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Drugs on the Web, Crime in the Streets:
The impact of Dark Web marketplaces on street crime

Diego Zambiasi
University College Dublin

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Abstract

The *Dark Web* has changed the way drugs are traded globally by shifting trade away from the streets and onto the web. In this paper, I study whether the *Dark Web* has an impact on street crime, a common side effect of traditional drug trade. To identify a causal effect, I use daily data from the US and exploit unexpected shutdowns of large online drug trading platforms. In a regression discontinuity design, I compare crime rates in days after the shutdowns to those immediately preceding them. I find that shutting down Dark Web markets leads to a significant increase in drug trade in the streets. However, the effect is short-lived. In the days immediately following shutdowns, drug-related crimes increase by five to almost ten percent but revert to pre-shutdown levels within ten days. I find no impact of shutdowns of *Dark Web* marketplaces on thefts, assaults, homicides and prostitution.

JEL classification: K42 L13

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1 Introduction

The number of Americans dying from drug overdose almost quadrupled in the last three decades, going from 16,849 in 1999 to 70,237 in 2017 (Center For Disease Control and Prevention, 2019). During these years a substantial fraction of trade in illegal drugs has moved online. This has been made possible thanks to cryptocurrencies and the rise of the *Dark Web*, a hidden part of the web where drug markets are hosted. The topic has been subject of widespread media coverage and public discourse (The Guardian, 2013; The New York Times, 2013), as the amount of drugs traded online continues to grow.

Dark Web marketplaces overcome some of the traditional problems of street drug trade, such as the risk of being sold impure substances. In fact, *Dark Web* marketplaces face lower rate of scams and higher drug purity than street drug trade (Galenianos et al., 2012; Bhaskar et al., 2017). The *Dark Web* and the availability of cryptocurrencies have therefore changed the business models of drug sellers.

A common side effect of street drug dealing is engagement in criminal activities. Criminal organizations use violence to settle disputes, while consumers engage in petty crimes such as theft and shoplifting to finance their addiction. The shift to online drug trading allows operators to reduce their exposure to criminal activity (Goldstein, 1985; Aldridge & Décary-Hétu, 2014; Barratt et al., 2016).

In this paper I analyze how on-line and off-line markets for illicit drugs are related. In particular, I test whether on-line and off-line drug markets are complements or substitutes and whether on-line drug markets can reduce criminal activity associated with off-line drug dealing. I study the relationship between on-line and off-line markets for illicit drugs by exploiting multiple plausibly exogenous shutdowns of marketplaces on the *Dark Web* in a regression discontinuity (RD) setup where time strictly determines treatment assignment. This allows me to causally identify the impact of shutdowns of *Dark Web* marketplaces on street drug dealing and drug-related crime.

From a theoretical standpoint, the effect of shutdowns of *Dark Web* marketplaces on street illicit drug trade and drug-related crime depends on the degree of substitutability between on-line and off-line markets. Following Galenianos et al. (2012), I describe the illicit drugs market through a search and matching framework, in which buyers engage in a costly search for a supplier and then, under certain conditions, maintain their relationship with the same supplier. In this setup

shutdowns of *Dark Web* marketplaces can be seen as a break in the existing matches between buyers and sellers. After the break, buyers need to look for a new match and, being on-line markets unavailable, they start trading in the off-line market.

In the first part of the paper I estimate the effect of shutdowns of *Dark Web* marketplaces on street drug trade by looking at trade in several drugs (ecstasy, crack cocaine, heroin and marijuana). I show that shutdowns of *Dark Web* marketplaces increase the amount of drugs traded on the street. This effect holds for crack-cocaine, heroin and marijuana, whereas I find no increase in the number of ecstasy-related crimes. Moreover, I identify crimes that are related with the supply and demand for drugs and show that supply-related crimes are driving my results. All increases in crime last for not more than two weeks, confirming previous evidence that shows how users of *Dark Web* marketplaces can quickly switch from one *Dark Web* marketplace to another after shutdowns (Décary-Hétu,& Giommoni, 2017).

In the second part of the paper I estimate the effect of shutdowns of *Dark Web* marketplaces on crimes that are usually connected with sale and consumption of illicit drugs (theft, homicide, assault and prostitution). I show that shutdowns of *Dark Web* marketplaces have no statistically significant impact on those outcomes.

Through the use of daily data, I can rule out alternative explanations to the results obtained. To bias my estimates any other shock affecting street crimes should systematically happen during the same days of shocks affecting on-line drug stores. My findings survive a wide range of robustness checks, such as different polynomial and bandwidth specifications, permutation tests and leave-one out exercises. Moreover, I estimate my main specification through multiple ways of slicing the data. This allows to make sure that arbitrary cuts of the data are not driving my results.

Taken as a whole, my findings show that on-line and off-line markets for illicit drugs are substitutes. After the shutdown of *Dark Web* marketplaces off-line drug trading increases. Consistently with previous literature about on-line drug trading I show that the substitution effect only occurs in the short run, as users of on-line markets go back to on-line trading as soon as another *Dark Web* marketplace becomes available.

Knowing how on-line and off-line markets are related is important for a number of reasons. Firstly, any policy aimed at fighting on-line drug trading needs to consider possible spillovers on off-line drug-trading. If law enforcement agencies are able to effectively fight on-line drug trading but drug trade moves back to the streets, shutting down on-line marketplaces can result in an actual overall increase in crime.

Secondly, it is important to understand whether engagement in drug-related criminal activity is lower for on-line drug trading.

These findings have two main implications for policy makers. Firstly, policy makers should consider potential spillovers on street drug dealing when shutting down a *Dark Web* marketplace. Secondly, policy makers should be aware that shutting down a single *Dark Web* marketplace is ineffective in the long run, as new *Dark Web* marketplaces will emerge and criminals will go back to their usual business on the new platform.

My work contributes to several strands of the literature. The literature about supply-side policy interventions in illicit drugs markets mostly considers interventions aimed at reducing access to inputs in the production of drugs (”precursor control”). These studies generally find that restricting access to inputs increases street prices but has very limited effects on illicit drugs consumption (Dobkin & Nicosia, 2009; Dobkin et al., 2014), either because of low price responsiveness (Cunningham & Finlay, 2016) or because of the presence of substitutes (Alpert et al., 2018). My paper can be seen as complementary to the ones cited above, analyzing a different type of supply-side policy intervention, and confirming that supply-side policies are not effective in reducing illicit drugs consumption.

More broadly I contribute to a recent literature that exploits exogenous shocks to identify their effect on crime (Di Tella & Schargrodsky, 2004; Bianchi et al., 2012; Pinotti, 2017; Rosenfeld, 2018; Dix-Carneiro et al., 2018). I expand upon this literature by providing the first estimates of the effect of shutdowns of *Dark Web* marketplaces on street crime.

2 Institutional Context

2.1 The Dark Web

The *Dark Web* is a hidden part of the internet that guarantees complete anonymity to its users. Accessing the *Dark Web* is straightforward, as users only need to download *The Onion Router* (TOR), an ordinary browser that allows to reach *.onion* domains, which are inaccessible through normal browsers.

Criminals use the *Dark Web* as an advanced technological infrastructure for drug trade. This became possible thanks to the availability of cryptocurrencies, such as bitcoin, which made money transactions completely anonymous, guaranteeing transactions on the *Dark Web* to be untraceable.

Selling drugs online started as a niche business in February 2011 with the opening of *Silk Road*, the first modern marketplace on the *Dark Web*. The owner and founder, Ross Ulbricht, started *Silk Road* as an "*Economic simulation to give people a first hand experience of what it would be like to live in a world without the systemic use of force*"(Business Insider, 2013). *Silk Road* quickly became the largest operating *Dark Web* marketplace and was shut down by the FBI in October 2013, seizing $28.5 million in bitcoins. Ulbricht was arrested and charged for money laundering, computer hacking, conspiracy to traffic narcotics and attempting to have six people killed. The shutdown of *Silk Road*, however, did not stop the flourishing business of *Dark Web* marketplaces, with new marketplaces opening immediately after the shutdown of *Silk Road*.

After *Silk Road*'s shutdown 87 *Dark Web* marketplaces opened in the next five years. The business of online drug trade grew rapidly, with the fraction of Americans buying drugs online almost doubling from 2014 to 2017 and with an estimated revenue of $14.2 million in January 2016 only (Kruithof et al., 2016a). [1]

What do *Dark Web* **marketplaces sell?** Illicit drugs represent roughly 85% of revenue and 60% of total listings on *Dark Web* marketplaces (Kruithof, 2016). The most sold substances are cannabis (37% of total revenues), stimulants (29% of total revenues) and ecstasy (19% of total revenues) (Kruithof et al., 2016b).

[1] According to the 2017 Global Drug Survey, available at https://www.globaldrugsurvey.com/pastfindings/gds2017-launch/results-released/

Dark Web marketplaces serve both the wholesale and the retail market. This can be inferred from heterogeneity in quantities sold, with some listings selling small quantities clearly aimed at the retail market and listings selling quantities that are too big to be for the retail market. Wholesale transactions represent roughly 25% of total revenue for drugs sold on-line (Kruithof, 2016).

2.2 How are drugs shipped?

Most of the drugs are shipped via ordinary mail. In 2017 a Drug Enforcement Administration criminal complaint (*Criminal Complaint*, 2017) described how an agent bought four different types of drugs from multiple sellers on the platform *Dream Market* and received all of them via Priority Mail. This is consistent with anecdotal evidence that sellers tend to primarily use ordinary state-managed shipping systems to deliver their substances.

Substances that are sent via mail face a risk of being seized. However, this does not lead to automatic detection of the sender, and does not constitute sufficient evidence to prove that the buyer bought the substance on the internet. The seller does not have to specify his address on an ordinary mail, the buyer can always claim that the substance was delivered to him by mistake. Moreover, the probability of the substances being seized is not as high as one would think, as *drug mails* do not differ particularly from ordinary mails and not every single ordinary mail gets checked by security.

2.3 Why are *Dark Web* marketplaces successful?

Dark Web marketplaces have been successful because they overcame some of the traditional market frictions of street drug dealing. The on-line market for drugs is more efficient than the street market, with lower rates of rip-offs and scams (Galenianos et al., 2012; Bhaskar et al., 2017).This efficiency improvement was due to several technological innovations that made the market more competitive and transparent. Firstly, street drug dealing is characterized by huge information asymmetries between buyers and sellers about the quality of traded substances. Drugs traded on the streets are often cut with additives that lower the quality of drugs and increase the probability of experiencing adverse health effects. Heroin, for example, can be cut with baking soda, sugar, starch, painkillers, talcum powder, powdered milk, laundry detergent, caffeine and rat poison (American Addiction Centers, 2019). When drugs are traded on the streets, consumers are not fully aware of the quality of the substance and, for obvious reasons, cannot complain about it. Marketplaces on the *Dark Web* overcame this by introducing a feedback system for buyers and vendors, which mirrors feedback systems of licit online markets such as

eBay. In this context future sales of vendors are also determined by the feedback received from previous buyers, giving strong incentives to sellers to deliver higher quality products (Bhaskar et al., 2017; Espinosa, 2019).

Secondly, the introduction of an escrow system, contributed to solve the seller moral hazard problem. With an escrow system *Dark Web* platforms hold the money until the good gets delivered and then proceed to pay the seller. As goods on *Dark Web* marketplaces are paid before they get delivered there is a substantial risk that the seller will not send the product after receiving the money, a situation that is highly likely for transactions of illegal goods.

2.4 Reasons for shutdowns

The main drawback of *Dark Web* marketplaces is the risk of a shutdown of the marketplace. This can happen in four different ways.

In the case of *voluntary* shutdowns administrators of the marketplace voluntarily shut down their marketplace and refund the money users are holding in the escrow system. Voluntary shutdowns happen mainly because marketplaces are considered unprofitable by administrators or because administrators are fearing a seizure by law-enforcement authorities.

Dark Web marketplaces can also shut down because they perform what is known as an *exit scam*. In this case the marketplace shuts down without any previous announcement and administrators keep the money that was in the escrow system of the marketplace. This case is known in the literature as platform moral hazard (Bhaskar et al., 2017).

Finally, *Dark Web* marketplaces can get shutdown either because they are hacked by unknown hackers or raided by law-enforcement authorities. In the case of a breach the objectives of hackers can be extremely heterogeneous and usually remain unknown. Anecdotal evidence suggests that hackers either try to steal the money on escrow accounts or aim at de-anonymizing the marketplace for unknown reasons. Law enforcement raids aim at shutting down *Dark Web* marketplaces, seizing the money that is held in the escrow system and arresting and prosecuting administrators of the raided marketplace.

Unexpected shutdowns of marketplaces on the *Dark Web* represent the major threat to the stability of the market. In particular, during the years between 2011 and 2016, 87 *Dark Web* marketplaces opened, 82 of which were shut down before the end of 2015. This hasn't discouraged operators on *Dark Web* marketplaces, who learned how to quickly move to new platforms after every shutdown, turning shutdowns into just a temporary shock to their ability to trade drugs online. This can be seen in Figure 1, where the monthly number of items listed in some of the most popular *Dark Web*

marketplaces is reported [2]. It is clear how after the shutdown of marketplaces (i.e. when the line is not in the graph anymore) competing marketplaces see the number of listings on their website increase and eventually reach pre-shutdown levels within a few months. In the light of these facts it is also not surprising that almost two thirds of sellers share the same nickname on multiple platforms.

3 Theoretical considerations

In this section I describe the causal mechanisms through which *Dark Web* marketplaces affect street crimes and drug trade. Previous studies have modeled trade in illicit drugs through a search and matching framework (Galenianos et al., 2012). Buyers engage in a costly search to look for a trustworthy supplier of drugs from whom they then keep buying substances. Trust is the key element in this model, as the market for illicit drugs faces serious *moral hazard* issues. Buyers do not know the quality of substances they are buying until they consume them, giving room to sellers to perform scams, that usually consist in cutting illicit drugs with cheaper substances. To find a good match, buyers need to find sellers who aim at maximizing their profit by creating a long-term relationship with customers. This means

[2] Data is obtained by scraping *Dark Web* marketplaces. Detailed information about the dataset can be found in the data section

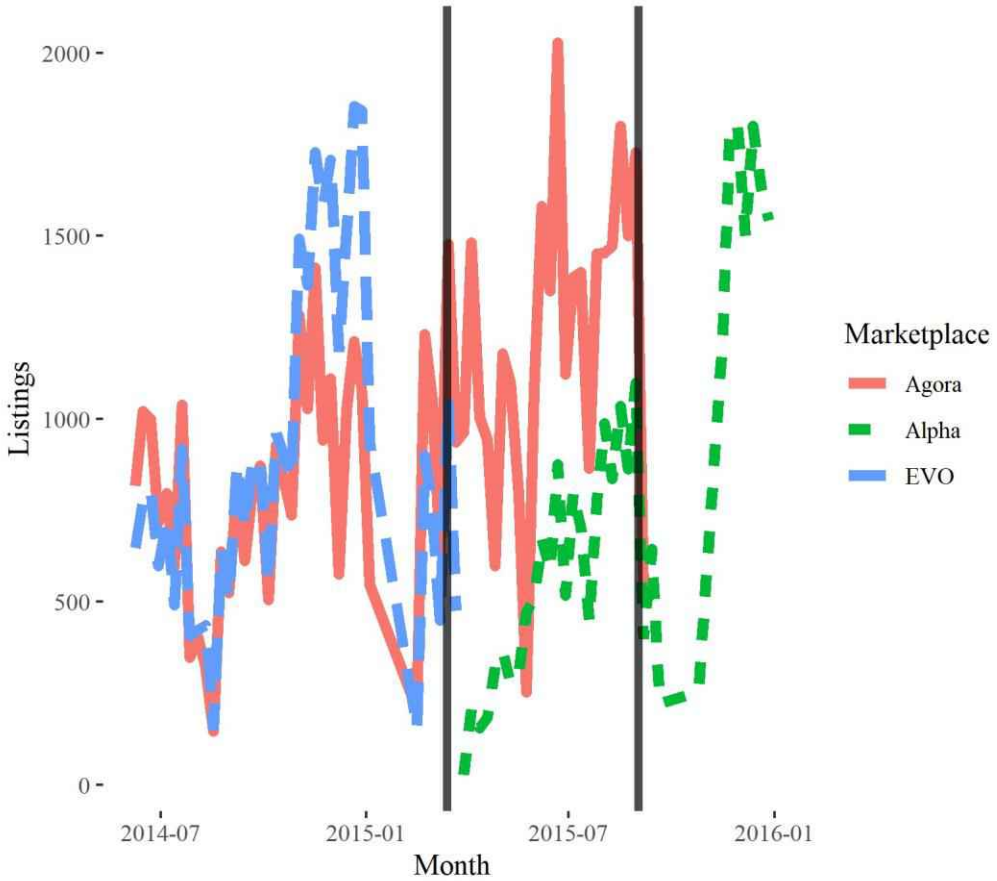

Figure 1: *Dark Web* Markeplaces Listings

Notes: This figure plots the monthly number of listings for every item sold (divided by 100), for the leading *Dark Web* marketplaces between June 2014 and December 2016 (*Evolution, Agora and Alphabay*). The data is obtained from scrapes of *Dark Web* marketplaces provided by *DNM-Archives*. The black lines indicate the months when *Evolution* and *Agora* got shut down.

that buyers will consume and then decide whether to keep buying from the same seller or to look for another.

The *Dark Web* introduced two major innovations aimed at improving trust between buyers and sellers. Firstly, marketplaces on the *Dark Web* allow users to leave a feedback for the vendors from whom they bought, allowing vendors to signal their trustworthiness. Secondly, most *Dark Web* marketplaces introduced an *escrow* system that allowed to complete the transaction only when both buyer and seller confirmed that the transaction was successful, thus preventing the risk of the seller not shipping the substance after the buyer payed for it. Shutdowns of marketplaces on the *Dark Web* disrupt the relationship between matched on-line buyers and on-line sellers, reducing the trust of operators in on-line markets.

Effects on street drug trade *Shutdowns of Dark Web marketplaces increase drug trade in the streets. The size of this effect is determined by the degree of substitutability between on-line and off-line markets. The duration of this effect is determined by the amount of time in which on-line matches can be re-established. Namely, how much time will buyers and sellers need to match in a new Dark Web marketplace*

To analyze the effect of shutdowns of *Dark Web* marketplaces on street drug trade I assume that on-line and off-line markets are, at least to some degree, substitutes in the sense described above. This means drugs can be traded both on-line and off-line, and operators are ready to operate in both markets. Moreover, I assume that operators in the on-line market are more risk averse and conduct their trades on-line to avoid the risks of trading off-line.

After the shutdown of a *Dark Web* marketplace on-line buyers and sellers are unmatched. Buyers look for another supplier and will be ready to purchase substances off-line. The risk aversion buyers who were previously buying on-line will make their relationship with off-line sellers unstable. Buyers continue to search for suppliers every time they feel the urge to consume. This process lasts until another *Dark Web* marketplace gains their trust and they find an on-line supplier with whom they can have a stable relationship. A similar process is followed by sellers. Sellers cannot sell their substances on-line, as the marketplace has been shut down and buyers don't trust themselves buying on-line. Demand rises in the off-line market and sellers move to the off-line market. After a new *Dark Web* marketplaces emerges, old on-line suppliers will move back to the on-line market. This process is going to be gradual and will continue until on-line buyers are all matched again with on-line sellers in a new *Dark Web* marketplace and the market goes back to its pre-shutdown steady state equilibrium.

Effects on drug-related crime *Drug-related crime will increase after shutdowns of Dark Web marketplaces. This effect will only take place if on-line operators behave in the same violent way as off-line operators when they start trading in the off-line market. The duration of this effect is determined by the amount of time in which on-line matches can be re-established.*

Shutdowns of *Dark Web* marketplaces can cause an increase in crimes related with drug consumption. Buyers and sellers in the off-line market tend to commit different type of crimes. Buyers tend to commit thefts or shoplifting to finance their addiction. Sellers tend to use violence to maintain local monopolies and to enforce payments. If after the shutdown of *Dark Web* marketplaces trades moves back to the off-line markets it is reasonable to expect that drug-related crime will increase.

Assuming that demand for drugs is inelastic, shutdowns of on-line markets can affect drug-related crime if it causes a major negative supply shock to the illicit drugs market. In this case the price increase of drugs sold on the off-line markets will

determine an increase in petty crimes committed to finance addiction. Namely, if prices in the street increase, due to a reduction in supply, addicts will have to steal more to finance their addiction.

4 Data

In this paper I use data from several sources. In particular, I combine incident level crime data with detailed information about shutdowns of *Dark Web* marketplaces. I also rely on publicly available scrapes of *Dark Web* marketplaces to provide additional evidence on substitutability of online drug trading platforms. Moreover, I use data from the American
Community Survey (ACS) to ensure the external validity of this study.

4.1 Openings and Shutdowns of Online Drug Markets

Table 1: Websites Considered

Market	Start	End	Closure	Life
Agora	2013-12-03	2015-09-06	voluntary	642
BlackBank Market	2014-02-05	2015-05-18	scam	467
Blue Sky	2013-12-03	2014-11-05	raided	337
BuyItNow	2013-04-30	2014-02-17	voluntary	293
Cloud-Nine	2014-02-11	2014-11-05	raided	267
East India Company	2015-04-28	2016-01-01	scam	248
evolution	2014-01-14	2015-03-14	scam	424
Mr Nice Guy 2	2015-02-21	2015-10-14	scam	235
Nucleus Marketplace	2014-10-24	2016-04-13	scam	537
Pirate Market	2013-11-29	2014-08-15	scam	259
Sheep Marketplace	2013-02-28	2013-11-29	scam	274
Silk Road 1	2011-01-31	2013-10-02	raided	975
Silk Road 2	2013-11-06	2014-11-05	raided	364
TorBazaar	2014-01-26	2014-11-05	raided	283

Notes: This table reports the *Dark Web* marketplaces that are considered in my main analysis. The initial sample of 88 *Dark Web* marketplaces has been shrinked to 14 marketplaces. From the initial sample have been excluded: websites that are still open nowadays, websites with a lifetime lower than the average lifetime, and websites that were shutdown within one month from a previous shutdown.

Data on openings and shutdowns of online drugs stores comes from the DNM-Archives website.[3] .The DNM-Archives Survival table provides the most complete archive of openings, shutdowns and reason for closure of online drug stores.[4]

I calculate the lifespan of each website and only consider those with a lifespan that is higher than the average lifespan for a *Dark Web* marketplace (232 days). This allows me to exclude websites that are expected to have little or no impact on the market. After applying this criterion the number of considered *Dark Web* marketplaces shrinks from 88 to 29. I also exclude *Dark Web* marketplaces where the cause of closure or the date of closure was unknown and websites that closed after 2017, shrinking the number of considered *Dark Web* marketplaces to 24.

I only consider shutdowns that happened at least 30 days after each other, this is to avoid some observations belonging to both the treatment and the control group in my identification
strategy.

The final sample consists of 14 online drugs stores, with an average lifetime of one year and six months. Out of 14 online drugs stores two closed voluntarily, five have been raided by authorities and seven have performed an exit scam.

In the robustness checks section I report results for a broad range of criteria applied when choosing the final sample(i.e. different lifetimes and difference in days after the previous shutdown). The final sample of websites is listed in Table 1 along with their opening and shutdown date and the reason for shutdown.

[3] https://www.gwern.net/DNM-archives

[4] Only English language markets are included in the dataset. Anecdotal evidence suggests that these markets satisfy the entire demand in the US.

4.2 Crimes in the US

Table 2: NIBRS descriptive statistics

Statistic	Days	Mean	St. Dev.	Min	Max
Illicit Drugs Variables					
Ecstasy	2,557	7.294	3.731	0	54
Crack	2,557	61.937	24.62	1	150
Heroin	2,557	135.722	40.876	20	249
Marijuana	2,557	552.94	96.869	159	990
Crime Variables					
Theft	2,557	3,825.76	565.453	1,543	6,274
Homicide	2,557	8.536	3.319	1	22
Assault	2,557	2,431.35	326.547	1,624	4,458
Prostitution	2,557	17.343	12.757	0	105

Notes: This table reports descriptive statistics for variables considered in this paper. The unit of observation is the daily count of crimes in the US for all agencies reporting to the NIBRS program continuously from 2010 to 2016. The variables theft, homicide and prostitution are self-explanatory. The variables Ecstasy, Crack, Heroin and Marijuana measure the number of daily crimes where any of those substances was detected. The variables Theft, Homicide, Assault and Prostitution count the number of daily crimes that fall under those categories.

Data on crime in the US comes from the National Incident-Based Reporting System (NIBRS). NIBRS is an incident-level dataset that collects information on reported crimes from local, state, and federal law enforcement agencies. The NIBRS dataset includes rich incident-level information on reported offenses, arrests and also specific codes for a variety of substances involved in the crime. One drawback of NIBRS data is that not all law enforcement agencies participate in the program. I only consider agencies reporting in all months from 2010 to 2016. I only include in my sample town and city police agencies. This is because I am interested in variations in ordinary crime, and I do not want to include data about big operations conducted by federal authorities. Moreover, this helps dealing with the concern that my findings could simply be reflecting the direct impact of seizures on the *Dark Web* when marketplaces get shut down by police authorities. For my main specification I collapse the data at the daily level, obtaining a daily time series for every type of crime for all the US.

Table 2 provides summary statistics for the variables of interest. The variables Ecstasy, Crack, Heroin and Marijuana measure the number of daily crimes where any

of those substances was detected. The variables Theft, Homicide, Assault and Prostitution count the number of daily crimes that fall under those categories.[5]

4.3 Additional data on individual listings on *Dark Web* market-places

The DNM-Archives provide the *Grams* dataset, which contains data on individual listings for more than 20 *Dark Web* marketplaces obtained by scraping the *Dark Web*. *Grams* was a search engine for *Dark Web* marketplaces that allowed users to search multiple marketplaces at the same time. The service used a custom API to scrape several *Dark Web* marketplaces. Results of these scrapes are available at DNM archives.

This dataset allows to see a detailed description of every item sold every day for every marketplace, as well as the vendor's nickname and the declared location from which products are sent. Data ranges from 2014-06-09 to 2016-04-17 with occasional gaps where no data is available (presumably for technical difficulties in scraping the *Dark Web* on that date).

[5] See the appendix for a detailed description of the NIBRS codes associated with each variable.

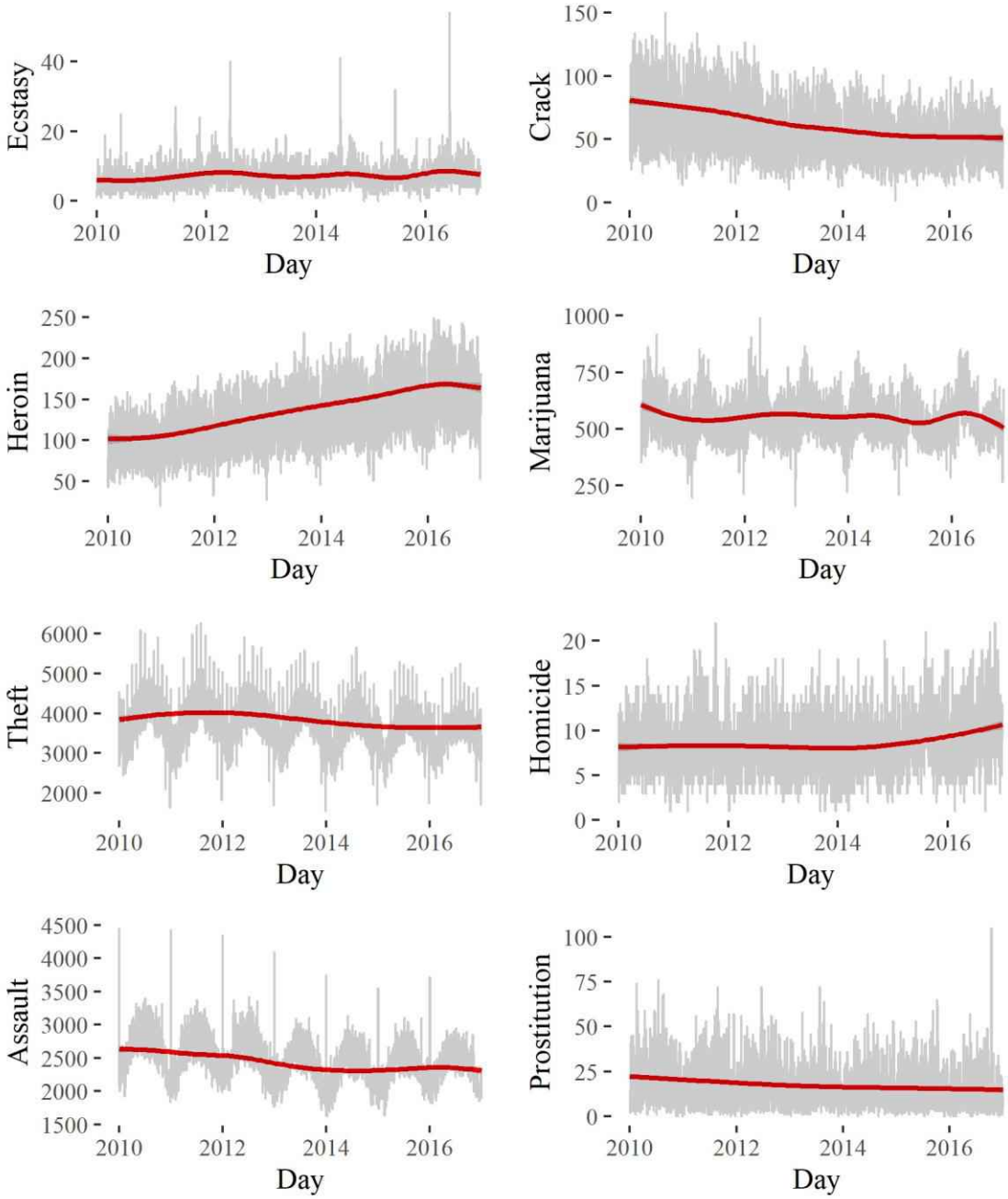

Figure 2: Crime Time Series

Notes: This figure plots daily levels of crime in the sample for the analyzed outcomes. The red line smooths the data and shows long run time trends.

4.4 Additional data on economic characteristics

Data on labor force participation, unemployment, percentage of individuals with cash assistance and median income at the state level in year 2010 comes from the ACS Selected Economic Characteristics tables. I use this data to ensure that states where agencies participate to the NIBRS program do not systematically differ with respect to states where agencies do not participate to the NIBRS program (Figure A.2 in the appendix).

5 Empirical strategy

5.1 Empirical Setting

My goal is to isolate the causal effect of online drug trading platforms shutdowns on street crime. The ideal experiment to analyze the causal effect of shutdowns of online drug stores on street crime would be to randomly shut down online drug trading platforms in some areas. By simply comparing difference in means across areas with and without access to the *Dark Web* one would be able to obtain causal estimates of the effects of shutdowns of online drug stores on street crime.

Since there is no geographical variation in availability of online drugs markets, as anyone with an internet connection can access them, it is challenging to properly identify a treatment and a control group.

To isolate the causal effect of shutdowns of online drug trading platforms on street crime, I use a regression discontinuity in time (RDiT) (Hausman & Rapson, 2018). I exploit exogenous time variation in availability of online drug markets in combination with high frequency data. In particular, I consider the number of street crimes in days immediately preceding shutdowns of online drug stores as a good counterfactual for what would have happened, in days immediately after shutdowns of online drugs stores, if those shutdowns would not have taken place.

5.2 Research Design

To evaluate the effect of online drugs stores on street crime, I use the following model that exploits the time discontinuity in accessibility to online drug stores:

$$\begin{aligned} StreetCrime_d = \delta \times Post_d + f^a(Time_d) \\ + f^b(Time_d) \times Post_d \\ + DayOfTheWeek_d + \epsilon_d \end{aligned} \tag{1}$$

The model is a sharp Regression Discontinuity Design (Lee & Card, 2008; G. W. Imbens & Lemieux, 2008; Lee & Lemieux, 2010). The variable $Time_d$, centered around shutdowns of online drug markets, strictly determines availability of an online drug market. The sample is constituted by every observation in a 30 days time window around shutdowns of online drug markets. This allows to interpret the coefficient of interest δ as the average effect of the shutdown of a *Dark Web* marketplace on street crimes in days immediately following the shutdown of an online drugs stores.

The two unknown functions f^a and f^b are assumed to be smooth and capture the potential endogenous relationship between $_d$ and the date of the shutdown. Under the identification assumption that $_d$ does not change discontinuously at time 0, the estimate of δ is unbiased even in the absence of controls for observable factors. My main specification considers f^a and f^b as local polynomial fits that are allowed to differ at both sides of the threshold. I also conduct robustness checks with linear, quadratic and cubic specifications.

The coefficient δ can be interpreted as causal if no other event that could potentially affect drug trade and street crime happened around the same day as shutdowns of *Dark Web* marketplaces. The use of daily data and multiple shutdowns makes this situation highly unlikely. Moreover, one would expect idiosyncratic events that affect drug trade to also have an impact on crimes that are not related to drug consumption. In this regard, I investigate the existence of a discontinuity in non drug-related crimes and find no effect.

A threat to identification comes from the time-series nature of the data (Hausman & Rapson, 2018). In particular it is likely that crime changes discontinuously around weekends.

I overcome this by adding day-of-week fixed effects and therefore only exploiting intra-day-of-the-week variation in the data.

In a RD design where time is the running variable, it is not possible to assess if units have sorted into treatment. In other words, one can not perform a McCrary test (McCrary, 2008) , as time has a uniform distribution. It is therefore not possible to formally test for sorting/anticipation/adaptation/avoidance effects (Hausman &

Rapson, 2018). However, it is unlikely that criminals are able to anticipate the date in which *Dark Web* marketplaces are going to be shut down. In this regard I also estimate equation 1 separately by type of shutdowns and find that unexpected shutdowns are driving my results.

6 The effect of shutdowns on drug trade and crime

6.1 Results for illicit drugs trade

Figure 3 illustrates the effect of shutdowns of online drugs stores on illicit drugs crimes. The solid red line represents a local polynomial fit that is allowed to vary at both sides of the threshold, and the bandwidth is optimally chosen, within a 30 day time window around shutdown dates, according to G. Imbens & Kalyanaraman (2012). The grey areas represent a 95% confidence interval. The discontinuity observed at the thresholds corresponds to the average increase in illicit drugs trade caused by the shutdown of *Dark Web* marketplaces. The same results are reported in Table 3. In the robustness section I report results for several polynomial specifications, bandwidth selection and time window selection.

Shutdowns of *Dark Web* marketplaces caused a statistically significant increase in all tested outcomes beside ecstasy. These effects generally last less than 10 days and represent an increase in crime around from 5.49% for marijuana-related crimes to 9.75% increase for crack cocaine. No statistically significant effect is found for ecstasy.

These results show that shutdowns of *Dark Web* marketplaces have an immediate effect on the amount of drugs traded on the street, diverting trade from the on-line to the off-line market already from the day after *Dark Web* marketplaces get shut down. My estimates are consistent with the number of drug users that reported buying drugs on the *Dark Web*

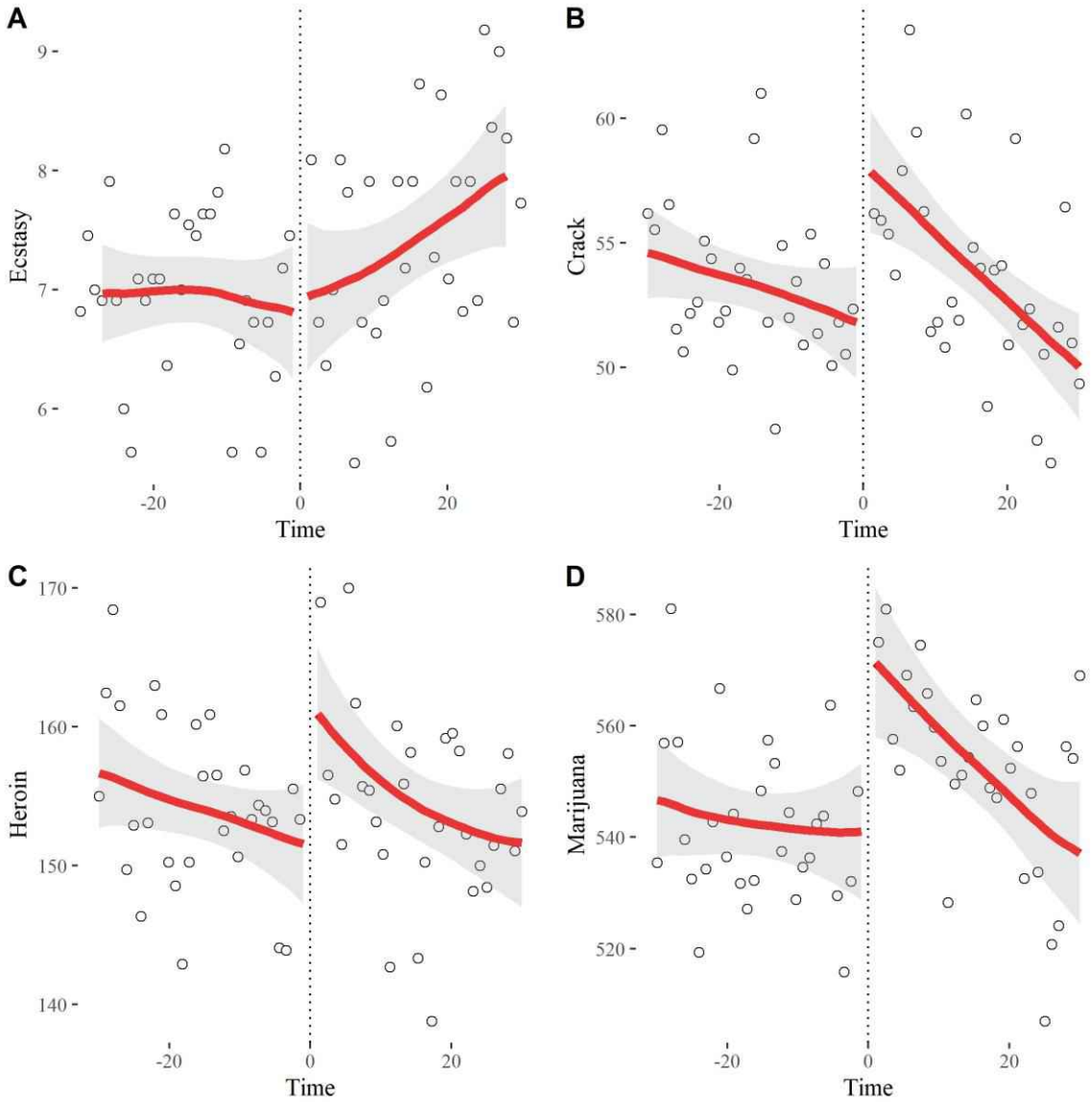

Figure 3: Shutdown effect on illicit Drug trade

Notes: This figure plots the average number of illicit drugs crimes across shutdowns in days before and after the shutdown of marketplaces on the *Dark Web*. The solid red lines represent a local polynomial fit ($f^a(Time_d)$ and $f^b(Time_d)$ in equation 1. The distance between the two red lines can be interpreted as the average impact of shutdowns of *Dark Web* marketplaces on street crime.

Table 3: The effect of shutdowns on illicit drugs trade

	Dependent variable:			
	Ecstasy	Crack	Heroin	Marijuana
Estimate	.134	6.039***	9.358**	30.355***
	(.547)	(2.132)	(4.550)	(10.993)
% Change w.r. average	1.84%	9.75%	6.89%	5.49%
Average outcome	7.294	61.937	135.722	552.940
Observations	671	671	671	671

Notes: This table presents the estimated coefficients for the impact of shutdowns of *Dark Web* marketplaces on illicit drug trade (the coefficient δ in equation 1). Robust standard errors are reported in parentheses. ***,**,* indicate significance at the 1, 5 and 10 percent levels. For each outcome the average of the variable across the whole sample period is reported. The row Change indicates the percentage change with respect the outcome average for every estimate. The number of observations is given by the number of shutdown dates considered, multiplied by the 61 days included in every estimation (30 days before and after the shutdowns plus the shutdown date).

in years between 2014 and 2016 in the United States (between 7% and 15% according to the Global Drug Survey.[6]) Moreover, the short-run effect can be explained by the ability of buyers and sellers to quickly switch marketplaces on the *Dark Web* as suggested by Figure 1 and by previous studies (Décary-Hétu & Giommoni, 2017). These estimates likely reflect also a temporary loss of trust in *Dark Web* marketplaces, caused by an increase in the perceived risk of failure of a transaction.

Effects on Demand and Supply of Drugs Demand and supply of drugs may respond differently to shutdowns of *Dark Web* marketplaces. Buyers and sellers may face different transaction costs for moving from one platform to another. Sellers need to rebuild reputation after switching platform, making their cost of transaction higher than the cost for buyers. Moreover, the income effect due to the loss of bitcoins that were held in the escrow system of *Dark Web* marketplaces is likely to be bigger for sellers than for buyers, as sellers are more likely to deal with multiple transactions at the time of the shutdown.

I identify drug crimes that are related to supply of drugs as those under the categories distributing/selling and transporting/transmitting/importing and to

[6] available at https://www.globaldrugsurvey.com/past-findings/gds2017-launch/results-released/

demand as those under the categories buying/receiving, possession/concealing, and using/consuming. I then

Table 4: Effect of shutdowns on supply and demand of drugs

	Dependent variable:	
	Supply Crimes	Demand Crimes
Estimate	16.546***	42.865*
	(5.467)	(25.944)
% Change w.r. average	8.8%	3.15%
Average outcome	188.101	1,361.859
Observations	671	671

Notes: This table presents the estimated coefficients for the impact of shutdowns of *Dark Web* marketplaces on supply-related and demand-related illicit drugs crimes (the coefficient δ in equation 1). Robust standard errors are reported in parentheses. ***,**,* indicate significance at the 1, 5 and 10 percent levels. For each outcome the average of the variable across the whole sample period is reported. The row Change indicates the percentage change with respect the outcome average for every estimate. The number of observations is given by the number of shutdown dates considered, multiplied by the 61 days included in every estimation (30 days before and after the shutdowns plus the shutdown date).

estimate equation 1 for supply and demand-related drug crimes. Figure 4 illustrates the effect of shutdowns of *Dark Web* marketplaces on supply and demand-related drug crimes. The same results are reported in Table 4.

Supply-related drug crimes increased by 8.8% and demand-related drug crimes increased by 3.15%. The increase is highly statistically significant for supply-related drug crimes and marginally statistically significant for demand-related drug crimes. Moreover, the effect lasts shorter for demand-related crimes with respect to supply-related crimes, with supply-related drug crimes reverting to pre-shutdown levels slower than demand-related crimes.

These results show how my estimates are mainly driven by supply-related drug crimes. This is consistent with the hypothesis that it is harder for sellers to move from one platform to another.

6.2 Results for crime

Figure 5 illustrates the effect of shutdowns of online drugs stores on illicit drugs crimes. The same results are reported in Table 5. In this case no statistically significant impact is found on any of the outcomes. Similar results are obtained if only drug-related crimes are considered (i.e. crimes where the offender was charged also for a drug offense or where the victim had drugs on them while being victimized).

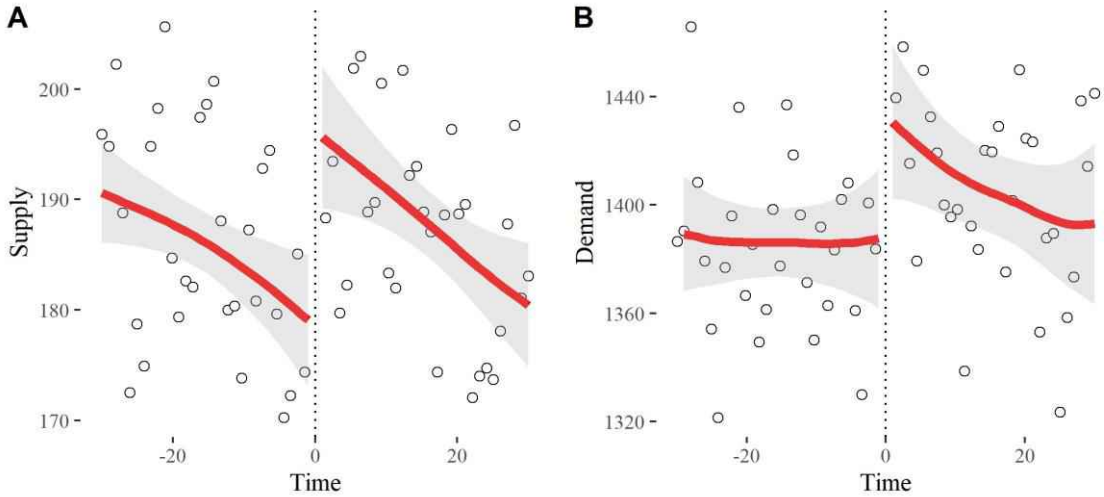

Figure 4: Shutdown effect on Supply and Demand of Drugs

Notes: This figure plots the average number of Supply and Demand-related crimes across shutdowns in days before and after the shutdown of marketplaces on the *Dark Web*. The solid red lines represent a local polynomial fit ($f^a(Time_d)$ and $f^b(Time_d)$ in equation 1. The distance between the two red lines can be interpreted as the average impact of shutdowns of *Dark Web* marketplaces on Supply and Demand-related crime.

The absence of a significant impact of shutdowns of *Dark Web* marketplaces on crime can be explained by how quick the shock on the market is, as long as one assumes a degree of stickiness in prices in the illicit drugs market.

The absence of a significant impact of shutdowns of *Dark Web* marketplaces on crime, however, increases the validity of the results obtained in the previous section. This is because if results for drug trade would merely reflect an increase in patrolling activity caused by shutdown of *Dark Web* marketplaces one would expect to see also an increase in detected thefts, homicides, assaults and prostitution crimes.

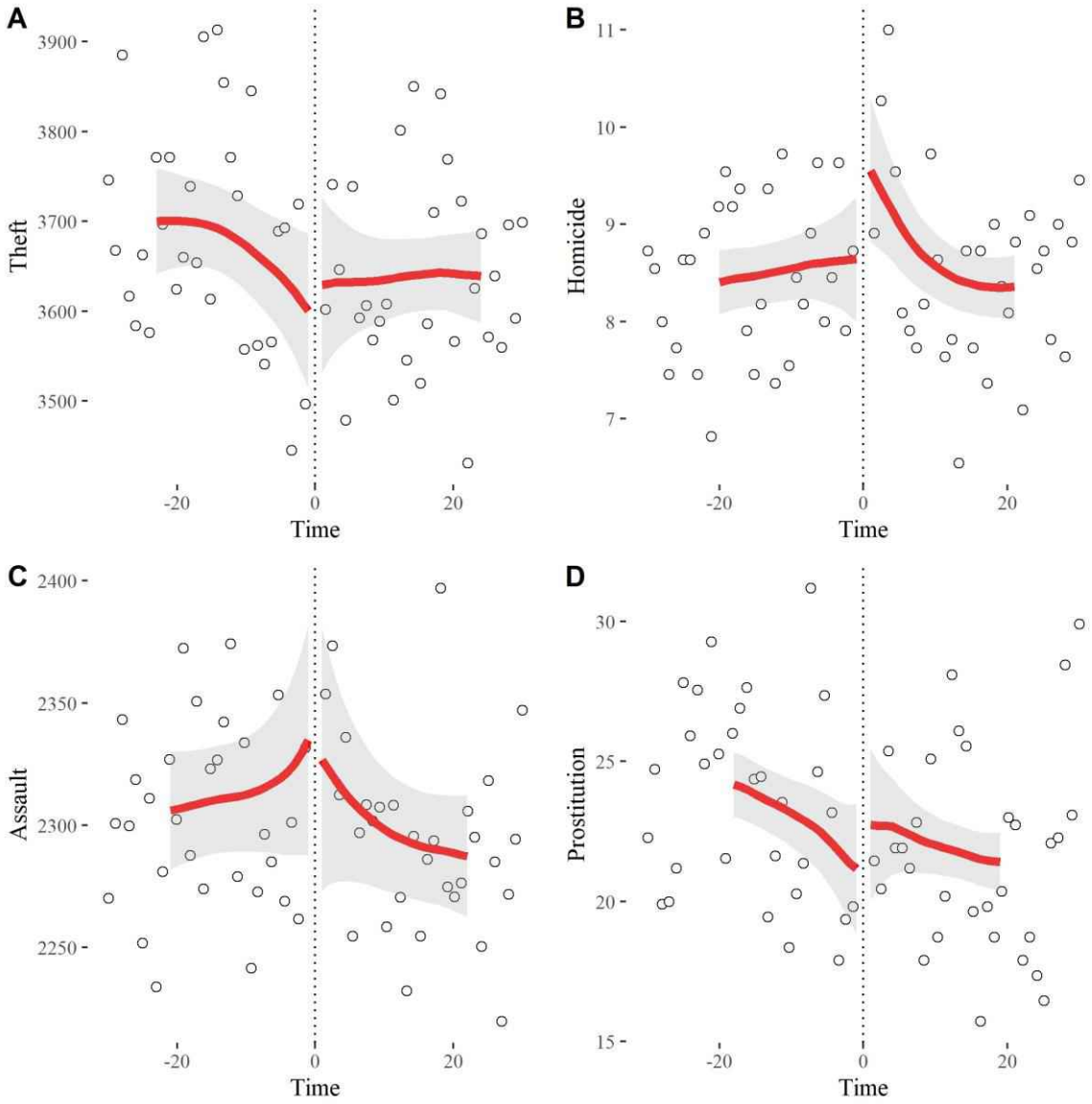

Figure 5: Shutdown effect on Crime

Notes: This figure plots the average number of crimes across shutdowns in days before and after the shutdown of marketplaces on the *Dark Web*. The solid red lines represent a local polynomial fit ($f^a(Time_d)$ and $f^b(Time_d)$ in equation 1. The distance between the two red lines can be interpreted as the average impact of shutdowns of *Dark Web* marketplaces on street crime.

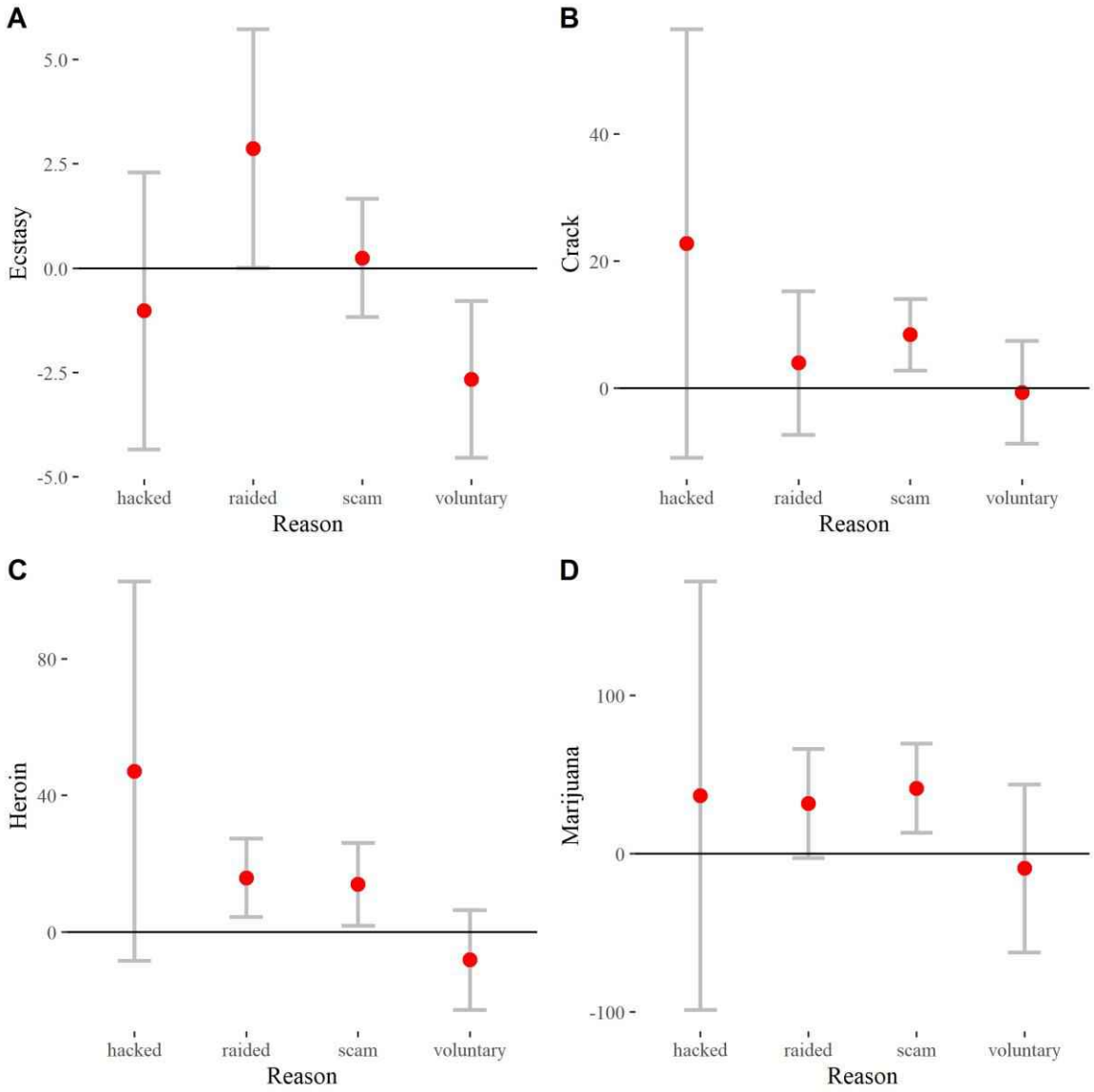

Figure 6: Estimates for different shut-down reasons

Notes: This figure plots point estimates for different reasons for shut-down with 95% confidence intervals.

Table 5: The effect of shutdowns on drug-related crime

	Dependent variable:			
	Theft (1)	Homicide (2)	Assault (3)	Prostitution (4)
Estimate	29.086	0.911	−8.044	1.573
	-83.749	-0.695	-52.622	-2.298
% Change w.r. average	0.76%	10.67%	−.33%	9.07%
Average outcome	3,825.77	8.536	2,431.36	17.343
Observations	671	671	671	671

Notes: This table presents the estimated coefficients for the impact of shutdowns of *Dark Web* marketplaces on crime (the coefficient δ in equation 1). Robust standard errors are reported in parentheses. ***,**,* indicate significance at the 1, 5 and 10 percent levels. For each outcome the average of the variable across the whole sample period is reported. The row Change indicates the percentage change with respect the outcome average for every estimate. The number of observations is given by the number of shutdown dates considered, multiplied by the 61 days included in every estimation (30 days before and after the shutdowns plus the shutdown date).

7 Heterogeneity and potential channels

7.1 Effects of different types of shutdowns

Shutdowns of *Dark Web* marketplaces can have a different effect on drug trade depending on the reason of shutdowns. In particular, websites that are shut down by authorities, hacked by other criminals and shutdowns that happen due to an exit scam performed by the owners of a *Dark Web* marketplace are likely to have a bigger effect on drug-related street crime with respect to voluntary shutdowns. This is because in the case of raids, hacks and exit scams buyers and sellers lose the bitcoins held in the escrow system of the marketplace. This is a negative shock to the distributional network of illicit drugs a negative income shock and a *reputational* shock (Espinosa, 2019).

Figure 6 plots estimates of the effect of different types of shutdowns on several drug-related crimes along with 95% confidence intervals. Estimates for ecstasy are relatively unstable across reasons for shutdowns being statistically insignificant for hacks and scams on the *Dark Web*, positive and statistically significant at the 5% level for raids and negative and statistically significant for voluntary shutdowns. The increase in ecstasy drug trade crimes after raids in consistent with the explanation of

substitutability between on-line and off-line markets. The negative estimate for voluntary shutdowns probably just reflects a short term reduction in the overall supply of ecstasy, considering that this is the most traded substance on *Dark Web* marketplaces and possibly the substance where on-line markets hold the biggest share with the respect to off-line markets when compared to other types of drugs.

For crack, heroin and marijuana estimates are quite stable across hacks, raids and scams and are always statistically significant for scams. The effect for raids is statistically significant at the 5% level for heroin crimes and marginally statistically significant for and marijuana crimes. Estimates are never statistically significant for voluntary shutdowns of *Dark Web* marketplaces for these three outcomes.

8 Robustness

Results in the previous section suggest a tight link between shutdowns of *Dark Web* marketplaces and street crime. I now subject these findings to a number of robustness checks to ensure that they are not driven by an endogenous relation between shutdowns and reallocation of police forces, a specific model specification or by arbitrary choices made when slicing the data.

Mechanical effect hypothesis One concern is that police agencies may prosecute buyers and sellers of *Dark Web* marketplaces immediately after shutdowns. In this case my main estimates could just mirror an increase in detection of offenses committed on *Dark Web* marketplaces.

To address this, I exploit detailed information contained in NIBRS, where it is indicated whether a crime was committed using a computer. I then estimate equation 1 for crimes committed using a computer. Figure 7 illustrates the effect of shutdowns of *Dark Web* marketplaces on crimes committed using a computer.

As shown in figure 7, crimes committed using a computer did not vary discontinously around shutdown dates. This suggests that my main estimates are not driven by what could be called a *mechanical* effect, but reflect a shift of crime from on-line to off-line.

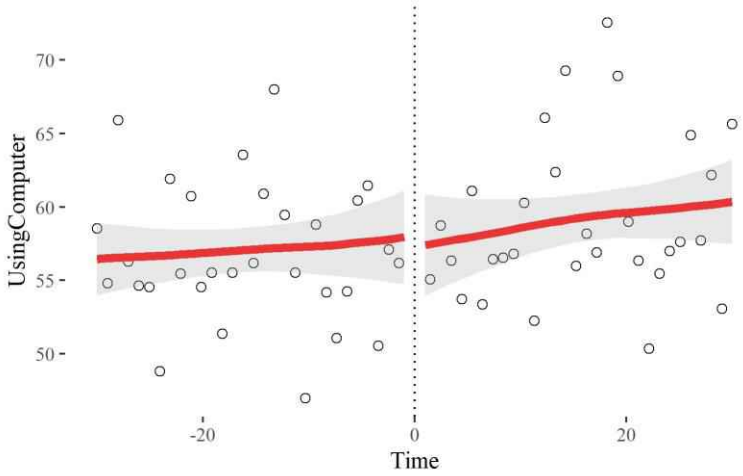

Figure 7: Effect on crimes committed with a computer

Notes: This figure plots the average number of crimes where computer equipment was used across shutdowns in days before and after the shutdown of marketplaces on the *Dark Web*. The solid red lines represent a local polynomial fit ($f^a(Time_d)$ and $f^b(Time_d)$ in equation 1). The distance between the two red lines can be interpreted as the average impact of shutdowns of *Dark Web* marketplaces on crimes where computer equipment was used to perpetrate the related offense.

Functional form and time window I test how sensitive my estimates are with respect to different functional form specification and time window selection. Figure 8 compares estimate of my main specification with alternative functional form specifications and time windows. In Figure 8 I report point estimates and 95% confidence intervals for different model specifications, and compare them with my main model specification (in red). In particular, I test for linear, quadratic and cubic functional forms and also for a 15 and 60 days time window around shutdown dates. Point estimates are stable across model specifications, confirming results obtained in the main estimation procedure. Estimates for crack, heroin and marijuana are statistically significant at the five percent level for most specifications.

Websites selection I also ensure that my results are not driven by the arbitrary choice of including in the analysis only *Dark Web* marketplaces that stayed open more than the average lifetime of *Dark Web* marketplaces. Figure 9 compares estimates of my main specification (in red) with estimates obtained by including *Dark Web* marketplaces with a lifetime higher than a specific percentile in the lifetime distribution showed in Figure A.1 in the appendix.

Estimates are stable especially for marijuana crimes up until the 80th percentile of the lifetime distribution.

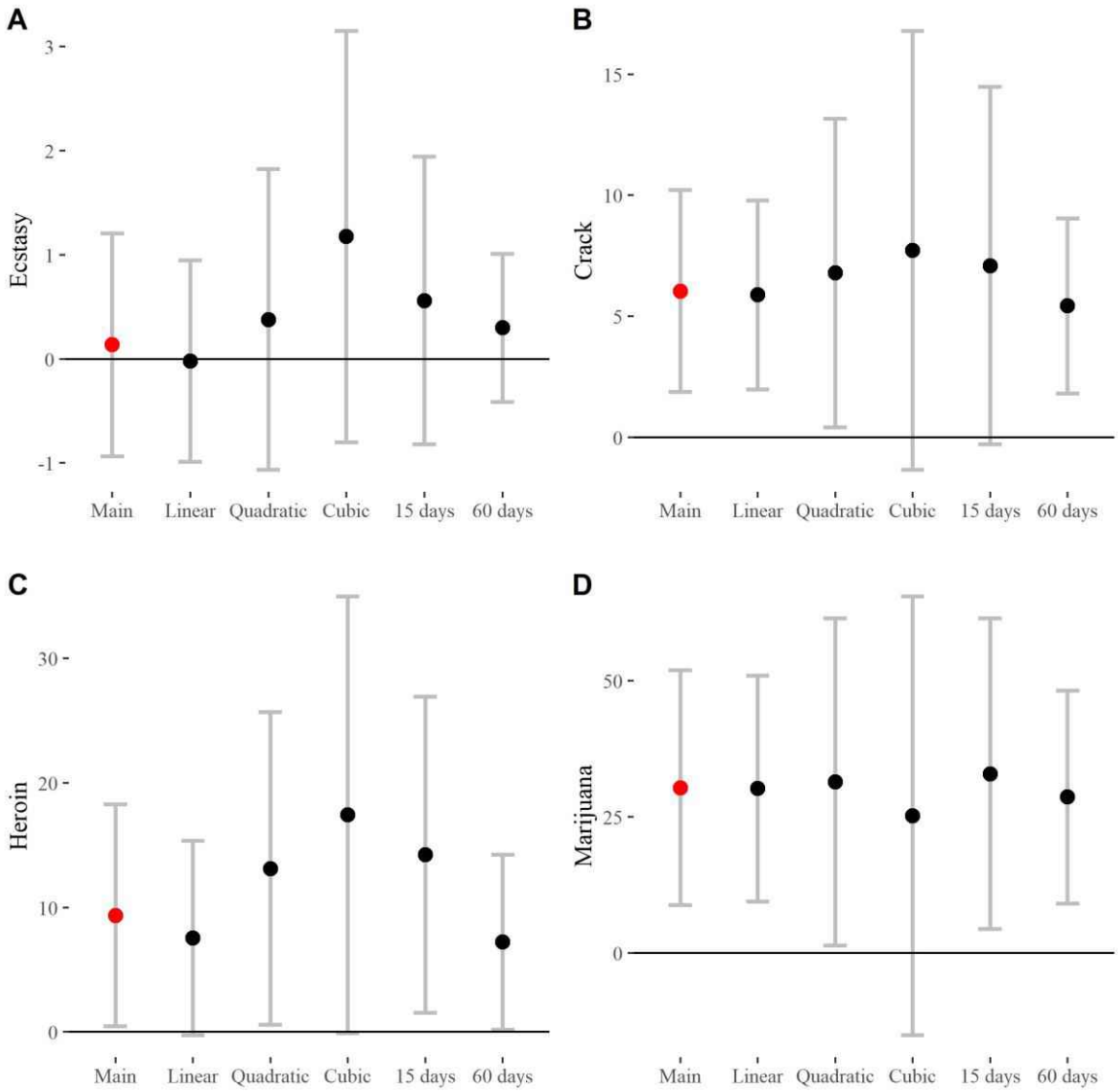

Figure 8: Estimates for different model specifications

Notes: This figure plots point estimates for different model specifications with 95% confidence intervals. The estimate of the preferred specification is represented by a red dot, whereas alternative specifications are represented by grey dots. For each outcome the estimate for linear, quadratic and cubic functional forms are reported as well as estimates for specifications where a 15 and a 60 days time window around shutdown dates is chosen.

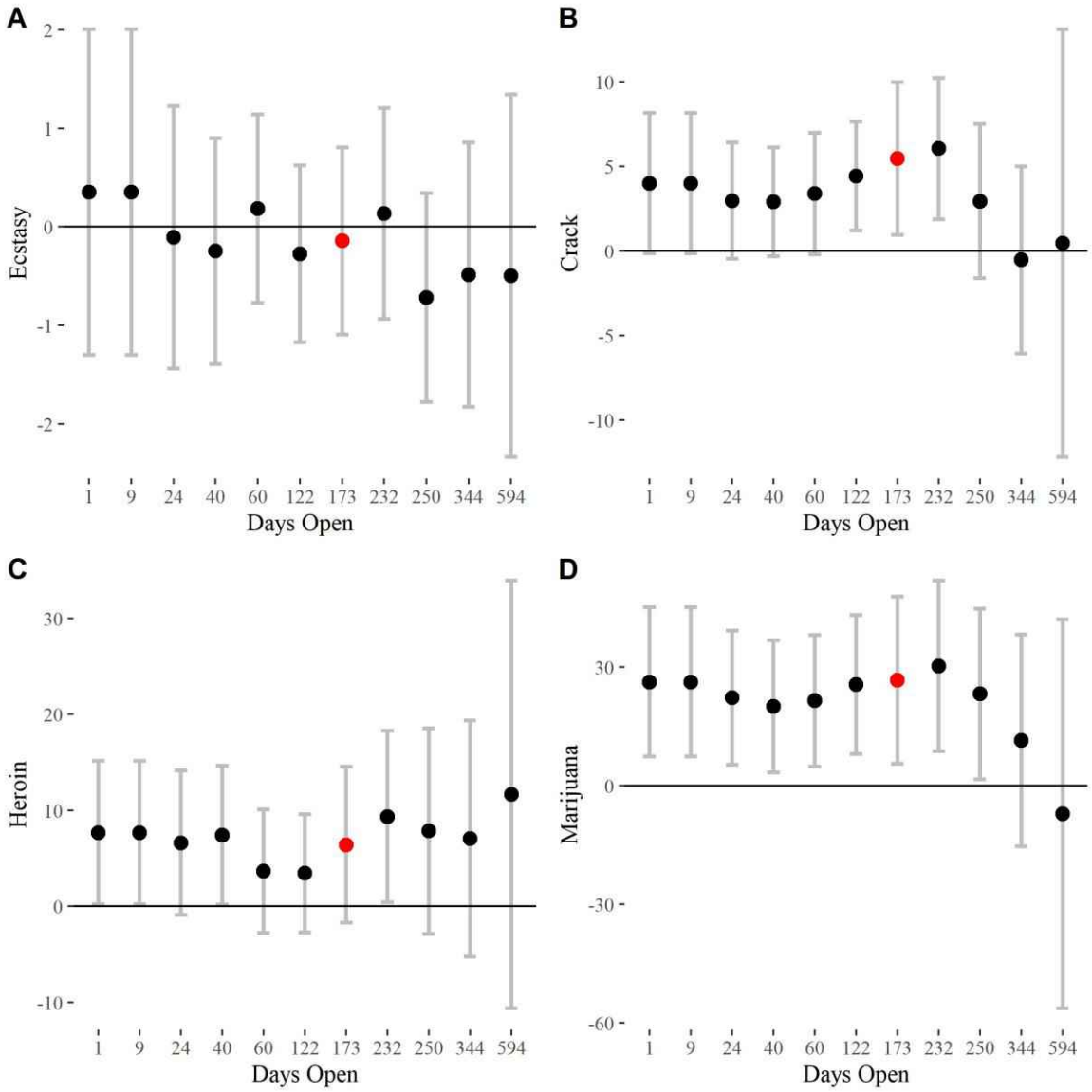

Figure 9: Estimates at different percentiles of marketplace lifetime distribution

Notes: This figure plots point estimates for different selections of websites considered when estimating equation 1. The black dots represent estimates of equation 1 obtained by including *Dark Web* marketplaces with a lifetime higher than the number of days reported on the x-axis of each plot (corresponding to the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th and 90th percentile of the lifetime distribution plotted in Figure A.1in the appendix) . The red dot in every panel reports the estimate obtained in my main specification, that only includes websites with a lifetime higher than the average lifetime of *Dark Web* marketplaces.

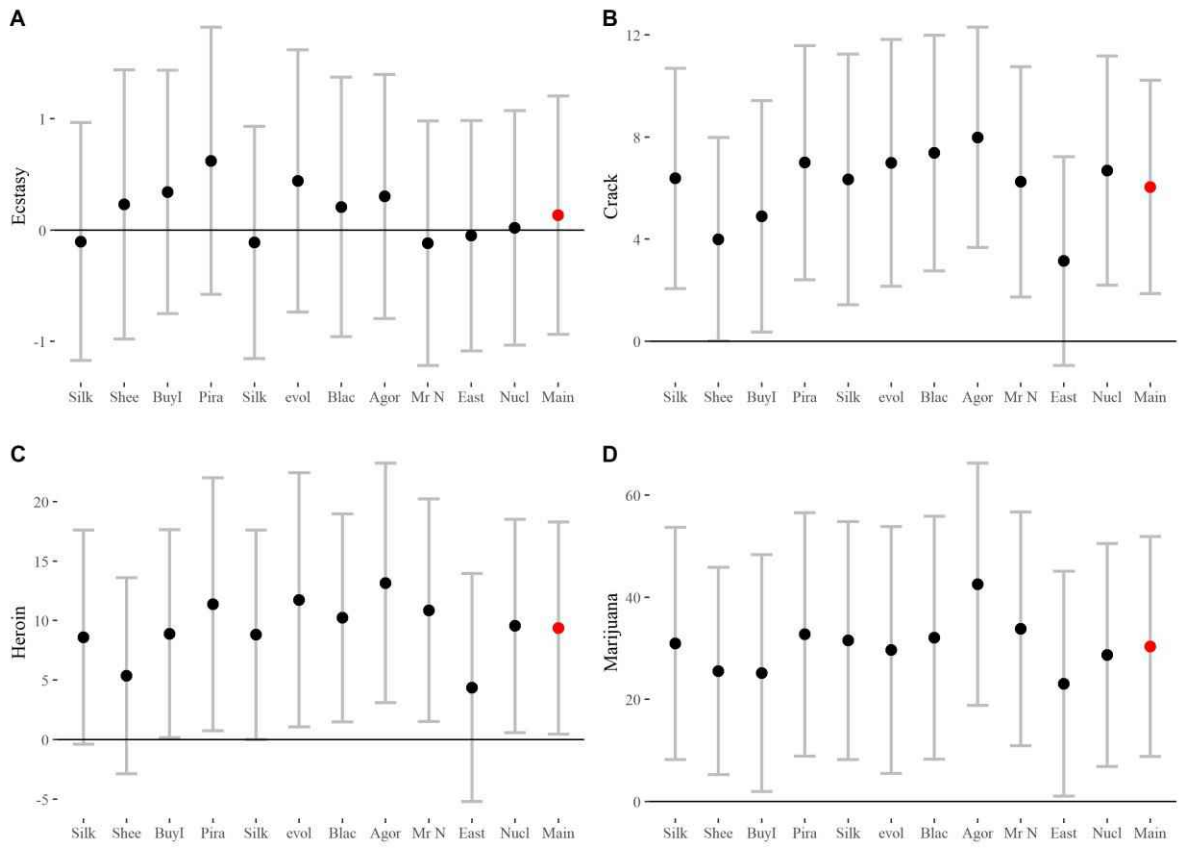

Figure 10: Leave-one-out estimates

Notes: This figure plots point estimates for different selections of websites considered when estimating equation 1. The black dots represent estimates of equation 1 obtained by including *Dark Web* marketplaces with a lifetime higher than the number of days reported on the x-axis of each plot (corresponding to the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th and 90th percentile of the lifetime distribution plotted in Figure A.1 in the appendix). The red dot in every panel reports the estimate obtained in my main specification, that only includes websites with a lifetime higher than the average lifetime of *Dark Web* marketplaces.

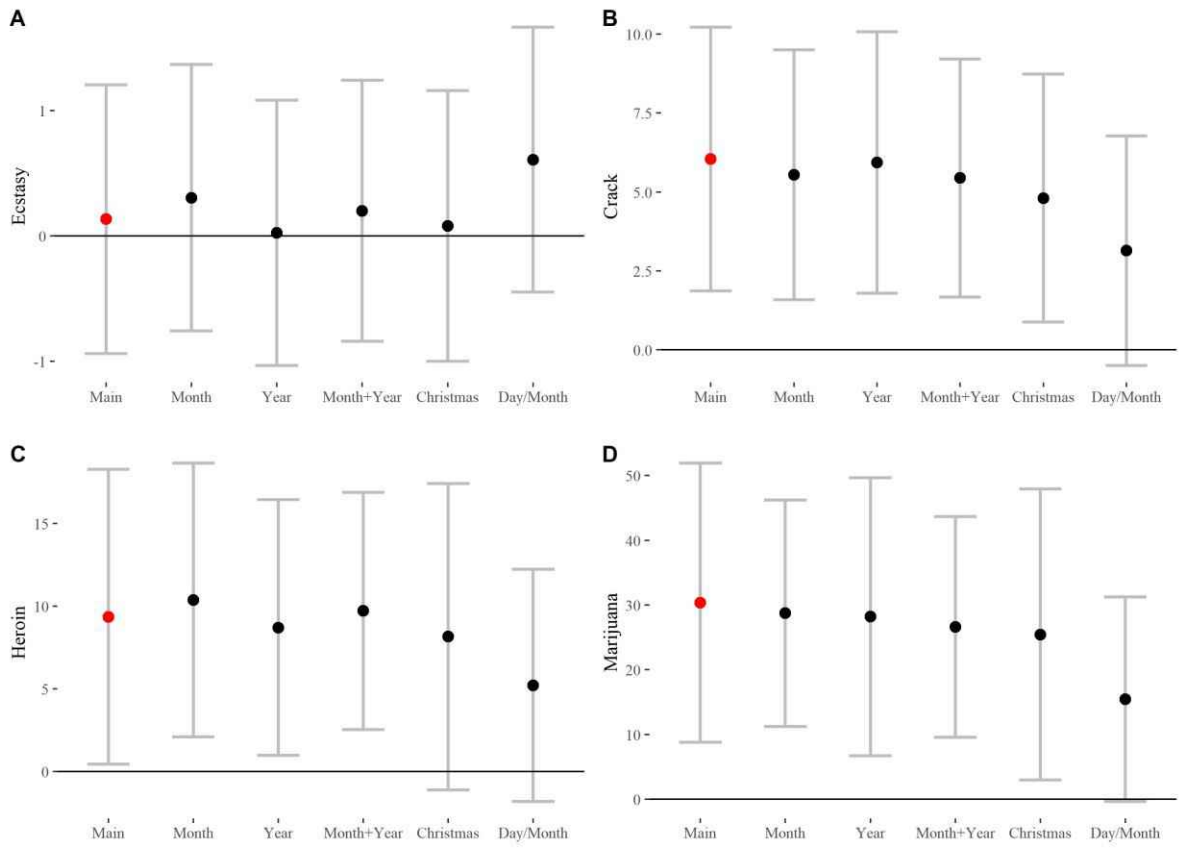

Figure 11: Estimates on Residuals of Fixed Effects

*Notes:*This figure plots point estimates of equation 1 when run on the residuals of several fixed effects regressions. The black dots represent estimates of equation 1 performed on the residuals of a fixed effects regression on the outcome of interest. Christmas and New Year fixed effect is a dummy that takes value 1 for days between December 23rd and 25th and December 31st and January 2nd. Day/Month represents a dummy for each day and month couple.

Leave-one-out analysis I test if my estimates reflect the average impact of shutdowns of *Dark Web* marketplaces by performing a leave-one-out exercise. I re-estimate the main specification by leaving out one shutdown at a time. Figure10 illustrates the results of this exercise. Estimates are never statistically different from each other across re-estimations. Estimates are stable when leaving one of the shutdowns out. The main driver for the results is the shutdown of East India Company for crack and heroin, and estimates are not statistically significant in both cases. Estimates for marijuana are always similar and statistically significant at the 5% level for marijuana.

Fixed Effects I estimate my main specification on the residuals of fixed effects regressions on drug trade. This allows to test if estimates are reflecting some regular patterns that systematically happen around the time of shutdown dates. In particular I estimate equation 1 on the residuals of regressions that include month, year, Christmas and New Year and day of the month (day and month couple) fixed effects.[7] Results of this exercise are reported in figure 11. For each outcome I plot point estimates of the effect of *Dark Web* marketplaces estimated on the residuals of a regression of each outcome on several fixed effects. Estimates are relatively stable across specifications and confirm the results obtained in the main specification. Estimates for ecstasy are relatively stable and never significantly significant. Estimates for crack cocaine are stable and statistically significant at the 5% level for all specifications, beside the day of the month specification, where the estimate is significant at the 10% level (p-value of 0.09). Estimates for Heroin are stable and statistically significant at the 5% level in specifications with month, year and month and year fixed effects. They are statistically significant at the 10% level (p-value of 0.08) for Christmas and New Year fixed effects and are not statistically significant day of the month fixed effects. Estimates for marijuana are stable and statistically significant at the 5% level for all specifications, beside the day of the month specification, where the estimate is significant at the 10% level (p-value of 0.07).

Permutation test Finally, I re-estimate my main model 5000 times with random shutdown dates for each estimation. Each simulated estimate provides a placebo effect for shutdowns of *Dark Web* marketplaces. In Figure 12 I report the empirical distribution of t-statistics of the estimates obtained from this exercise. The solid red line indicates the t-statistic of my main model, the dashed line indicates the 95th percentile of the empirical distribution of placebo estimates. This exercise allows to obtain an empirical p-value for a two-sided test, which is displayed in every panel of Figure 12. Following the order in the previous figures panel A indicates results of the exercise for ecstasy, panel B for crack, panel C for heroin, and panel D for marijuana crimes. The empirical p-values confirm that results are statistically significant for crack, heroin and marijuana drug trade crimes.

In the appendix I report the same results for thefts, homicides, assaults and prostitution. These results confirm that shutdowns of *Dark Web* marketplaces had no statistically significant impact on crime.

[7] Christmas and New Year fixed effect is a dummy that takes value 1 for days between December 23rd and 25th and December 31st and January 2nd.

9 Conclusions

In this paper I document a causal relationship between shutdowns of *Dark Web* marketplaces and drug trade on the streets. I find that street drug trade immediately increases after shutdowns of *Dark Web* marketplaces. The causal link is supported by the plausible exogeneity of shutdowns. I ensure that shutdowns of *Dark Web* marketplaces is the only factor causing an increase in crime in those days by ensuring that drug trade street crime is the only type of crime that varies discontinuously around shutdown dates. Furthermore I provide evidence for the robustness of my estimates by carrying numerous robustness checks aiming at testing whether my estimates are driven by a specific model specification or by arbitrary choices made when estimating my main model.

I expand upon an emerging interdisciplinary area of research investigating the impact of Dark Web marketplaces on drug trade (Aldridge & Décary-Hétu, 2014; Galenianos et al., 2012; Bhaskar et al., 2017; Décary-Hétu & Giommoni, 2017; Espinosa, 2019). My results provide novel evidence in this area by proving the connection between on-line and off-line markets for drugs. More research on the topic is needed to understand the exact mechanisms driving this connection. Moreover, in more recent years police authorities have increased their efforts to fight drug trade online, bringing to major successes such as the successful *Operation Bayonet* of 2017 (The Wall Street Journal, 2017).

Policy makers should be aware of the substitutability between on-line and off-line markets for drugs. This results very much highlight one of the well known risks for supply-side policies (Alpert et al., 2018) and suggest that policy makers should incorporate adverse consequences of those policies in their cost-benefit analysis when deciding which strategy to adopt to fight drug addiction.

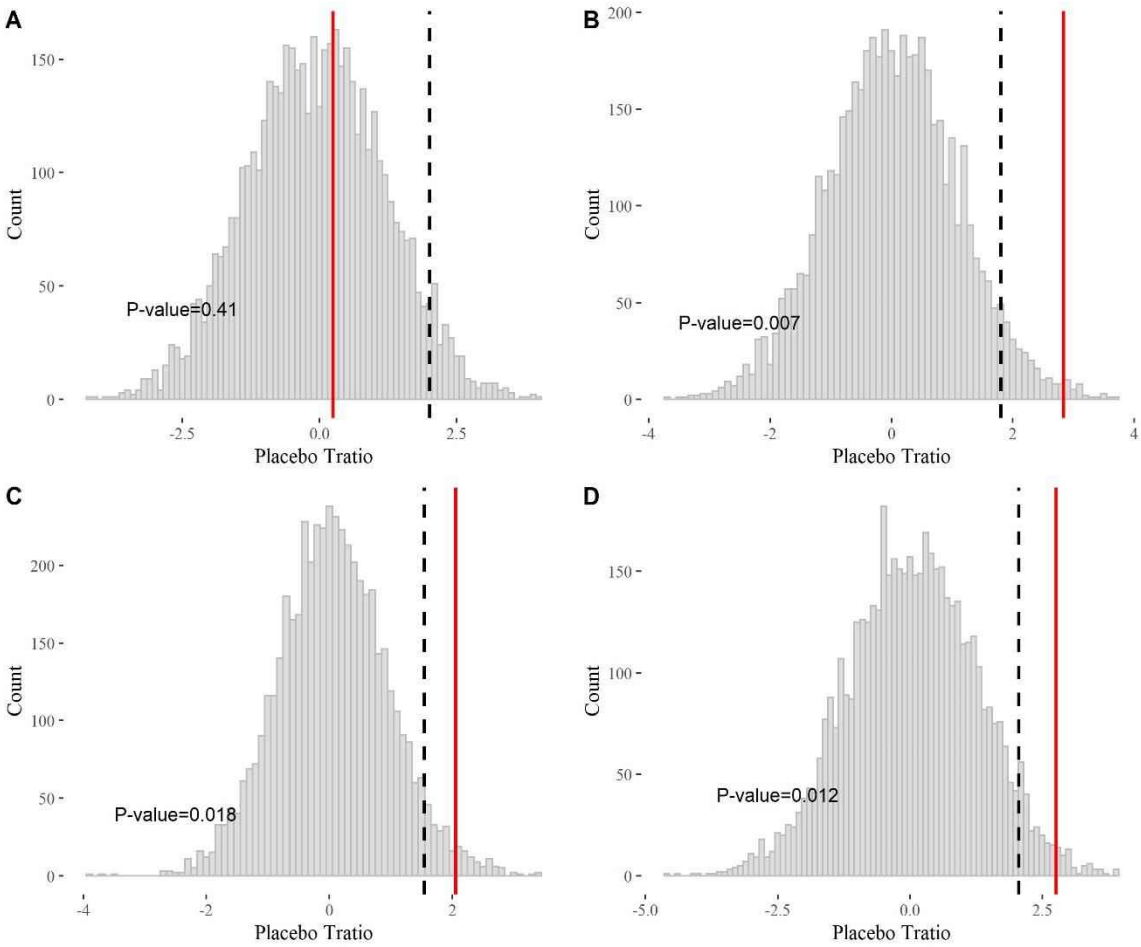

Figure 12: Placebo Estimates Distribution

Notes: This figure plots the empirical distribution of t-statistics for the 2000 placebo estimates obtained as described in the robustness section. Panel A refers to ecstasy, panel B to Crack, panel C to Heroin and panel D to Marijuana. The black dashed line indicates the 95th percentile of this distribution. The red solid line indicates the t-statistic of my main specification. The empirical p-value for a two-sided test for each outcome is also displayed.

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A Appendix

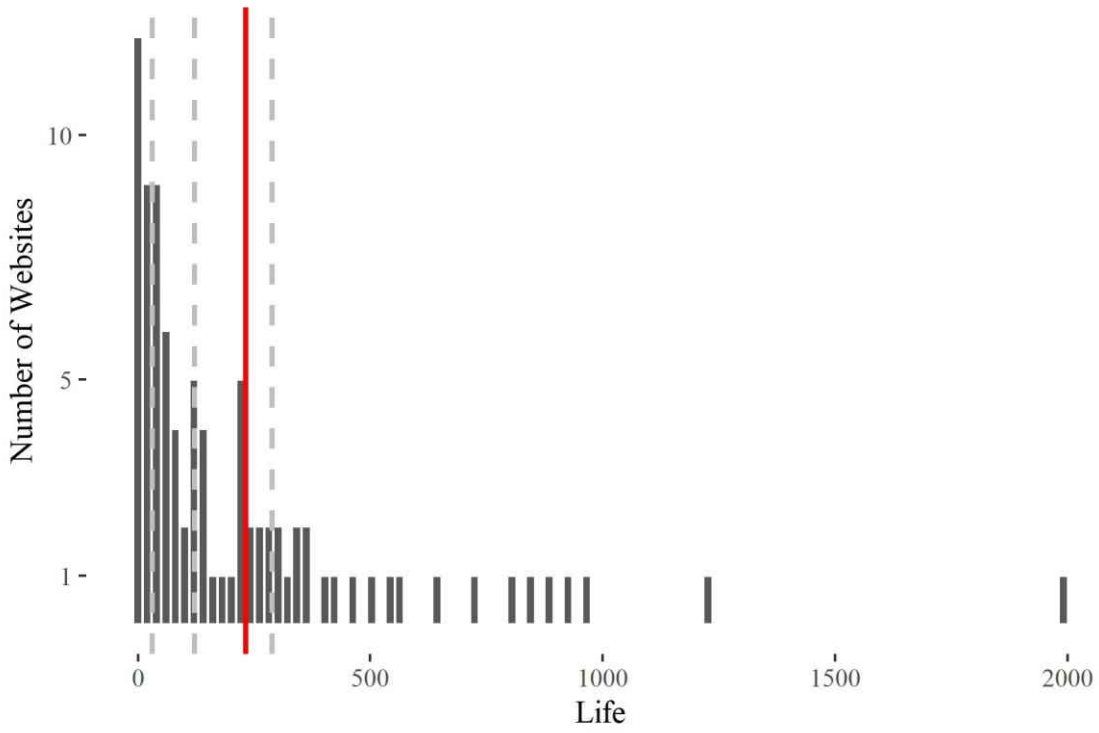

Figure A.1: Markets Lifetime

Notes: This histogram plots the distribution of days in operation for all *Dark Web* marketplaces included in the original dataset. Grey dashed lines indicate respectively the 25th, 50th and 75th percentile of the distribution. The red solid line indicates the average of the distribution. The final sample of *Dark Web* marketplaces for the main specification comprises websites to the right of the solid red line.

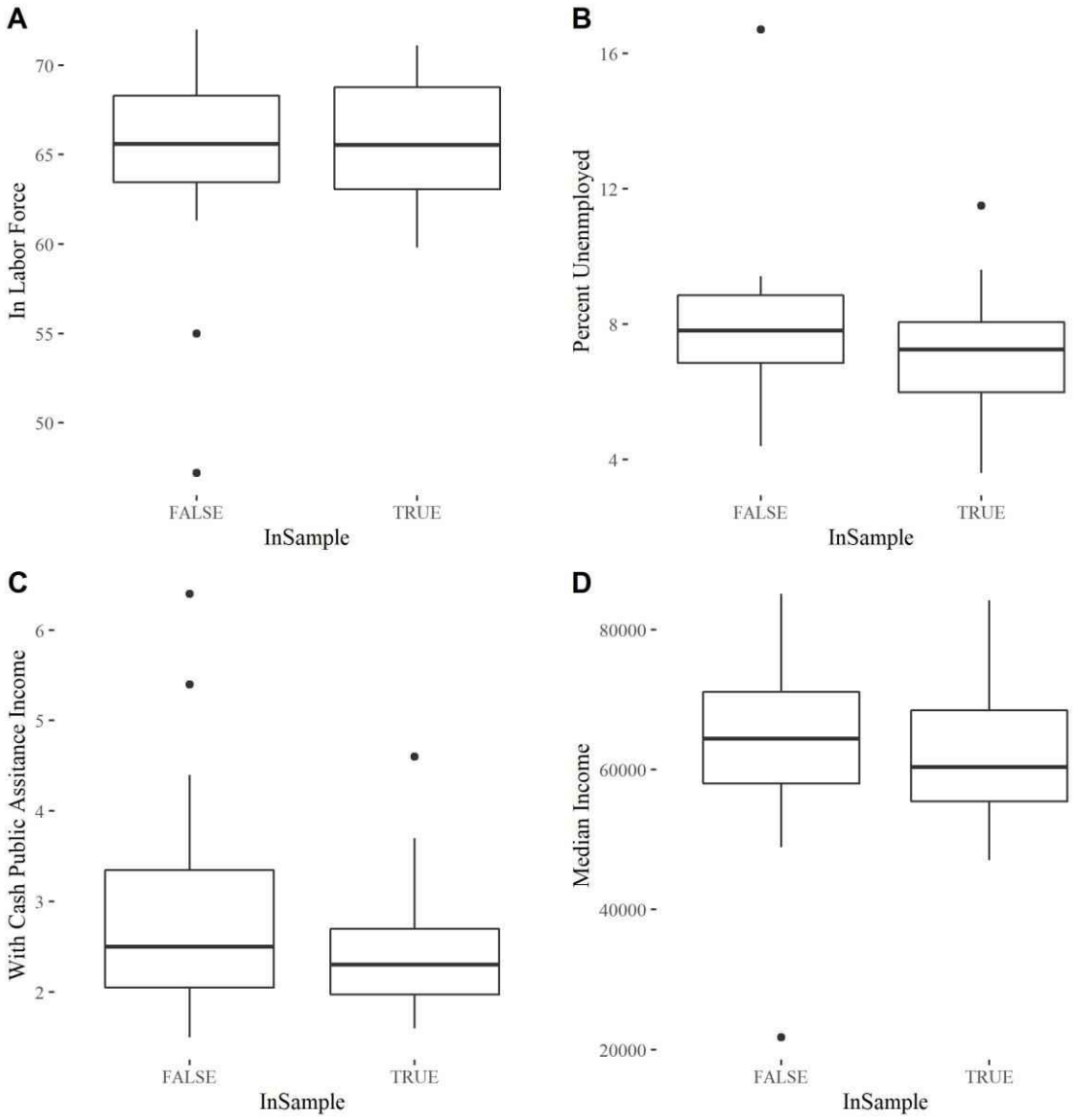

Figure A.2: Nibrs vs Non-Nibrs state characteristics

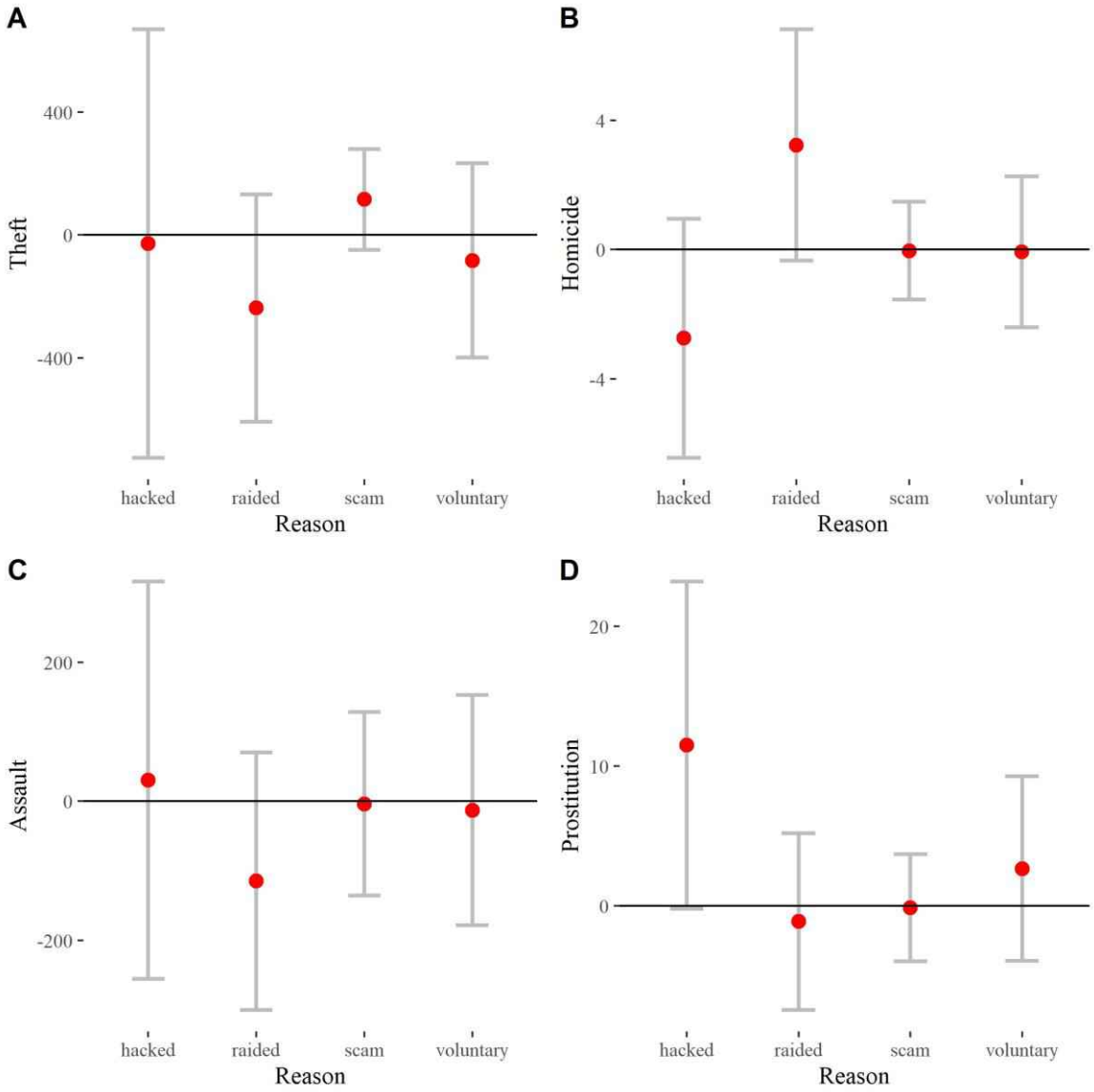

Figure A.3: Estimates for different shut-down reasons

Notes: This figure plots point estimates for different reasons for shut-down with 95% confidence intervals.

.png

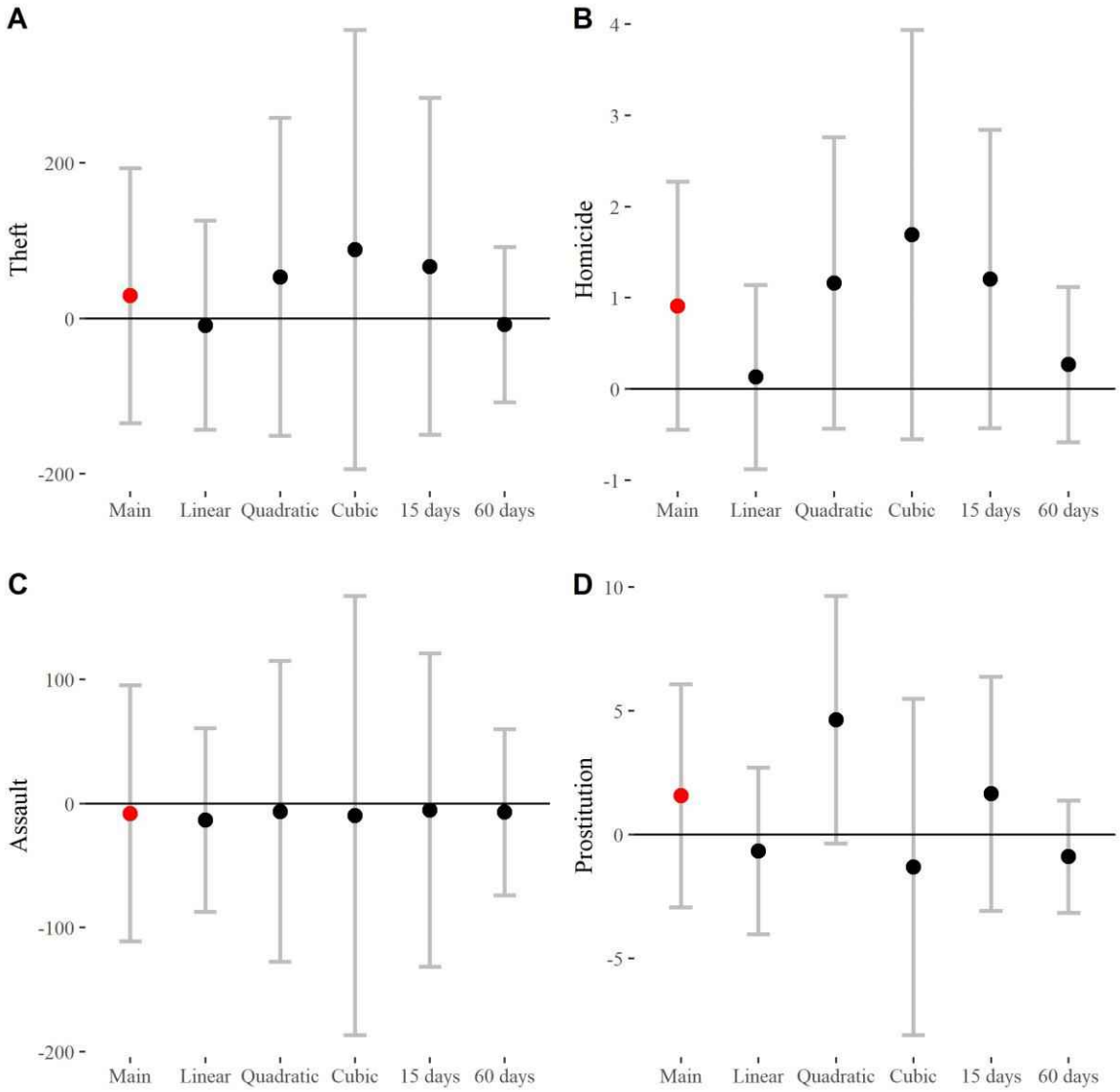

Figure A.4: Estimates for different model specifications

Notes: This figure plots point estimates for different model specifications with 95% confidence intervals. The estimate of the preferred specification is represented by a red dot, whereas alternative specifications are represented by grey dots. For each outcome the estimate for linear, quadratic and cubic functional forms are reported as well as estimates for specifications where a 15 and a 60 days time window around shutdown dates is chosen.

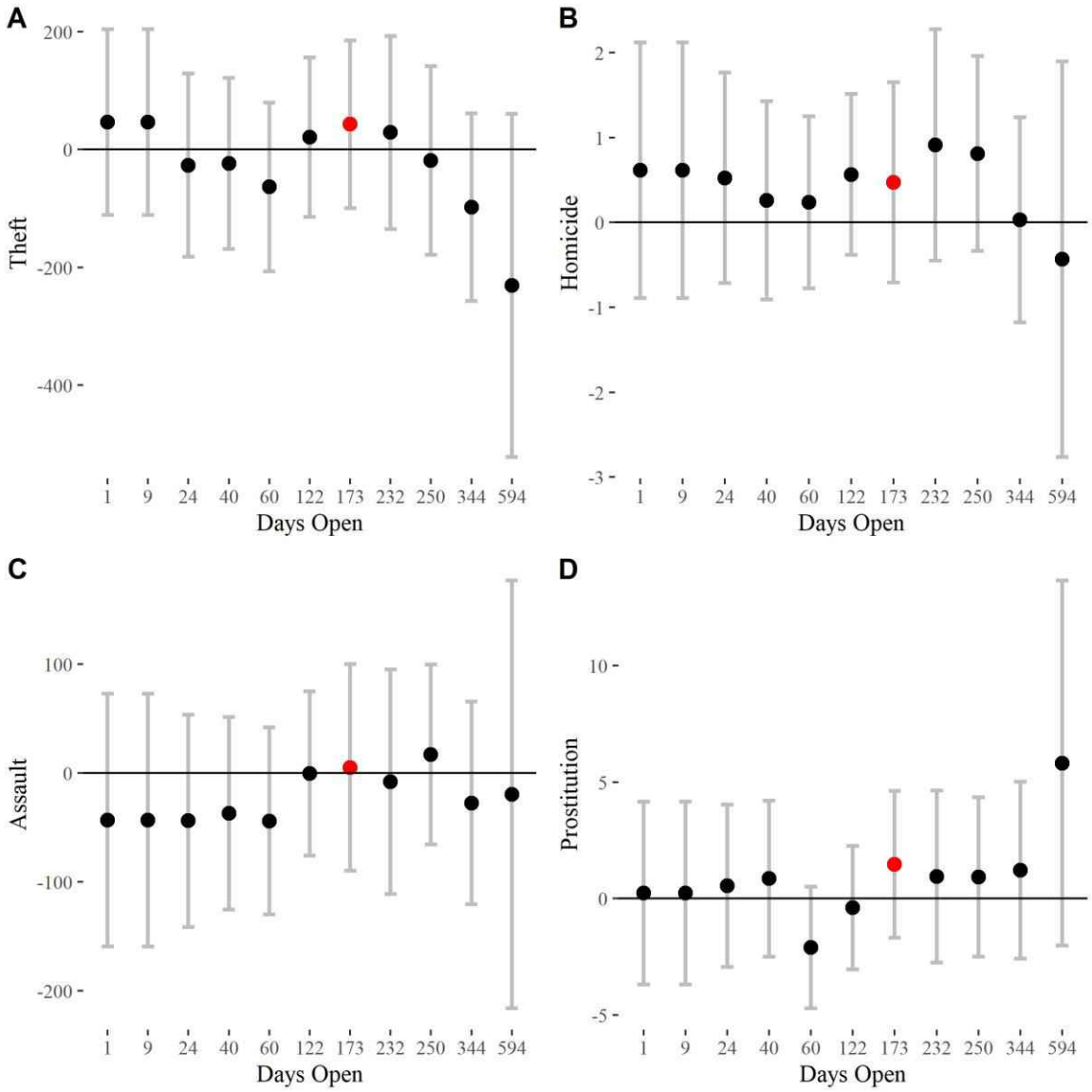

Figure A.5: Estimates at different percentiles of marketplace lifetime distribution

Notes: This figure plots point estimates for different selections of websites considered when estimating equation 1. The black dots represent estimates of equation 1 obtained by including *Dark Web* marketplaces with a lifetime higher than the number of days reported on the x-axis of each plot (corresponding to the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th and 90th percentile of the lifetime distribution plotted in Figure A.1 in the appendix) . The red dot in every panel reports the estimate obtained in my main specification, that only includes websites with a lifetime higher than the average lifetime of *Dark Web* marketplaces.