Claremont McKenna College

The Effects of Police Interventions on Darknet Market Drug Prices

Submitted to

Professor David Bjerk

by

Glenn Hull

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Abstract

This paper determines the effects of police interventions on darknet markets. Darknet markets have been rapidly growing and the amount of drugs being sold on them keeps rising. This paper finds no significant changes in prices of drug listings before and after drug busts, and no significant changes in price per unit of drugs across the entire market. The results are similar to prior research done on normal drug markets that determined that police interventions have no significant effect on changing drug prices. With the rapid growth of drugs being sold on darknet markets, it is critical for law enforcement to understand how the markets react to police interventions.

Table of Contents

I. Introduction

Over the past five years, there has been a sharp rise in the amount of illegal drugs sold on online drug markets (Kruithof et al. 2016). These online drug markets, known as darknet markets, are online marketplaces that can only be accessed through browsers that operate on the darknet, a portion of the internet that is not indexed by most search engines and requires a special web browser to access. Since 2013, the number of drug listings on darknet markets has increased approximately 600% and the number of vendors and transactions has nearly tripled (Kruithof et al. 2016). Kruithof et al. (2016) estimate the average monthly revenue of darknet drug markets to be in the tens of millions. There have been several large-scale law enforcement interventions to arrest the buyers and sellers of darknet markets; however, the efficacy of these interventions is questionable as the darknet markets keep rapidly expanding despite hundreds of arrests (EMCDDA 2016). The proliferation of darknet markets poses a significant challenge for law enforcement as they now have to find ways to combat a new type of drug trade.

There have been several studies that analyze how normal drug markets react to police interventions. Reuter and Kleiman (1986) find that changes in availability and price are different depending on which drug they targeted. For example, marijuana and cocaine had neither a change in availability or price after increased law enforcement operations, but heroin did. Pollack and Reuter (2014) did a review of several papers to determine the marginal effect of increases in law enforcement on drug prices and determined that the large costs of police interventions were ineffective and did not raise the prices of drugs. Caulkins and Reuter (2010) took a long-term view of 25 years of the market and determined that risk has dramatically increased and prices have substantially fallen.

There have been several studies published about darknet markets regarding their operations (Kruithof et al. 2016), the types of drugs sold (Christin 2013), their distribution patterns (Demant, Munksgaard, and Houborg 2016), along with other areas; however, the literature on how darknet markets react to police interventions is limited. To the best of my knowledge, there has only been one study examining how police interventions affect drug prices on darknet markets (Décary-Hétu and Giommoni 2016). They find that police crackdowns on darknet markets only affect participants for a short period of time, with prices not significantly changing and the number of listings stabilizing within weeks of the intervention taking place. Décary-Hétu and Giommoni (2016) however only look at one intervention and the five markets affected by the participation. My paper expands on this paper by evaluating the effects of other police interventions on different darknet markets. Further, I look at price dispersion and analyze changes in price per unit of certain drugs aggregated for the entire market. Lastly, my paper analyzes the similarities and differences of darknet markets compared to normal drug markets. While there has been strong evidence of price inelasticity of drugs in normal markets, I want to determine if it is the same for darknet drug markets.

Darknet markets are relatively new marketplaces and data on them has been difficult to obtain, making it challenging for quantitative research to take place. Public datasets are available; however, this data is embedded in HTML and requires web scraping to extract the data.[1] Using this data, I ran a linear regression to compare prices of listings both before and after police interventions to see if there are any significant changes in price. I found no significant change in price in any of the interventions on any of the markets. I looked at two police interventions, including the police intervention Décary-Hétu and Giommoni (2016) used. I also used different, smaller darknet markets than Décary-Hétu and Giommoni (2016). Further, I looked at price dispersion of different types of drugs before and after the interventions and found no significant change. The results validate what Décary-Hétu and Giommoni (2016) found and also provide evidence that darknet markets react similarly to police interventions.

The remainder of the paper is organized as follows. Section II provides background on the history and characteristics of darknet markets. Section III presents a review of existing literature regarding police interventions in both darknet markets and normal drug markets. I describe my data collection process and variable descriptions in Section IV. Section V discusses my empirical strategy and results. My conclusions are presented in Section VI.

[1] I wrote Python programs that scraped and extracted the data. Each market has different HTML, therefore each market needs its own web scraper. Some markets change their HTML over time causing them to need multiple scrapers. The scrapers took me approximately three months to program and were over 3,000 lines of code.

II. History and Characteristics of Darknet Markets

Drugs have been traded online since the internet was first created, but law enforcement was slow to respond and did not start large-scale investigations until the Silk Road gained popularity in 2011 (Buxton and Bingham 2015). The Silk Road and the majority of subsequent darknet drug markets can be intuitively thought of as an Amazon for drugs. Each category of drug has its own page and each page has listings of all drugs for sale including images and descriptions of the listing. Figure 1 shows an image of the darknet market Silk Road 3.0. People access these darknet markets through web browsers specifically made to search unlisted websites. These browsers, the most notable is named TOR, obscures an individual's internet activity, making it difficult for law enforcement to see what people are doing online. This combined with Bitcoin, a cryptocurrency which allows for pseudonymous payments that make it challenging to track to a person, created a desirable online marketplace for drugs due to the increased security for them. Law enforcement now faces increased difficulty policing people's internet activity due to TOR and increased difficulty tracking drug money due to Bitcoin (EMCDDA 2015).

Prior to the Silk Road, the largest online drug marketplace was only a few thousand people. But when the Silk Road was created and started to get media attention, it rose to hundreds of thousands of users (Buxton and Bingham 2015). Given the large increase in the online drug trade, law enforcement began to take notice and investigate. The FBI was able to identify the leader of the Silk Road through forum posts connecting his online identity to his real identity (Hern 2013). While darknet markets are supposed to be anonymous, there are a variety of ways that a person can get caught using them such as having product shipments intercepted by police officers, having the same username on the darknet markets as other internet accounts, and using improper encryption methods while interacting with darknet data. In the past few years there have been numerous interventions of varying sizes. Some interventions are large, involving Interpol and the FBI, and aim to arrest dozens of people. Other interventions only target one person or a couple people (EMCDDA).

After the Silk Road closed, several new darknet markets were created. A group of administrators from the Silk Road created the Silk Road 2.0 which quickly became one of the most popular darknet markets (Demant, Munksgaard, and Houborg 2016). Another large police intervention, Operation Onymous, targeted the Silk Road 2.0 on November 6, 2014 taking it down, making 17 arrests, and seizing over $1 million in Bitcoin (Afilipoaie and Shortis 2015). Operation Onymous was the focal point of Décary-Hétu and Giommoni (2016) that determined that police interventions did not affect the price of drugs on darknet markets. After markets are shut down, multiple new ones tend to emerge and even with the added police intervention, there are still thousands of new users joining (Kruithof et al. 2016). Similar to normal drug markets, darknet markets appear to be unaffected by police interventions.

III. Literature Review

Existing research provides evidence that drug prices on both online drug markets and normal drug markets do not have a significant reaction to police interventions. While there are data limitations in much of the research due to the challenges of getting accurate pricing information and an accurate view of the market, the risk of arrests for drug dealers has significantly increased over the past 25 years and the prices of drugs have fallen substantially (Caulkins and Reuter 2010). Caulkins and Reuter (2010) finds that the risk of incarceration has risen more than 500% since the late 1980s and that the United States is increasing the amount of money they are spending in an attempt to control the illegal drug markets. Caulkins and Reuter (2010) finds that when the drug markets are already established, law enforcement interventions are expensive and do a poor job of increasing the price of drugs.

While Reuter and Kleiman (1986) find that changes in price are different depending on the type of drug, they find that overall law enforcement interventions could not impose significant costs on “mass-market drugs”. Mass-market drugs are loosely defined by Reuter and Kleiman (1986) to be drugs with large quantities sold. Reuter and Kleiman (1986) believe that even if law enforcement could increase the price per kilo for cocaine or marijuana, it would probably not affect the prices at which individuals bought because there is a large premium on paying for small amounts. The Reuter and Kleiman (1986) paper is an important first step in showing that increased risks do not deter drug dealers from selling drugs or change the price of drugs.

Reuter and Kleiman (1986) and Caulkins and Reuter (2010) both provide evidence that normal drug markets do not react significantly to police interventions; Décary-Hétu and Giommoni (2016) demonstrate that police interventions in darknet markets do not result in long-term changes. Décary-Hétu and Giommoni (2016) find that the police interventions do not significantly affect prices, sales, or amount of new vendors in the long-run. Décary-Hétu and Giommoni (2016) focuses on Operation Onymous, a large-scale police intervention that lead to the arrest of 17 people and the closure of multiple darknet markets. There was a slight drop in price after Operation Onymous, but it was equivalent to other price drops that have been associated with changes in Bitcoin price. Further, there was a drop in new dealer registration on the sites, but after a few months it increased back to pre-intervention amounts. Estimated sales were two times higher two months after the intervention. To analyze changes in drug prices, Décary-Hétu and Giommoni (2016) grouped all listings by week and examined the 41 weeks before the operation and the 21 weeks after. Décary-Hétu and Giommoni (2016) found that after the police intervention, drug listings had below a 2% average price change, much of which was attributed to the change in Bitcoin price. Less than 25% of sellers took down their listings after 4 weeks (Décary-Hétu and Giommoni 2016). Overall, Décary-Hétu and Giommoni (2016) found that Operation Onymous did not decrease prices, sales, or new dealers long-term.

My paper examines price changes in drug listings after police interventions on darknet markets. I use Operation Onymous, the same police intervention as Décary-Hétu and Giommoni (2016), and another police intervention. Further, I analyzed the price dispersion of different categories of drugs to determine the changes in price per unit on darknet markets after police interventions. To the best of my knowledge this is the first analysis of price dispersion on darknet markets. I use quantile regression to determine if the price per unit of drug significantly changes across all listings in the market. Finally, I compare these results to normal drug markets to determine the similarities between darknet drug markets and normal drug markets.

IV. Data

The data set used for this research comes from Branwen et al. (2015). Branwen et al. wrote a web crawler which attempted to download every page on certain darknet markets. Branwen scraped dozens of markets between January 2014-March 2016. The data provided is 1.5 terabytes and is broken down by a folder for each market, then a folder for each date, and then the source code for each web page. To extract the data from the source code, I wrote Python scripts that iterate through each file and use regular expressions to extract the necessary data that was embedded in HTML code. Every market is programmed in a different way, therefore each has a different structure which required a new script. Further, some markets changed their layout over time so I needed to write multiple scripts for certain markets. Overall, I wrote several thousands of lines of code in order to extract all the necessary information.

The original dataset provided by Branwen has some limitations. The TOR network is difficult to scrape because web pages take a while to load and Branwen did not run the crawler every day. While data was collected every week, it was collected at different frequencies. Sometimes the data was collected multiple times a week while other times it was only once. Further, Branwen could not collect every single webpage on darknet markets due to the unreliability of TOR. Therefore, the dataset is incomplete; however, it is the most complete dataset publicly available and is used by prominent researchers in the field such as Décary-Hétu and Giommoni (2016) and Kruithof et al. (2016).

The dataset includes the market name, drug listing, drug listing description, drug category, price, date, price change, seller, week, and price per gram. The market name is the URL of the market in which the drug listing is posted. The drug listing is the name of the drug; an example of this is "7g SWEET GREEN JAMAICAN WEED." Along with the name of the drug, there is also a corresponding description to give the buyer more information about the product. The corresponding description of the example previously given for the drug listing is "Great outdoor pressed jamaican weed with some pips Nice high and strength Rapid delivery". To get drug categories, I used regular expressions to get keywords such as "MDMA", "weed", and "cocaine" out of the product descriptions and created dummy variables for listings that included a keyword. The four drug dummy variables I am using in my regression are marijuana, MDMA, cocaine, and heroin. The price is the price in United States dollars. Some markets listed the price of goods in United States dollars; however, most listed it solely in Bitcoin. I built a Python program that converts historic Bitcoin price to United States dollars and used the United States dollar price for my analysis. The program gets the conversation rate of Bitcoin to United States dollars from historical data at BitcoinCharts.com, the same site that Décary-Hétu and Giommoni (2016) used for their analysis. The date is the date that the webpage was scraped. I calculate the price change by writing an R program that finds and groups all listings that have the same name and description together and orders them by price. Then the program takes the difference between the current price and the previous price to get the price change. The seller is the name of the seller of the product listed on the website. The week variable is a dummy variable I created to indicate which week the listing is in. I determined price per gram by using regular expressions to extract the weight from the title to then divide price by weight in grams. While some of the listings did not have a weight attached to them, I was successful in getting approximately 71% of the listing's weights for MDMA, marijuana, cocaine, and heroin.

The dataset I worked with contains 965,376 observations from 7 different markets. Table 1 shows how many observations are in each market and the 25th percentile, median, and 75th percentile prices of the listings. The smallest market has 1,791 observations and the largest market has 325,829 observations. I looked at two busts, Operation Onymous and the arrest of seller "Shiny Flakes". I used Operation Onymous because it is the largest darknet bust that I have data available for and there is prior research to compare it with. The investigation of Shiny Flakes led to 38 search warrants being issued, at least 5 arrests, and $4,200,000 of drugs being seized (Fox-Brewster 2015). This particular bust had coverage by Vice, Forbes, along with several other forums and websites. The date I use for Operation Onymous is 2014-11-05, which is when the operation began. The date I use for the Shiny Flakes bust is 2015-03-11, which is when media began to publish articles about it.

There are multiple ways to analyze police intervention effects on darknet market prices. The first method is to look at change in price of the same drugs that are sold on the markets both before and after the interventions. This will show if the police intervention is causing prices of drugs to rise. The second method is to look at the market as a whole and see if the 25th percentile, median, and 75th percentile of listing price change before and after the intervention. This second method is valuable to see if the interventions may cause smaller dealers to leave the market. As seen in Table 2, overall prices in all the markets rose across the 25th, 50th, and 75th percentile after Operation Onymous in week 0. However, within a month prices appear to restabilize back to pre-operation levels. For the Shaky Flakes bust, there was no immediate reaction in the overall prices in the markets. The next section will show my empirical strategy for determining changes in price of the same drugs.

IV. Empirical Strategy and Results

To determine the effect of police interventions on price in darknet markets I ran a linear regression in the following form:

$$(1)\ \Delta\, Price_i = a_i + Week_i + Weed_i + Cocaine_i + Heroin_i + MDMA_i + Market_i + e_i$$

where the i subscript denotes each drug listing. Δ Price is the price change of a listing every week. The week variable is a dummy variable for a certain week and equals 1 if it is that week and equals 0 if it is not that week. Weed, Cocaine, Heroin, and MDMA are all dummy variables that equal 1 if the listing is that type of drug and 0 if not. I leave out the week of the intervention which is week 0 in my regressions and label my weeks as "1 week before bust" and "1 week after bust."

I find that no individual week had a significant impact on the change of price of a drug listing. Across all markets, increased police interventions did not significantly impact changes in price. These findings are consistent with the findings presented in Décary-Hétu and Giommoni (2016). While he only looked Operation Onymous, I also looked at the Shakey Flakes bust and see no week-to-week differences in the change of price variable (see Tables 3 and 4). The seven markets I evaluated were all different and smaller than the ones that Décary-Hétu and Giommoni (2016) studied. There is evidence that the different darknet drug markets operate similarly and darknet market prices in general do not significantly react to police interventions. Décary-Hétu and Giommoni (2016) offers multiple explanations for why price does not change. The first being that the perception of risk is not changed after drug busts. Sellers on darknet markets may already accurately factor in risk into the price of the drugs and are not surprised when the police interventions occur. Another explanation is that drug dealers in darknet markets are price-takers and not price-setters, as normal drug markets are (Décary-Hétu and Giommoni 2016). One last explanation is that they do not change the price but lie about the listing and put a smaller amount or a lower cost product. While the exact reason for the price staying stable after police interventions is not confirmed, it is important to find that regardless of size of police interventions, drug listings on darknet markets do not significantly change. Unlike Reuter and Kleiman (1986), I did not find that different drug react differently to police interventions. None of the drug types that I tested were statistically significant. This may be due to the new form of dealing or simply changes in drug behavior over the last three decades.

Further, I analyzed price dispersion amongst several drugs. To do this I looked at how the market price per unit of drug changes before and after the police intervention at the first, second, and third quartile. This quantile regression looks at every drug listing, unlike the previous regression which only looked at drug listings that appeared both before and after the police interventions. The regression is in the following form:

$$(2)\ PPG_i = a_i + Week_i + Weed_i + Cocaine_i + Heroin_i + MDMA_i + Market_i + e_i$$

where the i subscript denotes each drug listing. PPG is the price per gram of each drug listing. All other variables are the same as in the previous regression. Table 5 and 6 show the regression results for Operation Onymous and the Shaky Flakes intervention respectively.

I found no significant change in price per gram of drug after the police interventions occurred. While the previous regression shows that prices of the same drug did not significantly change after interventions, it is important to test if price per gram across the market increases. Theoretically, interventions may have caused changes in the market prices of the drugs as a whole, but not in the individual listings which were present both before and after the intervention. For example, new sellers may raise the prices of their drugs or sellers may begin to sell primarily in bulk, which can shift the price per gram of the average listing on the market. However, price per gram of each drug tested did not significantly change after the police intervention. While the price per gram of heroin, cocaine, MDMA, and marijuana did not significantly change, the market does have a slightly higher average listing as shown in Table 2. Figure 2 shows a graph of price per unit over time to help visualize any shift there may be. This could be due to several reasons such as higher price per units of drugs that I did not test or large sized listings. The lack of significant change in price per gram of drugs along with the lack of significant change in the same drug listings suggests that the darknet markets are not impacted by police interventions at the individual drug level, or the market as a whole.

V. Conclusion

Online drug markets have been rapidly growing and it is critical for law enforcement to understand these markets if they want to create effective interventions. Décary-Hétu and Giommoni (2016) found that police interventions did not have a long-term effect on prices of drugs on darknet markets. Caulkins and Reuter (2010) and Reuter and Kleiman (1986) found that police interventions do not increase prices of drugs on normal markets. Similarly, I found that prices on darknet drug markets are not significantly affected by police interventions. I also evaluate price changes for specific drugs and I continue to find no effect on price changes. Further, the overall price per unit of drug on darknet markets does not significantly change after police intervention. Given the lack of changes in price after police interventions, I argue that normal drug markets and darknet markets are similar in that the price of drugs is inelastic and does not significantly change after police interventions.

It is important to understand the underlying mechanisms of the rapidly growing darknet markets so law enforcement can effectively handle them. So far evidence has shown that darknet markets act similarly to normal drug markets in terms of seller behavior. If law enforcement wishes to tackle the darknet drug markets, they will need to realize that increasing arrests does not raise prices and may be counterproductive because of the added media attention. Buxton and Bingham (2015) argues that the police interventions may lead to higher usage of darknet markets due to more people becoming aware of them.

Interesting future studies would include finding if there is a correlation between the type of drugs the arrested seller sold and the prices of those drugs on the market, the drug composition of certain markets, and evaluating the amount of new sellers after a lot of media attention.

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Appendix

Figure 1: A screenshot of what a darknet market. Source: https://commons.wikimedia.org/wiki/File:Silkroad30.png

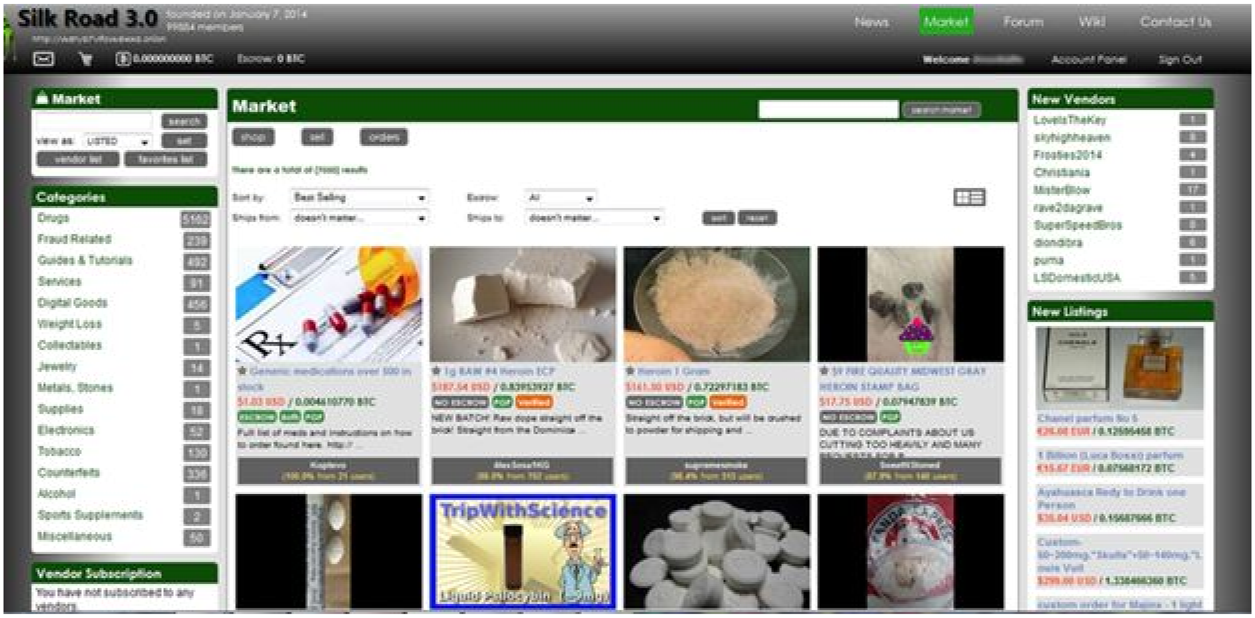

Figure 2: This graph shows price per gram of MDMA over time for the darknet market Dream.

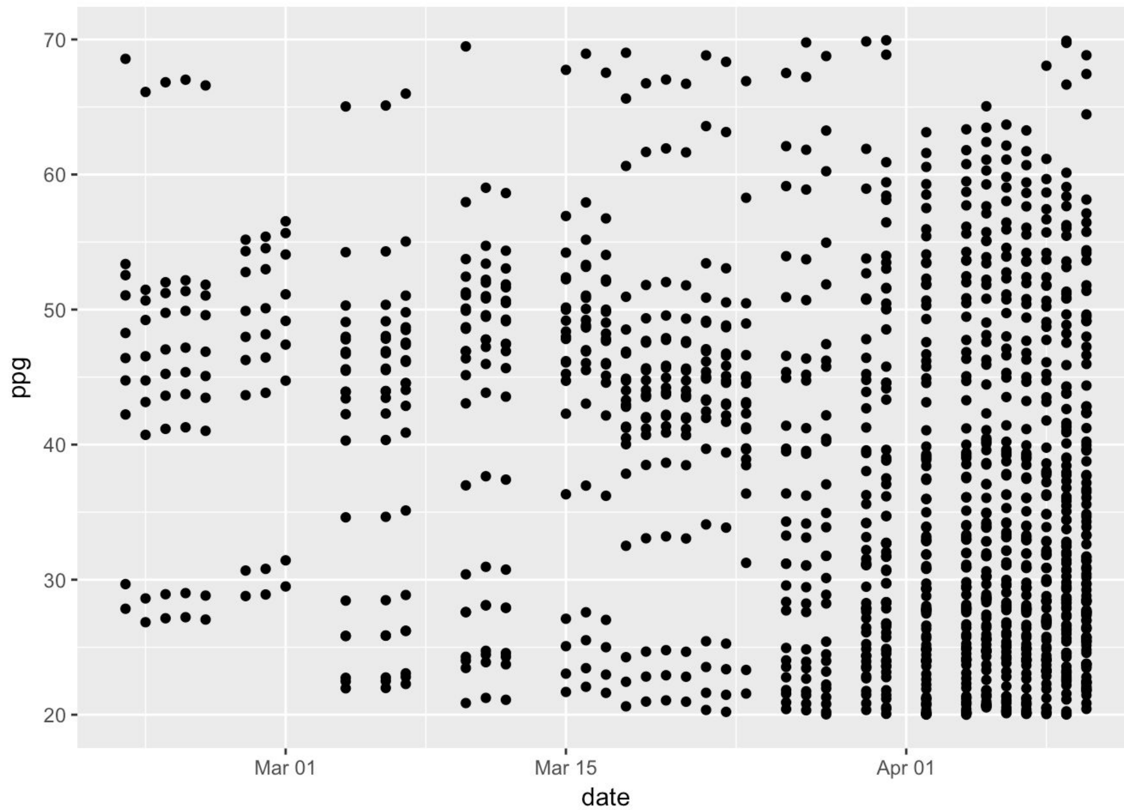

Table 1: Quartile prices of the entire drug catalog for each market studied

Market	Observations	25% Price	50% Price	75% Price
Pandora	204642	$32.58	$93.95	$300.85
Black Bank	325829	$17.20	$68.40	$220.60
Outlaw	76725	$34.00	$87.89	$233.27
Middle Earth	13509	$9.99	$39.66	$137.91
Diabolous	107758	$16.30	$61.01	$183.09
Dream	1791	$116.48	$255.44	$540.27
Cloud 9	235122	$18.28	$63.87	$217.03

Table 2: Quartiles of all darknet market listing prices before and after Operation Onymous.

Week	25th percentile	50th percentile	75th percentile
4 Weeks Before Bust	$15.39	$60.09	$173.06
3 Weeks Before Bust	$17.28	$64.66	$188.63
2 Weeks Before Bust	$17.46	$63.82	$188.8
1 Week Before Bust	$15.46	$57.32	$161.58
1 Week After Bust	$19.68	$67.96	$199.95
2 Weeks After Bust	$24.36	$73.25	$196.36
3 Weeks After Bust	$30.59	$84.02	$217.73
4 Weeks After Bust	$21.69	$63.58	$161.17

Table 3: Regression 1 (N=74,974) for Operation Onymous.

VARIABLES	Price Change (1)	Price Change (2)	Price Change (3)
2 Weeks Before Bust	-0.063	-0.062	-0.102
	(0.160)	(0.160)	(0.186)
1 Week Before Bust	-0.034	-0.034	-0.073
	(0.140)	(0.140)	(0.170)
1 Week After Bust	-0.020	-0.020	-0.057
	(0.139)	(0.139)	(0.170)
2 Weeks After Bust	-0.061	-0.061	-0.090
	(0.144)	(0.144)	(0.215)
3 Weeks After Bust	-0.039	-0.039	-0.081
	(0.180)	(0.180)	(0.226)
4 Weeks After Bust	-0.029	-0.029	-0.088
	(0.190)	(0.191)	(0.210)
MDMA		-0.005	-0.005
		(0.190)	(0.160)
Weed		0.002	-0.005
		(0.488)	(0.190)
Heroin		0.004	-0.002
		(0.670)	(0.238)
Cocaine		0.001	-0.048
		(0.504)	(0.208)
Black Bank Market			-.043
			(.594)
Pandora Market			-0.002
			(.112)
Cloud 9 Market			-0.129
			(.152)
Outlaw Market			0.004
			(.099)
Constant	0.034	0.034	0.089
	(0.106)	(0.107)	(.167)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Regression 1 (N=194,157) for the Shaky Flakes Intervention.

VARIABLES	Price Change (1)	Price Change (2)	Price Change (3)
2 Weeks Before Bust	-0.029 (0.090)	-0.011 (0.074)	-0.029 (0.876)
1 Week Before Bust	-0.000 (0.009)	0.0001 (0.003)	-0.002 (0.097)
1 Week After Bust	0.000 (0.008)	0.0001 (0.009)	-0.002 (0.086)
2 Weeks After Bust	-0.004 (0.086)	-0.023 (0.064)	-0.045 (0.085)
3 Weeks After Bust	-0.050 (0.802)	-0.040 (0.081)	-0.048 (0.801)
4 Weeks After Bust	-0.000 (0.080)	-0.006 (0.079)	-0.005 (0.080)
MDMA		-0.015 (0.059)	-0.010 (0.058)
Weed		0.014 (0.063)	0.014 (0.064)
Heroin		0.018 (0.099)	-0.015 (0.122)
Cocaine		0.016 (0.065)	-0.017 (0.065)
Black Bank Market			-.008 (.031)
Diabolous Market			0.014 (.037)
Middle Earth Market			0.110 (.072)
Dream Market			-0.062 (.044)
Constant	0.000 (0..007)	-.001 (0.007)	0.004 (.076)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Regression 2 (N=97,415) for Operation Onymous.

VARIABLES	.25	.50	.75
2 Weeks Before Bust	1.761 (1.802)	1.702 (1.654)	2.338 (2.186)
1 Week Before Bust	1.478 (1.609)	1.743 (1.454)	2.571 (2.413)
1 Week After Bust	1.322 (1.582)	1.414 (1.673)	2.603 (3.051)
2 Weeks After Bust	1.695 (1.545)	1.771 (2.011)	2.323 (2.482)
3 Weeks After Bust	1.864 (1.657)	1.827 (1.623)	3.089 (2.988)
4 Weeks After Bust	1.019 (1.097)	1.454 (1.349)	2.380 (2.210)
MDMA	-3.143*** (0.561)	1.053*** (0.014)	5.083*** (0.956)
Weed	-16.410*** (0.179)	-23.474*** (0.353)	-29.028*** (0.441)
Heroin	-5.259*** (0.355)	8.385* (3.263)	27.130*** (3.400)
Cocaine	-10.279*** (0.414)	17.566*** (2.633)	31.251*** (3.409)
Black Bank Market	0.148 (0.146)	-0.446 (0.587)	-2.331 (2.080)
Pandora Market	0.293 (0.248)	0.480 (0.516)	-0.418 (0.507)
Cloud 9 Market	0.212 (0.245)	0.928 (0.984)	-0.967 (0.909)
Outlaw Market	0.118 (.194)	0.084 (0.131)	0.313 (0.495)
Constant	23.387*** (0.56)	31.702*** (0.535)	41.142*** (0.604)

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Regression 2 (N=226,873) for the Shaky Flakes Intervention.

VARIABLES	Price Change (1)	Price Change (2)	Price Change (3)
2 Weeks Before Bust	1.254	1.674	1.945
	(1.563)	(1.832)	(1.874)
1 Week Before Bust	1.207	1.954	2.310
	(1.391)	(2.310)	(2.452)
1 Week After Bust	1.484	1.636	2.038
	(2.075)	(1.418)	(2.018)
2 Weeks After Bust	1.386	1.587	1.987
	(1.115)	(1.729)	(2.312)
3 Weeks After Bust	1.592	1.934	2.683
	(1.383)	(2.001)	(2.419)
4 Weeks After Bust	1.395	1.633	1.811
	(1.940)	(1.831)	(1.857)
MDMA	-7.414***	-1.539***	5.312***
	(-0.208)	(0.192)	(0.368)
Weed	-18.121***	-22.034***	-27.031***
	(0.385)	(0.442)	(0.686)
Heroin	-7.683***	4.231***	19.459***
	(0.814)	(.187)	(0.482)
Cocaine	-13.201***	25.861***	30.085***
	(0.523)	(0.998)	(1.302)
Black Bank Market	0.028	-0.134	-0.256
	(0.031)	(0.210)	(0.677)
Diabolous Market	0.313	0.028	-0.037
	(0.482)	(0.079)	(0.148)
Middle Earth Market	0.249	0.498	0.904
	(0.368)	(0.513)	(1.725)
Dream Market	0.089	0.641	1.096
	(0.134)	(1.001)	(0.992)
Constant	25.493***	32.714***	40.675***
	(0.910)	(0.908)	(1.083)

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$