Out of the Dark: The Effect of Law Enforcement Actions on Cryptocurrency Market Prices

Abstract—**The susceptibility of cryptocurrencies to criminal activity is a vigorously debated issue of high policy relevance. Not only the share of cryptocurrency turnover linked to crime is unknown, also the question which of several cryptocurrencies are prevalent on the darknet, and hence should be prioritized in building analytical capability for law enforcement, calls for empirical research. Using the event study methodology, we estimate the market reaction on cryptocurrency exchanges to news about successful law enforcement actions of systemic relevance for the cybercriminal ecosystem. The events studied include seizures of darknet marketplaces and shutdowns of cybercriminal data centers. Although the number of relevant events is still small, we observe significant cumulative abnormal returns to such news over the past couple of years. We cautiously interpret the results by cryptocurrency and direction of the effect, and derive implications for future research and policy.**

Index Terms—**cryptocurrency, darknet market, event study, law enforcement**

I. Introduction

Since their inception in late 2008 [1], cryptocurrencies are controversial and fascinating at the same time, chiefly for their anarchic, decentralized, and arguably not fully regulable nature. Ten years later, about 1.5% of the population in a euro area country stated that they own cryptocurrency [2]. While the initial promises to consumers, such as cheaper payments and democratic control [3], have been realized partly at best, there is ample evidence that cryptocurrencies facilitate crime. In particular, cryptocurrencies have contributed to the proliferation of darknet marketplaces where illicit goods and services are traded [4]. Customers of these platforms were among the early adopters of Bitcoin, who brought critical mass and stimulated demand [5]. The first and perhaps most notorious example is the Silk Road darknet market with an estimated annual turnover of $15 million [6]. Its seizure by the FBI in 2013 caused a surge of copycats, leading to a cat-and-mouse game between criminals, who continue to come up with new evasion techniques, and law enforcement taking down darknet platforms.

Several high-profile law enforcement operations took place in the last few years. In the first half of 2019, Wall Street Market (WSM) and Silkkitie (known as the Valhalla marketplace) were seized after a globally coordinated operation by German, U.S., Finnish and Dutch law enforcement agencies, and Europol [7]. WSM was the world's second-largest darknet market serving more than 1 million user accounts and 5 000 vendors exchanging illegal drugs, malicious software, stolen credentials, and weapons. Established in 2013, Silkkitie offered similar illicit goods. News in the second half of that year included the closure of Bestmixer.io, a money laundering machine that processed several million of dollars worth of cryptocurrency [8], and the raid against the German "cyberbunker," an illegal datacenter hosting darknet services [9]. The most recent events of this kind include the shutdown of the Berlusconi market, which was considered as one of the most important marketplaces in terms of offers and transactions [10], and the closure of the world's largest illegal marketplace DarkMarket, which happened in January 2021 [11].

All mentioned platforms routinely accepted payments in Bitcoin, Litecoin, or Monero, thereby reaffirming the use of cryptocurrencies for purposes related to financial crime. Foley et al. [12] estimate that almost a half of all Bitcoin transactions is associated with some illegal activity. By contrast, the recent report published by the blockchain analysis company [13] states that "illicit transactions comprised less than 0.5% of all economic Bitcoin activity in 2020." The striking divergence of estimates on this issue with high policy relevance calls for a systematic cross-check against other information sources.

The approach proposed in this work is to explore the market price of cryptocurrencies, i.e., their exchange rate against the dollar, as an indicator of their susceptibility to crime. Under the efficient market hypothesis [14], prices reflect the market participants' expectations, thereby revealing aggregated information that is hard to obtain otherwise. If crime was only a marginal use case of cryptocurrencies, their exchange rate would not react to news about successful law enforcement actions. Any significant reaction of the market price can be interpreted as evidence for a tighter connection.

But it is not straightforward to predict the sign of a reaction. If market participants expect that the closure of a darknet market leads to a sustained reduction of demand for cryptocurrency, e.g., because one of its uses would be irrecoverably eradicated, then prices should fall. This effect would be emphasized if darknet vendors liquidate earnings in cryptocurrency in order to secure their loot. However, one can bring forward at least as many arguments for a price rise. For example, prices could have been held down by darknet vendors cashing out earnings. This stream of cryptocurrency supply would stop if the market is seized. This is not only because sales stall. Vendors would not touch their cryptocurrency wallets in order to hide from prosecution (or because they are arrested). In addition, the positive news about successful law enforcement actions (or just any news about cryptocurrencies) might raise confidence and restore trust in cryptocurrencies, thus increasing demand and driving market prices upwards.

We take an empirical approach to shed light on this matter.

Our specific research question is:

> *What is the effect of news about successful law enforcement actions against darknet actors on the market price of cryptocurrencies?*

We restrict our analysis to the most popular cryptocurrencies (by the so-called market capitalization) that are also prevalent in the darknet (as evidenced by price quotes).

Our work complements studies of market reactions of cryptocurrency prices, transaction volumes, and estimated active users in response to regulatory statements and news [15]. It contributes to the state-of-the-art in at least three ways. We are the first to examine the effect of global law enforcement actions in the darknet on the market price of individual cryptocurrencies. This gives new insights into specific cryptocurrencies' popularity among criminals and adds to the current body of knowledge about the ecosystem, given that "... the opportunities and risks from business and societal (rather than technical) perspectives are not well understood" [16]. Second, we propose and compare methods to estimate the expected return of cryptocurrencies for the purpose of event studies. Third, our findings and related implications add to the existing body of research on cryptocurrency regulation and the evaluation of law enforcement operations [17].

The remainder of this paper is organized as follows: Section II-A reviews related work. Section II-B describes the event study methodology and its adaptation to the context of cryptocurrencies. Section II-C justifies our selection of events and cryptocurrencies. The empirical results are presented in Section III, and discussed in Section IV. Section V concludes.

II. Research Approach

A. Related Work

We queried Google Scholar for event studies related to cryptocurrency or law enforcement actions. With respect to studies examining law enforcement events, we used the search term ("event study" AND "law enforcement action") in Google Scholar and identified one relevant paper out of 9 results. Branson et al. [18] examine the impact of a series of U.S. online poker law enforcement and legislation events on brick-and-mortar gaming corporations. By relaxing the search term to ("event study" AND "enforcement action"), one can find event studies related to the effect of enforcement actions of the U.S. Securities and Exchange Commission (SEC). In particular, the work of Nourayi [19] has initiated this stream of research in the financial economics literature. These works study legal entities (mostly firms) presumably breaking the law, whereas our work examines extralegal entities in cyberspace that try to evade law enforcement.

The search term ("cryptocurrency" AND "event study") produces almost 400 hits on Google Scholar, which we condensed to 17 relevant works. Four studies [15, 20, 21, 22] investigate exchange rate reactions to news concerning the regulation of cryptocurrencies. Ante [23] analyzes actions in the ecosystem, specifically listings on cryptocurrency exchanges. Related, and closer to our work on the dark sides of cryptocurrencies are two studies of pump-and-dump schemes against illiquid crypto-assets [24, 25]. Several teams of authors use exchange rates to quantify the impact of adversarial technical events including security and privacy breaches [26], attacks against consensus protocols [27], or denial-of-service attacks against exchanges [28]. All newer studies of cryptocurrency price reactions were inspected for their methodological approach in order to inform the method and parameter choices of the present work. Studies at the intersection between conventional and crypto-finance include an analysis of cryptocurrency market prices in response to the launch of cryptocurrency future contracts on conventional financial markets [29]. Moreover, two papers describe (conventional) stock market reactions to corporate announcements [30] and patent filings indicating blockchain investments [31]. Strikingly, the special case of blockchain-related corporate name changes received attention from four different research groups [32, 33, 34, 35].

There is also ample empirical work studying market activities and actors on illicit darknet platforms. In [36], the authors examine cross-country social factors to explain cybercrime in the darknet as a sociological and economic phenomenon. Chua [17] seeks to measure trust by using vendors' returns on reputation as a novel proxy. Similarly to our work, the author refers to the need of developing new approaches for evaluating the effect of law enforcement operations beyond the more common metrics of demand, supply, and prices. Other work that connects to our paper focuses on behavioral profiling of darknet vendors and on how they differ in their security practices (e. g., in [37, 38, 39]).

B. Event Study Methodology

Event studies have a long tradition in the economics, finance, and accounting literature where scholars measure how a publicly listed firm's market value reacts to firm-specific or economy-wide news and events [40]. The core methodology was developed by [14, 41, 42] and evolved over time [43]. It is based on a comparison of the actual and predicted rate of change in a metric of interest (e. g., a stock price) over a certain event window. Therefore, the proper estimation of predicted (or normal) returns is crucial in such studies. We summarize the event study methodology in the context of our research work.

Every event study differentiates between the estimation period (T) and the event window (E). The estimation period covers a period over which the actual returns are evaluated to fit a model that can predict normal returns. The event window covers a period over which the abnormal returns are evaluated and tested for statistical significance. For cryptocurrency i and time period (day) t, the abnormal return is defined as:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t), \tag{1}$$

where $AR_{i,t}$, $R_{i,t}$, and $E(R_{i,t}|X_t)$ are the abnormal, actual, and normal returns, respectively. X_t conditions information that a darknet marketplace or service is still operational. The normal return models the expected market price movement of a cryptocurrency in the—counterfactual—absence of a law enforcement intervention. We calculate daily returns as

$$R_{i,t} = \frac{A_{i,t} - A_{i,t-1}}{A_{i,t}} \times 100\%, \tag{2}$$

where $A_{i,t}$ and $A_{i,t-1}$ are the reported closing prices of cryptocurrency i in dollars on day t and $t-1$, respectively.

The literature documents a number of statistical and economic approaches to predict the normal return [43]. The most common approaches derived from statistics are the mean-adjusted normal return (MAR) model [42] and the market model [44]. The former model extrapolates the mean return of a given asset, whereas the latter model requires a market index for the event window and assumes a linear relation between the market and asset return. Formally,

$$R_{i,t} = \mu_i + \xi_{i,t}, \quad E(\xi_{i,t}) = 0 \text{ and } var(\xi_{i,t}) = \sigma^2_{\xi_i} \tag{3}$$

$$R_{i,t} = \alpha_i + \beta_i R_{mt} + \varepsilon_{i,t}, \quad E(\varepsilon_{i,t}) = 0 \text{ and } var(\varepsilon_{i,t}) = \sigma^2_{\xi_i}, \tag{4}$$

where μ_i is the mean return over the estimation period, R_{mt} is the return of the market index, α_i and β_i are estimated parameters, and $\xi_{i,t}$ and $\varepsilon_{i,t}$ are residuals.

By convention, event studies analyze cumulative abnormal returns (CARs), which are hypothesized to be either positive or negative depending on the event's effect. The statistical significance of CARs can be tested by two common methods: the traditional method (TM) of Brown and Warner [42] or the standardized-residual method (SRM) of Patell [45]. Both tests considers the following null (H_0) and alternative (H_1) hypotheses:

$$H_0 : CAR(t_3, t_4) = 0$$
$$H_1 : CAR(t_3, t_4) \neq 0$$

where t_3 and t_4 refer to the start and end date of the event window. The TM calculates a Student-t test statistics according to this definition:

$$t^{\text{TM}} = \frac{CAR(t_3, t_4)}{\sqrt{VAR(CAR(t_3, t_4))}} = \frac{\sum_{t=t_3}^{t_4} \left(\frac{AR_t}{\sqrt{m}}\right)}{\hat{S}}, \tag{5}$$

where m is the number of periods in the event window $[t_3, t_4]$, and $\hat{S}$ is the standardized error from the residual of returns in the estimation period. The SRM, in turn, standardizes the abnormal change rate:

$$\begin{aligned} t^{\text{SRM}} &= \frac{SCAR(t_3, t_4)}{\sqrt{VAR(SCAR(t_3, t_4))}} = \frac{\sum_{t=t_3}^{t_4} \frac{SAR_t}{\sqrt{m}}}{\sqrt{\frac{T-2}{T-4}}}, \\ SAR_t &= \frac{AR_t}{\hat{S} \cdot \sqrt{1 + \frac{1}{T} + \frac{(R_{mt} - \overline{R}_{mT})^2}{\sum_{\tau=t_3}^{t_4} (R_{m\tau} - \overline{R}_{mT})^2}}} \end{aligned} \tag{6}$$

where $\overline{R}_{mt}$ is the mean market return in period t and T is the length of the estimation period. If a test statistic rejects the null hypothesis H_0, it is interpreted as evidence that the event has, in fact, caused the abnormal changes in the dependent variable.

C. Sample and Periods Selection

MacKinlay [43] outlines a common order of steps to be executed in any event study. First, we need to identify major events of interest. In our context, the earliest and best-known event dates back to 1 October 2013, when the FBI seized and shut down the Silk Road darknet marketplace [46]. Since then, a few of other high-profile darknet market closures were announced in official law enforcement press releases and disseminated by the media. Table I contains a list of the major successful operations that we collected by querying Europol's feed as well as Google News. The inclusion criteria guiding the selection process were primarily based on the size and sophistication of platforms. Besides the seizure of marketplaces, the table includes other noteworthy cases related to cryptocurrencies and of potential relevance for this study, e. g., the unprecedented closure of the world's largest cryptocurrency mixing service Bestmixer.io in May 2019 [8].

All darknet markets mentioned above accepted payments in Bitcoin, whereas some platforms supported other cryptocurrencies (e. g., Monero or Litecoin) in addition to Bitcoin. In order to get an idea about the potential impact of law enforcement operations on the ecosystem, we first plot the normalized market prices for the time period starting 50 days before and ending on 25th day after the event date. To this end and for the follow-up analysis, we collected historical market data (the closing price, to be precise) from Coinmarketcap.com [52] for the time period between 29 April 2013 and 31 August 2021. We restrict our analysis to Bitcoin, Bitcoin Cash, Litecoin, Monero, Zcash, and Dash, as those cryptocurrencies are known to be relevant on the darknet. The normalized price is computed as the difference between the actual daily price and the mean price for the preceding 15 days, divided by the standard deviation. Figure 1 shows the resulting plots with "0" indicating the date of the official press release. Expectedly, the plots confirm a well-known fact that cryptocurrency market prices fluctuate a lot. However, one can discern an upward trend for most events, as in certain cases the prices tend to go up in the first one or two weeks since the law enforcement announcement.

III. Empirical Results

Acknowledging the high volatility of cryptocurrency exchange rates, we apply both alternative statistical models for the prediction of normal returns. This allows us to better control for potential methodological limitations and to cross-check our findings. Following the MAR model, we have calculated the mean change rate over the estimation period and used it as a constant over the event window. The market model, in turn, assumes the presence of a reliable and broad market index. Unlike for conventional stocks, there is no objective market index available for cryptocurrencies, yet. Some initiatives on designing such an index rest on volume data, which are self-reported by exchanges and the credibility of which is highly questionable [53]. Moreover, Bitcoin is a heavyweight in this index, precluding the reliable estimation of abnormal Bitcoin returns. For these reasons, we have

#	Law enforcement action	Date of the official press release	Date of the actual shutdown*	Reference to the source	Accepted cryptocurrencies
1	Seizure and shutdown of the Silk Road	01 Oct 2013		U.S. DHS (2013)	Bitcoin
2	Shutdown of multiple darknet markets in the operation Onymous**	06 Nov 2014		U.S. DoJ (2014)	Bitcoin
3	Shutdown of AlphaBay and Hansa (Bayonet)	20 Jul 2017	05 Jul 2017	Politie Nederland (2017) and U.S. DoJ (2017)	Bitcoin, Monero
4	Shutdown of the Wall Street Market	03 May 2019	23 Apr 2019	BKA (2019)	Bitcoin, Monero
5	Shutdown of DeepDotWeb	08 May 2019		Europol [50]	Bitcoin
6	Shutdown of Bestmixer.io	22 May 2019		Europol [8]	
7	Shutdown of the illegal data center (Cyber-bunker) in Germany	27 Sep 2019		Die Rheinpfalz [9]	
8	Shutdown of Berlusconi Market	07 Nov 2019		Guardia di Finanza [10]	Bitcoin
9	Shutdown of Sipulimarket	11 Dec 2020		Europol [51]	Bitcoin
10	Shutdown of DarkMarket	12 Jan 2021		Europol [11]	Bitcoin, Monero

* if known.
** Pandora, Silk Road 2.0, Black Market, Blue Sky, Tor Bazaar, Topix, Hydra, Cloud 9 and Alp.

TABLE I: Sample selection of the major law enforcement actions in the darknet

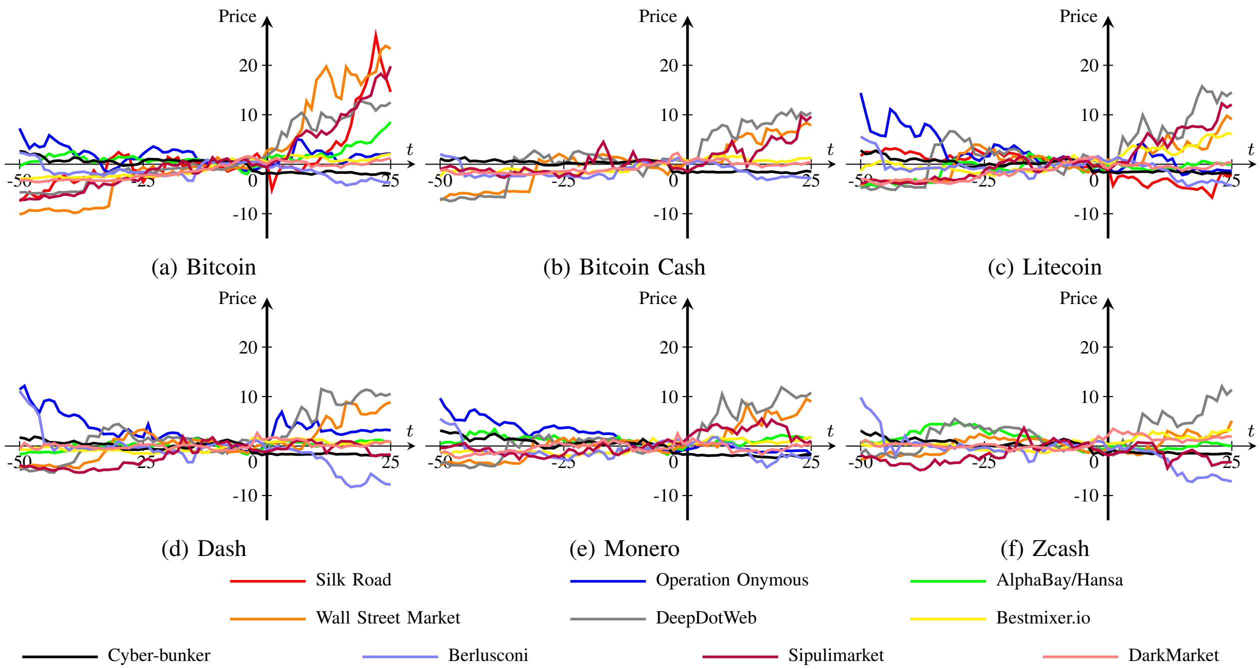

Fig. 1: Normalized market prices (in dollars) on the days before and after the event date (0).

adopted a synthetic approach and calculated our own proxy of the market index. The proxy is computed as a weighted average of the daily returns of Ethereum and Ripple. Both cryptocurrencies are listed in the top ten and are neither present nor directly associated with the darknet. We estimated α_i and β_i with ordinary least squares (OLS) and calculated the normal returns as predictions from the regression equation (4) over the estimation period T. Since Ethereum was released in 2015, this analysis is impossible for the earliest two events in our sample.

Tables II–IV report the empirical results, separated by law enforcement event and broken down by cryptocurrency. This way, we can compare the impact of a law enforcement action across currencies by their direction and magnitude. The shutdown of Silk Road did not cause a significant price effect on Bitcoin and Litecoin. Somewhat surprisingly, the operation Onymous led to significant positive CARs for Monero on the third day after the press release. Though Monero was not highly popular in the darknet at the time, the success of Onymous and the closure of multiple markets may have caused criminals (and perhaps concerned users) to convert their assets into less traceable cryptocurrencies, like Monero.

The shutdown of AlphaBay and Hansa caused positive abnormal returns for Bitcoin. This effect is strong in terms

Event period (m)	Silk Road (01 Oct 2013)		Operation Onymous (06 Nov 2014)			
	Bitcoin	Litecoin	Bitcoin	Litecoin	Dash	Monero
$[-5,-5]$	0.0	1.6	−3.4	−4.8	−6.1	−0.8
$[-5,-4]$	4.1	2.7	−3.1	−4.2	−6.1	0.9
$[-5,-3]$	4.7	−2.9	−2.3	−4.5	−7.2	3.1
$[-5,-2]$	6.5	0.1	−1.1	−4.2	−5.4	0.9
$[-5,-1]$	3.3	3.0	2.0	−2.8	1.3	8.1
$[-5,0]$	2.5	6.7	5.2	−2.6	15.7	15.0
$[-5,1]$	−11.2	−11.2	3.5	−5.0	23.3	21.2
$[-5,2]$	−3.0	−0.4	4.7	−5.0	52.1	28.4
$[-5,3]$	1.2	1.7	10.1	−3.0	62.3	43.2**
$[-5,4]$	0.7	0.2	11.4	−1.1	47.5	47.9**
$[-5,5]$	1.0	1.8	11.9	−1.6	44.2	48.3**
$[-5,6]$	−0.7	−0.7	27.4**	9.0	53.5	53.1**
$[-5,7]$	−1.6	−5.7	27.1**	9.7	51.8	52.0**
$[-5,8]$	2.0	−8.0	21.9	7.0	45.8	52.6**
$[-5,9]$	1.8	−1.6	16.8	3.5	49.8	48.4**
$[-5,10]$	2.0	1.1	20.2	4.3	60.5	53.2**

** denotes statistical significance at the 1% level.

TABLE II: Cumulative abnormal change rates (according to the mean-adjusted return model)

of magnitude on the press release date (32% for the MAR and 23% for the OLS models, respectively) and remains relatively high over the following days. With respect to the WSM, significant positive CARs are found for Bitcoin, Bitcoin Cash, Litecoin, and Dash. Interestingly, Monero, which was accepted on this marketplace, was not affected by this law enforcement action. The closure of the DeepDotWeb market is associated with significant positive CARs for Bitcoin, Bitcoin Cash, and other coins. The shutdown of the mixing service Bestmixer.io had practically no significant effects on the analyzed cryptocurrencies. The cyber-bunker event resulted in negative significant CARs for all cryptocurrencies in our sample, however chiefly in the MAR model. This lets us wonder if the event coincided with an exogenous turning point of the global cryptocurrency markets. Nevertheless, the highly significant CARs of the OLS models for Bitcoin, Bitcoin Cash, and Litecoin suggest that the news might still have had some reinforcing effect.

Observe that the seizure of the Italian and Finnish markets Berlusconi and Sipulimarket did not caused any effects on the cryptocurrency prices. This finding implies that the takedown of local or country-specific illicit marketplaces has no measurable impact on the global cryptocurrency market. By contrast, the recent closure of the largest DarkMarket had a significant negative effect on Bitcoin and Litecoin, and a significant positive effect on the Dash and Zcash, which have a reputation of offering higher privacy to users. Besides Bitcoin, the DarkMarket also accepted Monero, for which we do not find a consistent effect. The results for Dash and Zcash should be taken with a grain of salt due to unusually high volatility of both cryptocurrencies at the time the event ocurred.

IV. Discussion

Our event study provides empirical evidence for the relationship between news about the closure of darknet markets and the market exchange rate of individual cryptocurrencies to the dollar. Table VI presents a summary of the effects, broken down by the type of a law enforcement action and cryptocurrency. We find that news about police operations significantly and often positively impact the price of some cryptocurrencies. Moreover, we propose and compare a new variant of the event study method by using a synthetic index of less crime-prone cryptocurrencies. This variant is specifically tailored to the analysis of crime related to cryptocurrencies.

Referring back to our motivation for this research, we have found empirical evidence supporting that crime is not only a marginal use-case of cryptocurrencies. This holds for the leading multi-purpose cryptocurrency Bitcoin and for other cryptocurrencies in our sample that seem to be suited for illegal activities from the outset. Specifically, Dash, Monero, and Zcash are so-called “privacy” coins and were deliberately designed to make digital payments untraceable. Interestingly, our analysis has revealed that Zcash is impacted only by the shutdown of the DeepDotWeb, the cyber-bunker datacenter, and the DarkMarket. The presumable irrelevance of Zcash may be due to several factors. By design, Zcash untraceable or “shielded” transactions are an opt-in feature that requires much computational effort. The lion’s share of Zcash transactions however remains as traceable as Bitcoin. Perhaps, this explains why Zcash is not an alternative to Bitcoin on the darknet.

Besides the academic contributions mentioned above, our event study raises several practical implications. First, it offers a novel approach to demonstrate the effectiveness of coordinated law enforcement efforts and their impact on the global cryptocurrency and cybercriminal ecosystems. Enforcement operations against operators of darknet markets require careful planning, highly specialized resources, long periods of time for execution, and international coordination. Even though the history has shown that every closure of a darknet service was followed by new entrants, crime suppression remains a high-priority challenge for law enforcement agencies. To justify these efforts, sound scientific approaches are needed to measure the fruits of such costly law enforcement actions. The presented method may further mature to become a tool which

Event period (m)	Bitcoin		Bitcoin Cash		Litecoin		Dash		Monero		Zcash	
	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2
			Shutdown of AlphaBay and Hansa (Bayonet)								**(20 Jul 2017)**	
$[-5, -5]$	−9.8**	−6.2**			−9.1	−2.2	−12.6*	−3.3	−8.3	1.1	−6.6	6.7
$[-5, -4]$	−12.5**	−6.0			−4.1	8.4	−17.6*	−0.8	−15.2	1.5	0.3	24.3**
$[-5, -3]$	3.7	2.0			0.1	−3.3	−1.2	−5.8	4.4	−0.2	13.5	6.9
$[-5, -2]$	8.5	1.3			3.9	−10.2	2.0	−16.8	10.2	−8.7	25.9	−1.2
$[-5, -1]$	7.3	3.7			−4.0	−10.9	0.8	−8.5	7.9	−1.5	20.4	7.0
$[-5, 0]$	32.0**	23.2**			6.2	−10.9	22.4	−0.4	24.1	1.3	37.3*	4.5
$[-5, 1]$	27.4**	19.0**			7.7	−8.5	21.4	−0.3	25.5	3.8	38.0*	6.9
$[-5, 2]$	33.5**	22.4**			9.4	−12.0	26.8	−1.7	37.7*	9.0	48.3*	7.2
$[-5, 3]$	31.4**	19.7**			4.0	−18.7	25.1	−5.2	34.4*	4.0	50.7*	7.2
$[-5, 4]$	33.0**	20.9**			4.7	−18.8	32.3	0.9	42.5*	11.1	50.4*	5.4
$[-5, 5]$	27.3**	17.0			−0.3	−20.1	28.5	2.0	33.1	6.6	42.6	4.6
$[-5, 6]$	26.2**	15.8			−0.4	−20.4	28.3	1.5	47.0*	20.1	49.0*	10.6
$[-5, 7]$	32.6**	21.4			−0.7	−22.2	28.5	−0.2	47.1*	18.3	50.0	8.8
$[-5, 8]$	38.4**	28.3**			−4.4	−24.1	24.6	−1.7	45.5*	19.2	49.0	11.2
$[-5, 9]$	36.2**	23.7**			−3.2	−27.4	24.8	−7.5	46.7*	14.3	58.5*	12.1
$[-5, 10]$	38.1**	26.0**			−5.0	−28.4	18.5	−12.9	38.3	6.9	54.4	9.4
			Shutdown of the Wall Street Market (WSM)								**(03 May 2019)**	
$[-5, -5]$	0.2	−0.1	−2.3	−2.6	−2.2	−2.6	1.6	1.2	−1.6	−2.2	−1.4	−1.7
$[-5, -4]$	−0.6	−0.5	−8.8	−8.8	−3.5	−3.5	0.6	0.7	−2.3	−2.2	−3.2	−3.1
$[-5, -3]$	1.3	−2.7	5.2	1.5	7.0	1.5	5.1	0.6	0.8	−5.6	1.4	−2.0
$[-5, -2]$	2.2	−1.5	7.6	4.2	7.3	2.3	10.9*	6.9	5.9	0.1	3.2	0.2
$[-5, -1]$	4.0	−0.3	7.9	3.9	8.6	2.8	12.0*	7.3	5.5	−1.3	1.9	−1.6
$[-5, 0]$	8.7	1.9	17.2*	11.0	17.3*	8.2	16.3**	8.9**	10.1	−0.7	7.6	2.1
$[-5, 1]$	9.7	3.7	17.6	12.1	16.9*	8.8	16.7**	10.4**	11.7	2.2	5.7	0.8
$[-5, 2]$	9.0	2.9	19.3	13.7	15.4	7.2	16.8*	10.2**	9.7	0.0	4.8	−0.1
$[-5, 3]$	8.1	−0.6	18.0	10.0	15.2	3.5	18.8*	9.3	10.9	−2.9	6.2	−0.9
$[-5, 4]$	9.4	1.2	18.6	11.0	16.0	4.9	17.4*	8.4	9.8	−3.3	3.4	−3.3
$[-5, 5]$	11.9	2.8	19.3	10.9	17.1	4.8	18.8*	8.8	13.0	−1.5	5.2	−2.3
$[-5, 6]$	15.1*	6.1	19.4	11.2	17.7	5.6	15.0*	5.2	9.6	−4.6	3.1	−4.3
$[-5, 7]$	18.3*	7.7	21.5	11.8	22.8*	8.6	16.4*	4.8	15.3	−1.5	5.8	−2.8
$[-5, 8]$	31.1**	12.5**	46.3**	29.1	39.6**	14.5	27.5**	7.1	29.8*	0.2	17.9*	2.7
$[-5, 9]$	27.8**	11.7	46.5**	31.6	35.6**	13.8	28.7**	11.0	25.9*	0.3	13.1	−0.1
$[-5, 10]$	39.8**	19.4**	56.0**	37.2	40.9**	13.4	35.7**	13.3	33.1*	0.7	19.8*	3.1
			Shutdown of the DeepDotWeb								**(08 May 2019)**	
$[-5, -5]$	4.4*	2.7	8.6*	6.2	7.8*	4.7	3.4	1.1	4.1	1.3	5.6*	3.5**
$[-5, -4]$	5.0*	4.31**	8.2	7.1	6.5	5.1	3.1	2.1	5.4	4.1	3.6	2.6
$[-5, -3]$	4.0	3.5	9.2	8.4	4.1	3.1	2.0	1.3	2.9	2.0	2.7	2.0
$[-5, -2]$	2.8	0.4	7.2	3.9	3.1	−1.3	3.0	−0.1	3.7	−0.2	3.9	0.9
$[-5, -1]$	3.8	2.1	7.0	4.6	2.9	−0.2	0.7	−1.6	2.2	−0.6	1.1	−1.1
$[-5, 0]$	6.0	3.9	7.0	4.0	3.1	−0.8	1.2	−1.6	5.1	1.6	2.7	0.0
$[-5, 1]$	8.8*	7.1	6.4	4.0	2.8	−0.3	−3.5	−5.8	1.2	−1.6	0.5	−1.7
$[-5, 2]$	11.7*	9.0**	7.7	3.9	7.1	2.1	−3.1	−6.7	6.5	2.0	3.2	−0.3
$[-5, 3]$	24.3**	15.4**	31.7*	19.2	23.0*	6.5	7.1	−4.9	20.6*	5.8	15.2*	3.7
$[-5, 4]$	20.6**	14.0**	31.2*	21.9	18.1	5.8	7.2	−1.6	16.3	5.4	10.3	1.8
$[-5, 5]$	32.3**	22.6**	39.9**	26.2	22.5*	4.4	13.3	0.3	23.0*	6.9	16.9*	4.3
$[-5, 6]$	34.2**	13.6**	41.3**	12.1	26.8*	−11.5	20.7*	−6.9	28.1*	−6.1	23.7**	−2.9
$[-5, 7]$	36.4**	8.1**	45.0**	5.0	38.1**	−14.5	28.6**	−9.4	41.4**	−5.5	38.5**	1.9
$[-5, 8]$	32.1**	4.0	44.1**	4.4	32.4*	−19.8	26.2**	−11.5	33.9**	−12.6	36.8**	0.5
$[-5, 9]$	24.8**	1.3	35.7*	2.5	25.8*	−18.0	18.9*	−12.6	28.3*	−10.7	34.6**	4.3
$[-5, 10]$	23.4**	2.0	33.9*	3.5	23.5	−16.4	20.8*	−7.9	25.4*	−10.1	34.2**	6.5

** denotes statistical significance at the 1% level, * – at 5% level.

TABLE III: Cumulative abnormal change rates (CAR_1 – mean-adjusted return model, CAR_2 – OLS)

allows to analyze the interplay between law enforcement and the cryptocurrency ecosystem on regular basis.

However, it is worth emphasizing that the link between enforcement action and market reaction is always moderated by the communication accompanying (or following) the action. This highlights the need for law enforcement agencies to carefully plan and time their communication strategy. A key consideration should be to reduce potential undesirable effects, such as giving advantage to traders with superior information, or creating false confidence in cryptocurrencies among legitimate users. In this context, a striking alternative interpretation of our results is that law enforcement agencies not only have done a valuable service to society, but also made some investors in cryptocurrencies richer (e. g., by a total of 9 billion dollar in the case of Bitcoin and the Bayonet operation).

Our event study suffers from a number of limitations which need to be addressed in future research. First, this work highlights a general limitation of the event study methodology

Event period (m)	Bitcoin		Bitcoin Cash		Litecoin		Dash		Monero		Zcash	
	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2
Shutdown of Bestmixer.io (22 May 2019)												
$[-5,-5]$	-9.0^{*}	-5.3	-10.8	-4.7	-8.4	-0.8	-9.0^{*}	-3.2	-7.6	-0.4	-4.1	3.9
$[-5,-4]$	-12.1^{*}	-6.3	-15.0	-5.4	-12.5	-0.5	-8.7	0.5	-12.4	-0.9	-6.5	6.3
$[-5,-3]$	-1.4	1.0	0.5	4.6	-4.0	1.0	10.6	14.5^{**}	-0.4	4.5	1.2	6.5
$[-5,-2]$	-6.2	-1.5	-3.8	4.1	-9.5	0.3	7.8	15.4^{**}	-5.5	3.9	-2.5	8.0
$[-5,-1]$	-8.5	-3.1	-4.9	4.0	-11.0	0.2	5.5	14.1	-5.8	4.9	-5.4	6.5
$[-5,0]$	-14.2	-6.3	-13.2	-0.1	-16.1	0.3	-3.0	9.5	-13.8	1.9	-12.4	5.0
$[-5,1]$	-13.6	-5.2	-12.1	1.9	-16.5	1.0	-5.0	8.4	-14.3	2.4	-11.4	7.2
$[-5,2]$	-14.4	-5.6	-13.6	1.1	-6.0	12.4	-5.4	8.6	-15.0	2.6	-12.0	7.5
$[-5,3]$	-15.7	-6.3	-16.5	-0.8	-4.7	14.9	-7.2	7.8	-15.2	3.5	-13.0	7.7
$[-5,4]$	-10.1	-1.9	-12.3	1.3	2.3	19.3	-4.6	8.3	-11.2	5.0	-9.5	8.5
$[-5,5]$	-10.7	-3.2	-12.1	0.4	6.8	22.4	-3.5	8.4	-6.6	8.3	-9.5	7.1
$[-5,6]$	-13.7	-5.9	-16.3	-3.2	2.7	19.1	-3.9	8.7	-10.4	5.3	1.2	18.6
$[-5,7]$	-16.5	-7.6	-14.2	0.7	1.3	20.0	-6.0	8.3	-14.4	3.5	-0.7	19.1
$[-5,8]$	-22.6	-11.0	-23.0	-3.7	-5.7	18.5	-10.7	7.8	-18.4	4.7	-3.8	21.8
$[-5,9]$	-21.6	-10.7	-20.5	-2.4	-1.9	20.8	-11.0	6.3	-18.8	2.8	3.7	27.7
$[-5,10]$	-23.8	-11.6	-25.2	-4.8	-5.1	20.4	-13.7	5.7	-20.9	3.4	-1.9	25.1
Shutdown of the illegal data center (Cyber-bunker) (27 Sep 2019)												
$[-5,-5]$	0.4	1.1	-1.9	0.6	-1.8	1.0	-2.9	-0.7	0.4	2.3	-3.7	-0.7
$[-5,-4]$	-3.2	-1.5	-7.3^{*}	-1.4	-10.3^{**}	-3.7	-8.5^{*}	-3.3	-5.9	-1.3	-8.2^{*}	-1.1
$[-5,-3]$	-14.7^{**}	-10.0	-32.0^{**}	-15.4^{**}	-27.4^{**}	-9.0	-26.0^{**}	-11.2	-19.8^{**}	-7.2	-26.9^{**}	-7.1
$[-5,-2]$	-16.4^{**}	-12.1	-29.4^{**}	-14.3^{**}	-24.6^{**}	-8.0	-26.5^{**}	-13.2	-18.9^{**}	-7.5	-21.6^{**}	-3.8
$[-5,-1]$	-20.9^{**}	-16.1^{**}	-35.6^{**}	-18.8^{**}	-28.9^{**}	-10.2	-32.7^{**}	-17.8	-22.8^{**}	-10.0	-29.8^{**}	-9.8
$[-5,0]$	-19.4^{**}	-14.9	-33.2^{**}	-17.4^{**}	-27.9^{**}	-10.5	-29.6^{**}	-15.5	-22.2^{**}	-10.1	-22.7^{**}	-3.9
$[-5,1]$	-19.6^{**}	-14.9	-30.9^{**}	-14.3	-29.7^{**}	-11.3	-30.6^{**}	-15.8	-22.4^{*}	-9.7	-15.7^{*}	4.1
$[-5,2]$	-21.5^{**}	-16.3	-35.1^{**}	-16.9^{**}	-32.7^{**}	-12.5	-34.8^{**}	-18.6	-25.7^{**}	-11.8	-22.1^{**}	-0.4
$[-5,3]$	-19.3^{**}	-15.1	-32.2^{**}	-17.3^{**}	-30.1^{**}	-13.6	-33.2^{**}	-20.0	-24.6^{*}	-13.3	-20.7^{*}	-3.0
$[-5,4]$	-18.9^{**}	-14.1	-34.2^{**}	-17.3^{**}	-30.6^{**}	-12.0	-34.9^{**}	-19.9	-26.5^{*}	-13.6	-21.9^{*}	-1.9
$[-5,5]$	-18.4^{**}	-13.8	-34.2^{**}	-17.9^{**}	-30.4^{**}	-12.4	-35.2^{**}	-20.8	-26.2^{*}	-13.8	-22.4^{*}	-3.1
$[-5,6]$	-20.2^{**}	-14.8	-36.2^{**}	-17.5^{**}	-30.9^{**}	-10.2	-37.2^{**}	-20.6	-26.0^{*}	-11.7	-24.9^{*}	-2.7
$[-5,7]$	-21.0^{**}	-15.8	-36.4^{**}	-18.3^{**}	-30.9^{**}	-10.8	-38.0^{**}	-21.9	-23.6^{*}	-9.8	-25.3^{*}	-3.7
$[-5,8]$	-21.8^{**}	-16.4	-37.0^{**}	-18.1	-31.5^{**}	-10.5	-38.1^{**}	-21.3	-25.8^{*}	-11.3	-26.7^{*}	-4.2
$[-5,9]$	-23.9^{**}	-18.3	-37.4^{**}	-17.8	-34.6^{**}	-12.8	-39.1^{**}	-21.6	-27.7^{*}	-12.7	-29.1^{*}	-5.7
$[-5,10]$	-20.9^{**}	-16.2	-33.1^{**}	-16.9	-30.8^{**}	-12.9	-38.6^{**}	-24.2	-25.9^{*}	-13.5	-25.4^{*}	-6.1

** denotes statistical significance at the 1% level, * – at 5% level.

TABLE IV: Cumulative abnormal change rates (CAR_1 – mean-adjusted return model, CAR_2 – OLS)

for cryptocurrency research which is rooted in the lack of a good market model. Our approach to use Ethereum and Ripple as "neutral" baseline is limited to our application on law enforcement actions. Even there it may become less valid in the future as Ethereum gets more exposed to crime related to the so-called decentralized finance (DeFi) sector [54], and Ripple's price is allegedly manipulated [55]. Second, in contrast to the typical financial economics literature, our research has analyzed very few events due to the specifics of our research context. Third, this study is also susceptible to a common issue of imprecise information about the timing of an event, which can lead to an essential decrease in the power and reliability of standard event study methods [56]. In certain cases, the darknet marketplaces were shut down or their operation was suspended earlier than the public announcement, which certainly led to rumors and discussion threads on underground forums. Our future research question is therefore to compare the empirical results for the date of actual shutdowns to the date of the press release, and enrich the findings with data from underground forums. Likewise, it is of interest to test and compare the effects of shutdowns by law enforcement to other reasons for termination, such as exit scams.

In addition, there is room for improvement of the estimation method itself, given the volatility of cryptocurrency markets. Since cryptocurrency returns cannot be assumed to be independently and identically distributed, more advanced univariate forecasting models (e. g., exponential smoothing or stochastic time-series methods such as Autoregressive Integrated Moving Average models) need to be fitted to the historical data and evaluated in future work. For example, Chu et al. [57] provide the first GARCH modeling of the seven most popular cryptocurrencies and statistically confirm the extreme volatility of the time series. A different method, based on computing impulse responses of cryptocurrency prices proposed in [58], may offer an alternative to the standard event study methodology in this domain.

V. Conclusion

We have shown, to the best of our knowledge for the first time, that the effect of darknet market shutdowns by law enforcement are present and measurable in the exchange rates of popular cryptocurrencies. Although the number of events is still very limited and the signal is comparatively weak, the approach allows us to estimate the susceptibility of individual cryptocurrencies to criminal activity through the aggregate expectations of market participants. We have sketched many

Event period (m)	**Bitcoin**		**Bitcoin Cash**		**Litecoin**		**Dash**		**Monero**		**Zcash**	
	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2	CAR_1	CAR_2
Shutdown of the Berlusconi market											**(07 Nov 2019)**	
$[-5,-5]$	0.1	−0.3	2.9	2.4	−0.3	−0.7	0.4	0.1	1.7	1.4	−0.1	−0.5
$[-5,-4]$	−1.5	−0.2	2.4	4.2	−0.5	0.9	−1.1	−0.1	2.9	3.7	−2.0	−0.9
$[-5,-3]$	−0.2	−1.4	0.8	−0.9	4.2	2.8	0.7	−0.3	1.6	0.8	−0.3	−1.4
$[-5,-2]$	−1.6	−3.6	0.2	−2.7	6.7	4.4	2.7	1.1	0.7	−0.6	1.7	−0.1
$[-5,-1]$	−2.0	−6.0	3.3	−2.5	7.9	3.4	2.8	−0.3	2.0	−0.7	2.1	−1.4
$[-5,0]$	−3.6	−3.2	−2.1	−1.5	3.8	4.3	0.7	1.0	0.2	0.5	1.3	1.7
$[-5,1]$	−9.2	−4.5	−8.7	−1.9	1.3	6.6	−3.9	−0.2	−4.6	−1.4	−4.7	−0.6
$[-5,2]$	−9.7	−5.6	−8.2	−2.3	3.4	8.0	−3.9	−0.6	−3.1	−0.4	−4.2	−0.5
$[-5,3]$	−7.6	−4.5	−5.6	−1.2	6.1	9.6	−1.6	0.9	−1.1	1.0	−2.0	0.7
$[-5,4]$	−11.5	−6.0	−9.0	−1.1	2.8	8.9	−3.4	1.0	−4.8	−1.1	−4.7	0.2
$[-5,5]$	−11.5	−5.5	−9.5	−1.0	1.5	8.2	−3.5	1.3	−5.0	−1.0	−4.5	0.7
$[-5,6]$	−12.2	−6.5	−11.7	−3.5	0.9	7.2	−4.1	0.5	−0.7	3.1	−4.5	0.5
$[-5,7]$	−13.9	−6.8	−15.4	−5.1	−2.2	5.8	−5.4	0.3	−1.1	3.7	−5.6	0.7
$[-5,8]$	−17.0	−6.2	−21.9	−6.4	−5.2	6.9	−6.9	1.7	−7.2	0.0	−7.0	2.5
$[-5,9]$	−17.0	−7.2	−22.0	−7.9	−4.2	6.7	−6.8	1.1	−7.8	−1.3	−7.3	1.3
$[-5,10]$	−17.3	−8.0	−22.9	−9.5	−2.8	7.5	−7.0	0.4	−8.3	−2.1	−7.7	0.5
Shutdown of the Sipulimarket											**(11 Dec 2020)**	
$[-5,-5]$	0.0	−0.1	−2.2	−2.4	−1.2	−1.3	−2.7	−2.9	0.1	0.0	1.9	1.7
$[-5,-4]$	−1.8	−0.8	−4.2	−0.7	−2.8	−0.5	−5.1	−2.1	2.4	4.2	2.1	5.4
$[-5,-3]$	−7.3	−4.0	−11.2	0.3	−12.8	−5.0	−13.7	−4.1	−0.7	4.9	−6.0	4.5
$[-5,-2]$	−7.0	−3.9	−11.9	−1.0	−13.6	−6.3	−15.0	−5.8	−3.8	1.5	−7.8	2.1
$[-5,-1]$	−9.6	−5.2	−14.1	0.9	−18.6	−8.6	−19.4	−6.9	−3.7	3.6	−12.7	1.0
$[-5,0]$	−11.7	−5.9	−17.8	2.3	−24.0	−10.5	−21.1	−4.3	1.2	11.0	−16.0	2.4
$[-5,1]$	−8.5	−1.7	−15.7	8.0	−19.3	−3.4	−21.5	−1.7	4.0	15.6	−15.4	6.3
$[-5,2]$	−7.7	−0.7	−14.0	10.3	−14.1	2.2	−20.6	−0.2	6.6	18.6	−14.3	8.0
$[-5,3]$	−8.2	−0.1	−14.8	13.3	−15.4	3.4	−23.3	0.1	6.3	20.0	−15.3	10.4
$[-5,4]$	−8.3	1.1	−11.7	20.7	−18.3	3.5	−24.9	2.1	4.4	20.2	−15.0	14.7
$[-5,5]$	0.5	7.3	−4.9	18.9	−6.0	9.9	−18.7	1.1	8.6	20.2	−11.2	10.5
$[-5,6]$	6.5	13.8	−6.4	18.8	1.1	18.0	−17.3	3.8	8.7	21.1	−7.2	15.9
$[-5,7]$	7.0	14.6	−6.8	19.7	7.7	25.5	−19.5	2.6	4.5	17.5	−8.6	15.6
$[-5,8]$	9.2	17.5	−6.2	22.7	16.2	35.7	−21.0	3.1	3.8	18.0	−9.9	16.6
$[-5,9]$	6.5	16.4	2.0	36.1**	9.6	32.5	−22.0	6.5	1.3	18.0	−11.1	20.1
$[-5,10]$	2.7	14.5	−8.8	32.1**	−0.5	27.0	−28.6	5.6	−3.6	16.4	−20.6	16.8
Shutdown of the DarkMarket											**(12 Jan 2021)**	
$[-5,-5]$	4.4	2.8	−3.3	−12.5	−2.5	−10.4	5.8	−0.2	1.0	0.5	9.6	1.1
$[-5,-4]$	5.6	4.0	−7.3	−16.2	−3.2	−10.8	3.8	−2.1	1.1	0.6	10.7	2.6
$[-5,-3]$	1.8	−0.1	20.6	10.1	−3.6	−12.6	18.2*	11.3	5.1	4.5	24.6*	14.9
$[-5,-2]$	−5.4	−7.1	23.6	14.4	−10.1	−17.9	53.6**	47.6**	31.0**	30.5**	49.0**	40.5**
$[-5,-1]$	−15.2*	−15.6	0.9	−1.4	−31.6*	−33.5	38.2**	36.7**	17.2	17.0	41.0**	38.9**
$[-5,0]$	−22.3*	−22.5**	−7.4	−8.7	−39.2*	−40.2**	41.3**	40.5**	17.1	17.1	54.3**	53.1**
$[-5,1]$	−14.8	−15.7	0.5	−4.5	−30.9	−35.1	46.0**	42.7**	26.5*	26.2	73.1**	68.4**
$[-5,2]$	−12.3	−13.4	4.5	−1.8	−30.6	−35.9	46.2**	42.1**	21.9	21.6	67.4**	61.6**
$[-5,3]$	−20.8*	−21.4	−4.1	−7.6	−38.6*	−41.6	40.6**	38.3**	18.9	18.7	61.9**	58.7**
$[-5,4]$	−25.0*	−25.9	−6.6	−11.6	−41.4*	−45.6	41.9**	38.6**	18.4	18.1	68.3**	63.7**
$[-5,5]$	−28.6*	−29.4	−11.3	−15.8	−45.5*	−49.4	40.8*	37.9**	21.2	21.0	62.1**	57.9**
$[-5,6]$	−28.7*	−29.8	−6.9	−12.7	−41.6	−46.5	46.1**	42.3**	20.0	19.7	65.3**	59.9**
$[-5,7]$	−32.7*	−34.5**	−8.9	−18.5	−43.6	−51.7	43.5*	37.2**	20.9	20.4	65.8**	56.9**
$[-5,8]$	−36.7**	−38.4**	−13.4	−23.2	−48.7*	−57.1	40.9*	34.5	18.5	18.0	59.1*	50.0**
$[-5,9]$	−52.4**	−52.7**	−31.5	−32.9	−64.8*	−65.9**	24.1	23.2	4.0	4.0	47.9*	46.7**
$[-5,10]$	−47.8**	−48.7**	−28.5	−33.2	−62.2*	−66.2**	29.7	26.6	8.8	8.5	51.3*	46.9**

** denotes statistical significance at the 1% level, * – at 5% level.

TABLE V: Cumulative abnormal change rates (CAR_1 – mean-adjusted return model, CAR_2 – OLS)

avenues for future interpretation of the causal links behind the observed effects.

Acknowledgment

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Law enforcement action	Date	Traceable coins			Privacy coins		
		Bitcoin	Bitcoin Cash	Litecoin	Dash	Monero	Zcash
Closure of darknet marketplaces							
Silk Road	01 Oct 2013	–		–			
Operation Onymous	06 Nov 2014	↗		–	–	↗	
AlphaBay and Hansa	20 Jul 2017	↗		–	–	↗	↗
Wall Street Market	03 May 2019	↗	↗	↗	↗	⊘	⊘
DeepDotWeb	08 May 2019	↗	↗	⊘	⊘	⊘	⊘
Berlusconi	07 Nov 2019	–	↗	–	–	–	–
Sipulimarket	11 Dec 2020	–	–	–	–	–	–
DarkMarket	12 Jan 2021	↘	–	↘	↗	–	↗
Other actions							
Bestmixer.io	22 May 2019	–	–	–	–	–	–
Cyber-bunker	27 Sep 2019	↘	↘	↘	↘	↘	↘

↗ significant positive effect, ↘ significant negative effect, ⊘ inconsistent effect between the models, – no effect, *(empty)* not applicable. Accepted cryptocurrencies are highlighted in gray.

TABLE VI: Summary of the effects of LE actions on cryptocurrency market prices

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