.77%
Fraud	13,048	2.55%
Drug equipment	2,697	0.53%
Electronics	2,860	0.56%
Weapons	2,008	0.39%
Total	510,841	100.00%

Table A5 Breakdown of Listings by Number of Deals Categories on Agora

Category	Listings	Percent
1 to 2 deals	3,356	0.66%
3 to 5 deals	4,056	0.79%
6 to 10 deals	6,412	1.26%
10 to 15 deals	4,969	0.97%
15 to 25 deals	12,367	2.42%
25 to 40 deals	14,792	2.90%
40 to 55 deals	15,301	3.00%
55 to 70 deals	12,689	2.48%
70 to 100 deals	23,432	4.59%
100 to 150 deals	43,007	8.42%
150 to 200 deals	39,022	7.64%
200 to 300 deals	57,340	11.22%
300 to 500 deals	74,314	14.55%
500 to 1000 deals	78,497	15.37%
1000+ deals	40,970	8.02%
1000 to 1500 deals	25,020	4.90%
1000 to 2000 deals	17,094	3.35%
2000 to 3000 deals	12,300	2.41%
3000 to 4000 deals	5,915	1.16%
4000 to 5000 deals	4,831	0.95%
5000+ deals	15,158	2.97%
Total	510,842	100.00%

Table A6 Dates Used for Number of Transaction Analysis

Date	Used for
10-Aug-14	Aug-14
10-Sep-14	Sep-14
4-Oct-14	Oct-14
5-Oct-14	Oct-14
6-Oct-14	Oct-14
8-Oct-14	Oct-14
3-Nov-14	Nov-14
6-Nov-14	Nov-14
7-Nov-14	Nov-14
9-Nov-14	Nov-14
4-Dec-14	Dec-14
6-Dec-14	Dec-14
7-Dec-14	Dec-14
2-Jan-15	Jan-15
6-Jan-15	Jan-15
8-Jan-15	Jan-15
1-Feb-15	Feb-15
2-Feb-15	Feb-15
3-Feb-15	Feb-15
5-Feb-15	Feb-15

Table A7 Number of Vendors with the first listing in month in Evolution

Year	Month	Number of vendors with the first listing in month	Percent
2014	Aug 8 to Sep 7	776	59.37
2014	Sep 8 to Oct 7	234	17.90
2014	Oct 8 to Nov 6	233	17.83
2014	Nov 7 to Dec 5	47	3.60
2014-2015	Dec 6 to Jan 5	12	0.92
2015	Jan 6 to Feb 4	5	0.38
	Total	1,307	100.00

Table A8 Number of vendors with the first listing in month in Agora

Year	Month	Number of vendors with the first listing in month	Percent
2014	Jan 6 to Feb 4	281	10.47
2014	Feb 4 to Mar 6	431	16.06
2014	Mar 6 to Apr 5	165	6.15
2014	Apr 6 to May 6	65	2.42
2014	May 7 to Jun 6	184	6.86
2014	Jun 7 to Jul 7	55	2.05
2014	Jul 8 to Aug 7	155	5.77
2014	Aug 8 to Sep 7	101	3.76
2014	Sep 8 to Oct 7	142	5.29
2014	Oct 8 to Nov 6	119	4.43
2014	Nov 7 to Dec 5	147	5.48
2014-2015	Dec 6 to Jan 5	110	4.10
2015	Jan 6 to Feb 4	118	4.40
2015	Feb 4 to Mar 6	103	3.84
2015	Mar 6 to Apr 5	141	5.25
2015	Apr 6 to May 6	90	3.35
2015	May 7 to Jun 6	51	1.90
2015	Jun 7 to Jul 7	191	7.12
2015	Jul 8 to Aug 7	35	1.30
	Total	2,684	100.00