**The Dark Web and Cannabis Use in the United States:
Evidence from a Big Data Research Design**

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Key Words: Dark Web; Cryptomarkets; Cannabis; Silk Road; Google Trends;
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Abstract (319):

Background: Cannabis is the most commonly sold drug on cryptomarkets. Because of the anonymity-granting functions of Tor, no study has traced the within-country effect of the Dark Web on cannabis consumption patterns. This article uses a big data research design to examine the association between revealed interest in the Dark Web and self-reported cannabis use within US states from 2011 when Silk Road launched to 2015 when Operation Onymous shuttered nine markets.

Methods: This study uses mixed effects ordinary least squared regressions to analyse U.S. state/year panel data, using robust standard errors to correct for heteroscedasticity. Marginal effect plots illustrate substantive effects. The dataset consists of state-level variables drawn from the Uniform Crime Report (UCR), the American Community Survey (ACS), the National Survey on Drug Use and Health, the Correlates of State Policy Project, and the Bureau of Justice Statistics Justice Expenditure and Employment Extracts. Data for the Dark Web interest measure are drawn from Google Trends. The proxy for Dark Web interest is an index of eight Dark Web related search terms.

Results: The regression analysis indicates that Dark Web interest in US states positively correlates with cannabis consumption rates overall and among older adults (26+), but not youth (12-17) or younger adults (18-25). Additionally, Dark Web interest is positively associated with more frequent cannabis usage rates (use in the past month, but not in the past year) overall and among older adults, but not among youth or younger adults. Interacting Dark Web interest with state-level legalization regimes indicates that the association between Dark Web interest and cannabis consumption in the past year is no different in medically legalized states and amplified in states with recreational legalization. Lastly, the Dark Web interest term does not correlate with first time cannabis either overall or for any age category.

Conclusions: Interest in the Dark Web is associated with increased cannabis use in U.S. states from 2011-2015, but the effect is concentrated in states with more frequent cannabis users, older users, and in states with recreational legalization of cannabis.

Introduction

Cannabis is one of the most commonly used illicit substances both globally and in the United States (Hawdon, 2005; McCance-Katz, 2017; A. Winstock et al., 2019; A. R. Winstock, Barratt, Maier, & Ferris, 2018). Dark Web cryptomarkets have facilitated the anonymous sale of cannabis since the early 2010s, lowering barriers to access and posing new challenges for law enforcement (Jardine, 2015; Martin, 2014b). In this paper, we explore whether interest in the Dark Web is associated with increased cannabis use within US states. Due to the anonymity functions of The Onion Router (Tor), the most common Dark Web platform, directly observing Dark Web usage within a country is largely impossible (Dingledine, Mathewson, & Syverson, 2004). In place of direct observation of state-level Dark Web usage rates, we employ a big data research design leveraging Google Trends data to estimate state-year levels of interest in a Dark Web index variable. Using a series of mixed effects ordinary least square panel estimations with robust standard errors, we show that interest in the Dark Web is associated with four distinct trends in self-reported cannabis use at a state level within the United States.

- 1) Dark Web interest correlates positively with cannabis use within the past year for the whole sample (those aged 12 or older), but does not matter equally across all age subsets;
- 2) Dark Web interest correlates positively with more frequent cannabis usage (use within the past month), but does not correlate with the more casual use of cannabis in the past year;
- 3) Interaction models suggest that the correlation between Dark Web interest and cannabis consumption in the past year is even stronger in states with recreationally legalized cannabis, but exhibits no statistically significant differences in states with medical legalization;
- 4) Dark Web interest does not correlate with first-time use of cannabis, a pattern which suggests the Dark Web may not be a powerful direct gateway technology for drug use.

Related Literature

Cannabis is one of the most commonly sold illicit substances on cryptomarkets (Christin, 2013; Dolliver, 2015; Martin, 2014b; Soska & Christin, 2015). On the Agora marketplace, for example, 24.4% of all product listings were for cannabis. Within the United States, cannabis listings account for an average of 44.2% of listings among putatively US-based Agora cryptomarket vendors (Van Buskirk, Naicker, Roxburgh, Bruno, & Burns, 2016). The general prevalence of cannabis on cryptomarkets mirrors use both globally (A. R. Winstock et al., 2018) and within the US (Hawdon, 2005). Indeed, according to the 2017 National Survey on Drug Use and Health, over 15% of the US population—or some 40.9 million people aged 12 or older—used marijuana in the past year (McCance-Katz, 2017).

Cryptomarkets potentially alter cannabis consumption patterns in a number of ways. First, cryptomarkets can reduce geographical barriers to obtaining drugs (Broséus, Rhumorbarbe,

Morelato, Staehli, & Rossy, 2017; Dolliver, Ericson, & Love, 2018; Norbutas, 2018; Van Buskirk et al., 2016). Additionally, they can potentially minimize the harm from drug consumption (Aldridge, Stevens, & Barratt, 2018; Barratt, Lenton, Maddox, & Allen, 2016) and reduce drug market violence (Barratt, Ferris, & Winstock, 2016), all while providing consumers with heightened security (Hout & Bingham, 2013a, 2013b; Jardine & Lindner, 2019; Van Hout & Bingham, 2014).

These effects make cryptomarkets a tempting tool for potential drug users, leading to greater usage rates over time. The 2019 Global Drug Survey, for example, shows that at its peak in 2018 some 18.1% of respondents who purchased drugs in the United States in the past year indicated that they used cryptomarkets to secure illicit substances during that period (A. Winstock et al., 2019). This total represents an increase of nine percentage points from 2015. These changes are particularly noteworthy because the Dark Web has grown in popularity even as over half of the US states have legalized medical cannabis and, since 2011, nine states have legalized recreational weed. These regulatory changes have expanded access to cannabis, yet sales of marijuana on cryptomarkets continues to grow year over year (Christin, 2013; Soska & Christin, 2015).

Despite indicators that the Dark Web is playing an increasingly large role in the distribution of marijuana in the U.S., less is known about the overall magnitude of the association between the Dark Web and cannabis use within a country, how the Dark Web may facilitate infrequent and/or more regular cannabis usage, how these consumption patterns vary across age subsets, and whether the Dark Web’s potential association with cannabis usage might vary based upon state-level legalization regimes.

Data and Methods

Data

Past research has been largely unable to trace macro effects of the Dark Web on cannabis use within a country due to the anonymity-granting features of Tor, which minimize if not eliminate the ability to pinpoint where users of cryptomarkets are actually located (Dingledine et al., 2004). Ideally, a measure of cryptomarket use by location would provide the best estimation of potential effects. Barring that, a measure of use of the Tor network by geographical location would be the next best data type. Unfortunately, neither measure is immediately possible given the anonymization effects of Tor. Data on Tor network clients is made publicly available by the Tor Project, but only at the national level (Project, 2018). These data have been leveraged to investigate the association between political repression and Tor usage rates (Jardine, 2018b) and could be used to assess national-level drug trends either within a country over time or cross-nationally. Yet similar data over more fine-grained spatial units are not available, as smaller territorial blocks, especially in areas with sparse use of the Dark Web, would effectively de-anonymize the users of Tor and negate the whole point of the system.

To overcome this data limitation, we use Google Trends search query data to capture a US state-year level of interest in a Dark Web index variable. Google Trends provides population normalized search popularity data on a per-query basis. For each new query, the time or place with peak popularity for that search term is given a value of 100. All other values are reported as percentages of that level of interest. For example, a state with a value of 15 on the search term “Tor” has fifteen percent of the search popularity for that term at the peak.

The data for this project were drawn from Google Trends for the time period from 2011 to 2015. Over this period, Google Trends only provides data at a monthly level. Data were then aggregated from months into years. Following methods used in past research with Google Trends data, all state-year estimates have been standardized to represent search popularity as a proportion of the peak across all states for the full time range of the data, which was in Kansas in 2015 (DiGrazia, 2017). This procedure corrects for the changing underlying absolute value of, say, a 15 on the Google Trends data over time. The Dark Web index variable used in this study consists of eight generic search terms and topics drawn from Google Trends in a joint query: “darknet,” “dark net,” “dark net” (the topic), “darkweb,” “dark web,” “dark web” (the topic), “tor,” and “tor” (the topic). These eight terms provide wide coverage of general searches related to the Dark Web and the technology used to access the system.

Term selection is an important feature of all research designs using Google Trends (Mavragani, Ochoa, & Tsagarakis, 2018; Nuti et al., 2014; Stephens-Davidowitz, 2018). Big data do not invalidate basic concerns over construct validity (Boyd & Crawford, 2012; Lazer, Kennedy, King, & Vespignani, 2014). Picking the wrong terms can lead to, at a minimum, model overfitting and spurious correlations. In this case, selected terms need to approximate interest in potentially using the Dark Web, in general, and cryptomarkets, in particular, to procure cannabis. Two sets of terms could theoretically work in this regard: generic terms related to the Dark Web and cryptomarket specific terms.

The generic Dark Web index term employed in this study is likely a better measure of interest in the Dark Web than more cryptomarket-specific terms such as “Silk Road” or “Agora.” First, the cryptomarket terms are noisier than the general terms. For example, a Google search for Silk Road could be for the cryptomarket, but it could also be for the historical trade route. Searching “Silk Road” in Google returns a first page of results with only references to the historical trade route. In contrast, a search for the term “Dark Web” returns a first page including only stories related to the Dark Web.

Second, searches for cryptomarket specific terms are quite temporally dependent. Law enforcement raids, exit scams, hacks, and voluntary closures create a highly transient cryptomarket ecosystem. During the sample period from 2011 and 2015, for example, there were 53 cryptomarket closures of various types (EMCDDA, 2017). However, searches for Silk Road in 2015, two years after its

closure, would still return a series of results, but the site itself would not be an active and available cryptomarket. In contrast, while specific cryptomarkets come and go, generic terms such as “Dark Web” or “Tor” remain core features of the Dark Web lexicon, providing better longitudinal coverage of interest in the technology.

Third, those who are interested in using the Dark Web and cryptomarkets might undertake an initial period of discovery using generic terms, but then transition to using the anonymizing Tor browser to complete their hunt for specific cryptomarket names, how to guides, and .onion addresses. This substitution would systematically bias the cryptomarket search terms extracted from Google Trends away from an accurate measure of interest in the Dark Web and cryptomarkets.

Finally, aspects of the generic index term employed in this study are an essential prerequisite of use of the Dark Web, while cryptomarket terms are not. Tor-hosted hidden services cannot be accessed by normal browsers and require the use of the Tor browser, which is downloadable from the Tor Project website. While searches for cryptomarket-specific terms might reveal some degree of interest in particular cryptomarkets, they do not indicate if people are searching for the technologies they need to actually access the Dark Web. In contrast, searches for “Tor” are more directly connected to searches for the anonymity-granting platform that provides actual access to the Dark Web, making the terms a better potential representation of interest in the potential use of the Dark Web. Of course, interest in the Dark Web or Tor does not necessarily imply that those searching for these terms are necessarily seeking out drug cryptomarkets, as a number of other factors from individual level preferences toward privacy (Jardine, 2018a) and structural features at a US state-level (Lindner & Xiao, 2018) all influence support for the Dark Web and interest in the technology.

Google Trends has been used effectively in a number of research settings (Mavragani et al., 2018; Nuti et al., 2014). While not without its limitations (Lazer et al., 2014), Google Trends data has effectively modeled a number of health and drug-use related issues, including suicide rates in the United States (Ma-Kellams, Or, Baek, & Kawachi, 2016; Nuti et al., 2014), the flu (Eysenbach, 2006; Ginsberg et al., 2008), and Lyme disease (Seifter, Schwarzwald, Geis, & Aucott, 2010). Moreover, Google Trends data accurately predict emergent use of novel psychoactive drugs within the United States (Perdue, Hawdon, & Thames, 2018), which suggests that query data can predict usage of drugs in some cases.

[Table 1 here]

This study makes use of four dependent variables (DVs) related to the frequency of cannabis use within U.S. states. These variables are taken from the National Surveys on Drug Use and Health, 2011-2015. Table 1 provides descriptive statistics for both the overall sample and means for each year to capture the longitudinal trends in the data. The four DVs are:

- 1) *Use in the past year*: This DV is a self-reported measure of overall cannabis use in the past year per 100,000 people;
- 2) *Use in the past month*: This DV is a self-reported measure of cannabis use in the past month per 100,000 people, minus first time users;
- 3) *Infrequent use*: this DV is calculated by subtracting the number of users of cannabis in the past month from the ‘use in the past year’ measure, leaving the rate per 100,000 people who used cannabis in the past year but not the past month;
- 4) *First use*: this DV measures the rate per 100,000 people who used cannabis for the first time during the past year.

[Figure 1.1 and 1.2 here]

Figures 1.1 and 1.2 plot the longitudinal trends for both the Dark Web interest variable and the cannabis use in the past year (12+) dependent variable. The Dark Web interest variable (Figure 1.1) is generally increasing over time, particularly from 2013 onwards. These time trends are also visible in the subsequent regression models, where there are several statistically significant temporal effects. There is also considerable state-level variation in this trend, especially prior to 2014. Past year cannabis consumption levels for whole sample (Figure 1.2) also exhibits a positive trajectory, but at a modest overall rate and with considerable and persistent cross-state variation.

We also include in the models a series of state-level demographic controls. These variables include: the percentage of the population that is over 35 years of age, percentage college educated, percentage African-American, income inequality (as measured by the state-level Gini coefficient), median household income, two measures of state level political ideology, drug arrest rates and the percentage of the state’s budget spent on policing. We also include two dummy variables representing the state-level legalization regime, including legalization of both medical cannabis and recreational use. These factors were chosen as they represent a number of structural features at a state-level that might correlate with cannabis use.

The socio-demographic measures are 1-Year estimates drawn from the American Community Survey (for complete measurement information see: <https://www.census.gov/programs-surveys/acs>), while the measures of drug arrests, state political ideology, and policing budget are drawn from the Uniform Crime Report (UCR), Correlates of State Policy Project, and the Bureau of Justice Statistics Justice Expenditure and Employment Extracts (BJS JEEE), respectively. The drug legalization measures were coded by the authors based on a report by Third Way (See: <https://www.thirdway.org/report/americas-marijuana-evolution>).

In total, the data consist of 250 observations across 50 states from 2011 (when Silk Road launched the modern-day cryptomarket (Barratt, 2012; Barratt & Aldridge, 2016; Martin, 2014a, 2014b)) and the end of 2015, when Operation Onymous temporarily upset the cryptomarket ecosystem by taking down nine separate platforms (Décary-Héту & Giommoni, 2017).

Methodology

To analyze the data, we perform a series of mixed effects ordinary least squared regressions with robust standard errors to correct for heteroscedasticity in the statistical package Stata 15. Each model controls for the state-level variables mentioned in the previous section in order to isolate for the significance and effect size of the Dark Web interest index variable. Test parameters calculated by Stata 15 also indicated the need to include time dummy variables in order to correct for temporal trends. We present the results of some models graphically with coefficient plots to ease interpretation. To estimate potential substantive effects, we provide marginal plot graphs for the observed range of the Dark Web interest variable.

Overall, we estimate four potential relationships between the Dark Web interest variable and cannabis consumption patterns within U.S. states. First, we model the relationship between Dark Web interest and general cannabis use, segregated by age subsets. Second, we estimate contrasting models of cannabis usage in the past month and infrequent use. Third, we interact the Dark Web interest variable with state-level legalization regimes to look for conditional effects on use in the past year. Finally, we specify the potential correlation between the Dark Web interest variable and first time cannabis use both overall and by age bracket.

Results

Overall, interest in the Dark Web correlates with an increase in declared cannabis use in the past year overall, but only among older adults (26+) and not youth (12-17) or young adults (18-25) (finding 1). Dark Web interest predicts cannabis usage rates in the past month both overall and among older (26+) adults, but does not correlate with use in the past month by youth (12-17) or younger adults (18-25) or with infrequent cannabis usage rates in any age subset (finding 2). The correlation between Dark Web interest and use of cannabis in the past year is even more pronounced in recreationally legalized states, but no different in medically legalized ones (finding 3). Lastly, interest in the Dark Web fails to predict first-time use of cannabis (finding 4).

[Table 2 here]

Table 2 presents four models estimating the correlation between the Dark Web interest variable and state-level cannabis use in the past year. For the whole sample (Model 1), the effect is positive and significant (95% CI: 7.80–36.90; $p = 0.003$) for those aged 12+. Disaggregating the results by age subset paints a more nuanced picture. The Dark Web interest variable is not significant (95% CI: -1.43–3.00; $p = 0.488$) for youth aged 12-17 (Model 2) or young adults aged 18-25 (95% CI: -1.86–7.05; $p = 0.254$) (Model 3). The Dark Web interest variable correlates highly (95% CI: 8.11–30.22; $p = 0.001$) with use of cannabis among those who are 26 years or older (Model 4).

[Figures 2.1 to 2.2 here]

Figures 2.1 and 2.2 present two margin effect estimations for Models 1 and 4. The figures plot the substantive effect of the Dark Web interest variable on overall past year cannabis consumption rates across the observed range of the Dark Web variable (i.e. 12.50-100) for both the whole sample (Figure 2.1) and those aged 26+ (Figure 2.2). Movement from the smallest to the largest observed value results in a predicted increase in cannabis users of 20.7% (9,718 to 11,730 per 100,000 people) for the whole sample and a 32.6% increase (5,293 to 7,018 per 100,000 people) for the 26+ age subset.

By way of comparison, the substantive effect size of the Dark Web interest variable across the observed range is comparable to the effect of state-level recreational legalization of cannabis. For example, Model 1 in Table 2 suggests that states with recreational legalization have 2,107 more cannabis users in the past year per 100,000 people than states without legalized cannabis. Movement from the minimum to the maximum of the observed range in the Dark Web interest variable (Figure 2.1) results in a predicted increase of 2,011 cannabis users per 100,000 people. While regulatory regime change has a far larger effect over a one-unit change, the Dark Web interest variable can also be interpreted across its full range as having a meaningfully comparable effect on cannabis consumption as something as wide ranging as recreational legalization.

[Figure 3 here]

Figure 3 presents a coefficient plot of eight models contrasting the correlation between increased Dark Web interest on both infrequent use of cannabis (last year but not last month) and use in the past month (minus first time users), including controls for the same factors as found in Models 1-4 and broken down across both the whole sample (12+) and the three available age subsets. Uniformly, the Dark Web interest variable fails to predict change in cannabis usage rates among infrequent users for either the whole sample (95% CI: -3.75–14.37; $p = 0.25$) or the 12-17 (95% CI: -1.56–1.35; $p = 0.890$), 18-25 (95% CI: -2.89–4.53; $p = 0.665$), or 26+ (95% CI: -1.62–11.55; $p = 0.139$) brackets. However, mirroring the overall results, greater Dark Web interest does positively correlate with increased use of cannabis in the past month both for the whole sample (95% CI: 8.20–31.61; $p = 0.001$) and for older adults aged 26+ (95% CI: 7.69–25.06; $p = 0.000$). As with the overall results for cannabis use in the last year, the Dark Web interest variable does not correlate with more frequent consumption among youth (CI: -0.060–2.63; $p=0.061$) or young adults aged 18-25 (CI: -2.36–6.04; $p=0.390$).

[Figures 4.1 & 4.2 here]

Figures 4.1 and 4.2 plot the predicted marginal effects when the Dark Web interest variable moves from the observed minimum to the maximum for past month cannabis users for both the whole sample (12+) and older adults (26+). For the whole sample, moving from the minimum to the maximum value on the Dark Web interest variable results in a 37.6% predicted increase in the rate of past month cannabis use (4,769 to 6,561 per 100,000 people). Similar movement across the

observed range of the Dark Web interest variable for the 26+ age subset results in a predicted increase in past month cannabis users of 48.4% (3,047 to 4,521 per 100,000 people).

[[Figure 5.1-5.2 here](#)]

Figures 5.1 and 5.2 depict the marginal effect plots for two models interacting the Dark Web interest variable with both state-level recreational (Figure 5.1) and medical legalization (Figure 5.2) to predict cannabis usage rates in the past year for the whole sample (12+). There are no statistically significant differences in the Dark Web variable's association with cannabis use in the past year in medically legalized states compared to other states. However, again when compared to other states, the Dark Web interest variable is even more strongly correlated with cannabis use in the past year in states with recreational legalization of cannabis, particularly at the highest levels of demonstrated interest.

[[Table 3 here](#)]

Lastly, Table 3 presents four models to assess the relationship between increased Dark Web interest and first time cannabis use. The Dark Web interest variable is not a significant predictor of first time use overall or among any age subset.

Discussion

The results suggest that greater interest in the Dark Web within US states during the 2011-2015 period correlates with overall cannabis consumption rates, controlling for other state-level factors that likely drive variation in the use of drugs. However, the emerging story is not one of simple linear effects. More interest in the Dark Web does not unequivocally lead to greater cannabis use. Instead, the emergent relationships are highly sensitive to age, consumption pattern, and policy regime effects. Generally, the results suggest that interest in the Dark Web correlates with use of cannabis overall (12+) and among older adults (26+) in the past year, but not with cannabis consumption among youth (12-17) or young adults (18-25). Likewise, the evidence suggests that interest in the Dark Web correlates with more frequent (past month) cannabis usage, again both overall and for those aged 26+. Interest in the Dark Web does not correlate, however, with past month use among youth or younger adults, nor more infrequent use of cannabis. The correlation between interest in the Dark Web and cannabis consumption in the past year is even more pronounced in states with recreational legalization, but is not statistically different in states allowing medical usage. Lastly, the results provide little support for the idea that the Dark Web might be acting as a direct gateway technology for new cannabis users, although its indirect effects may still be quite pronounced.

The finding that increased Dark Web interest is associated with higher cannabis consumption overall is consistent with the results of the Global Drug Survey. According to the 2019 GDS, from 2015 to 2019, among those respondents who do purchase drugs from the Darknet, the proportion

of respondents securing cannabis rose from 38.3% to 51.6%, making it the third most commonly purchased drug (A. Winstock et al., 2019). Yet, the current results provide additional context to these global survey results. Interest in the Dark Web does correlate positively with overall cannabis consumption rates within US states over the past year, but does not do so equally across all demographic brackets. Dark Web interest does not tend to be associated with cannabis consumption within the past year among youth (12-17) or young adults (18-25). Plausibly, this result emerges due to the interaction of two mechanisms that are not directly tested here. First, the cryptomarket crime script involves at least two steps—funding a cryptocurrency wallet and providing a vendor with a secure physical address for shipping—that are far harder for youth to complete (Jardine & Lindner, 2019). Secondly, youth and young adults tend to be more deeply enmeshed in wide social networks, making access to illicit substances through more traditional peer-based channels comparatively easy (Hawdon, 2005). In contrast, adults who are older than typical US college age (26+) likely have an easier time completing the cryptomarket script and are, on average, less enmeshed in wide social networks, leading to greater cryptomarket use as a source for cannabis.

The results also suggest that Dark Web cryptomarkets are not a tool of casual drug procurement and infrequent use in any age range. Instead, greater interest in the Dark Web positively correlates with comparatively high volume (i.e. use in the last month) cannabis use. This result is intuitive in light of the asynchronic nature of cryptomarket transactions. To secure the purchase of cannabis on a Dark Web market such as Silk Road, Agora, AlphaBay or Dream Market (Aldridge & Décary-Héту, 2014; Barratt, Ferris, & Winstock, 2014; Dolliver, 2015; Hout & Bingham, 2013a, 2013b; Martin, 2014b; Phelps & Watt, 2014; Van Hout & Bingham, 2014), users need to select a product listing, assess the vendor’s reputation, confirm the purchase, transfer funds into escrow, and then wait for the vendor to securely package and mail the product. Often, the chosen illicit substance may even travel across national borders (Barratt et al., 2014; Broséus et al., 2017; Dolliver et al., 2018; Norbutas, 2018; Van Buskirk et al., 2016). Assuming the product is shipped and not intercepted in transit, this process takes time, making the Dark Web a poor avenue of casual and spontaneous drug use. In contrast, older, high volume consumers who either have the intention of consuming large quantities of cannabis over prolonged durations or wish to distribute locally can source significant supply with relatively low risk to themselves.

In recent years, many US states have legalized cannabis for either medical or recreational usage. Interacting the Dark Web interest variable with each state’s overarching policy environment indicates that medical legalization does not statistically alter the association of between the Dark Web interest variable and cannabis usage rates. However, recreational legalization actually amplifies the Dark Web interest variable’s correlation with yearly cannabis consumption rates. A part of this finding may be due to a selection effect issue, wherein high cannabis consumption states are both more likely to have high levels of interest in the Dark Web and legalized

recreational use of the illicit substance. However, the Dark Web might also be acting as an alternative sourcing technology in states that have legalized recreational use of cannabis, particularly where adequate retail infrastructure is not yet in place or purchasing caps are set too low. California, for example, recently legalized recreational cannabis use, but upwards of 80 percent of the state’s municipalities still do not allow retail shops, limiting local supply infrastructure (Fuller, 2019). Dark Web cryptomarkets tend to provide increased convenience of access, greater perceptions of safety, and higher quality drugs than street purchases (Aldridge et al., 2018; Barratt, Ferris, et al., 2016; Hout & Bingham, 2013a, 2013b; Maddox, Barratt, Allen, & Lenton, 2016; Van Hout & Bingham, 2014). In states with legalized recreational use but insufficient supply infrastructure to meet demand, the Dark Web can, then, become an even more pronounced tool of cannabis procurement. A permissive legal environment, therefore, may not decrease the utility of the Dark Web as a source for cannabis, but actually encourage its use to satisfy potentially diverse brand demand in a convenient way. Further investigation of this potential amplification effect is warranted.

Lastly, the evidence suggests that interest in the Dark Web is not correlated with new direct ‘gateway’ use of cannabis. The 2019 Global Drug Survey indicates that the proportion of respondents who both use the Darknet to buy drugs and did not previously use drugs before purchasing them from a cryptomarket is relatively constant over time, ranging from 4.5% in 2015 to 5% in 2019 (A. Winstock et al., 2019). Even these small proportions are somewhat at variance with the current findings. However, it is plausible that this roughly 5% of new drug users is not evenly spread across all drug types and might cluster in substance classifications that are harder to procure locally. If this were the case, then the Dark Web could play an important drug diffusing role across geography (Demant, Munksgaard, Décary-Hétu, & Aldridge, 2018; Dolliver, 2015; Dolliver et al., 2018; Van Buskirk et al., 2016), but not act as a particularly powerful gateway technology for more socially ubiquitous drugs such as cannabis within the United States.

However, while the current results suggest that the Dark Web is potentially not acting as a direct gateway tool for first time cannabis use in the United States, the indirect gateway effects of cryptomarkets on new users may still be significant. For example, Silk Road marketplace, which was the primary cryptomarket for much of our observed time range, did act as a considerable source of wholesale supply (Aldridge & Décary-Hétu, 2014, 2016). Wholesale volumes on Silk Road varied across drug type. Yet cannabis was the second most commonly purchased wholesale drug (behind ecstasy), with 24% of monthly sales crossing a \$1,000 wholesale threshold and upwards of \$482,126 in monthly wholesale revenue overall (Aldridge & Décary-Hétu, 2016). Additionally, some 5% of all drug listing for the United States were for wholesale items (>\$1,000), making up some 24% of the estimated market share (Aldridge & Décary-Hétu, 2016). These wholesale results suggest that cryptomarkets likely do act as an indirect gateway technology by facilitating wholesale purchases of cannabis and local redistribution within the United States.

Limitations

As with all studies, the current investigation into the correlation between interest in the Dark Web and cannabis consumption within US states has a number of limitations.

One such limitation involves questions of causal direction. While increased Dark Web interest might lead to more cannabis consumption, as modeled here, it is also possible that increases in cannabis consumption (or at least the culture that surrounds such activities) may lead to a greater interest in the Dark Web. Both causal directions have some analytical merit. However, it is plausible that the underlying causal story in this case is one where increased Dark Web interest corresponds with perceptions of weakened deterrent effects, mixed with increased convenience and perceptions of safety when using cryptomarkets to secure cannabis (Barratt, Ferris, et al., 2016; Jardine & Lindner, 2019). Combined these perceptions could link Dark Web interest with increases in cannabis consumption, rather than the other way around.

Second, the use of Google Trends data, while needed given the lack of better measures to study geographically specific uses of the Dark Web, also introduces potential concerns over construct validity, overfitting, and spurious correlation (Boyd & Crawford, 2012; Lazer et al., 2014). While the terms used in the Dark Web interest variable were carefully selected to best represent interest in the potential use of the Dark Web, there is still the possibility that these measures only partially correlate at a subnational level with actual usage of the Dark Web in general or cryptomarkets in particular for the 2011-2015 period.

Third, the Dark Web has a wide variety of functions, many of which do not involve drugs at all and are in fact not even illegal within the United States. Categorizations of available Darknet .onion hidden services have consistently found large volumes of legal content on the Tor-hosted Dark Web (Faizan & Khan, 2019; Moore & Rid, 2016; Owen & Savage, 2015), which also mirrors studies of single Dark Web social networking sites (Gehl, 2016, 2018). Indeed, increased political repression correlates with actual Tor usage rates at a national level, suggesting that the Dark Web is a powerful tool of rights-based expression (Jardine, 2018b). These additional functions indicate that the generic Dark Web terms might be capturing some noise related to non-drug consumption functions.

Conclusion

This study explored how demonstrated interest in the Dark Web relates to cannabis usage rates among US states from 2011-2015. The results indicate that increased Dark Web interest correlates positively with greater cannabis use overall, but the effect is not consistent across all age brackets. Interest in the Dark Web correlates with past month cannabis usage rates but not more infrequent use. The correlation between increased Dark Web interest and yearly cannabis consumption rates is more pronounced in states with recreational legalization, but not states with medical

legalization. Lastly, Dark Web interest does not correlate with first time use of cannabis both overall and for any age subset.

The results raise a number of interesting points for further study. First, the results suggest that the age of cannabis users and offline social networks are potentially interacting with the Dark Web as a procurement technology, leading to more frequent cannabis consumption among older adults and not youth or college age individuals. The nature of the cryptomarket crime script and individual embeddedness in social networks might help to explain these trends, but more work is needed. Likewise, the reasons why recreational legalization regimes seem to amplify the association between Dark Web interest and cannabis consumption rates needs to be explored in more detail.

Overall, these results have interesting implications for health and drug control policy, suggesting that the Dark Web as a tool of drug consumption (at least for cannabis) is potentially variable depending on a) the age of the potential users; b) the potential usage pattern of the illicit substance; and c) the overarching legalization regime that is in place.

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Tables and Figures

Table 1. Descriptive Statistics Across 50 States

Measure	Mean	SD	Min	Max	2011 Mean	2012 Mean	2013 Mean	2014 Mean	2015 Mean
Past Year Cannabis Use, 12+	10701.873	2833.883	5998.817	19287.264	10059.580	10242.440	10423.140	11331.000	11453.200
Past Year Cannabis Use, 12-17	1058.276	185.021	691.187	1596.345	1122.447	1094.354	1066.770	1011.738	996.070
Past Year Cannabis Use, 18-25	3503.584	698.145	2413.725	5802.329	3462.613	3469.796	3476.560	3567.049	3541.903
Past Year Cannabis Use, 26+	6136.217	2120.147	2626.701	12901.742	5470.230	5673.630	5874.771	6747.239	6915.215
Infrequent Use, 12+	4144.548	742.301	2555.709	6383.352	4029.353	4117.851	4205.470	4189.615	4180.450
Infrequent Use, 12-17	481.751	82.219	276.475	768.409	505.308	502.574	499.985	450.635	450.251
Infrequent Use, 18-25	1405.295	276.200	868.381	2750.827	1402.160	1420.113	1437.825	1400.251	1366.124
Infrequent Use, 26+	2277.901	592.684	958.391	4122.069	2144.209	2216.691	2288.457	2355.327	2384.820
Past Month Cannabis Use, 12+	5645.176	2173.140	2403.145	12698.828	5123.573	5223.840	5322.694	6218.013	6337.761
Past Month Cannabis Use, 12-17	179.119	100.325	0.000	478.904	196.287	180.585	165.063	182.131	171.526
Past Month Cannabis Use, 18-25	1724.827	568.010	801.048	3913.476	1697.917	1686.421	1674.856	1774.328	1790.613
Past Month Cannabis Use, 26+	3768.024	1604.976	1497.612	9354.229	3261.777	3385.884	3508.604	4280.282	4403.571
First Cannabis Use, 12+	912.149	85.011	732.373	1273.693	906.651	900.749	894.980	923.375	934.991
First Cannabis Use, 12-17	394.129	46.800	264.226	531.030	416.528	408.602	400.797	375.423	369.296
First Cannabis Use, 18-25	426.409	58.591	297.527	607.207	417.040	416.579	416.098	441.288	441.039

First Cannabis Use, 26+	90.293	35.850	0.000	211.333	64.243	71.055	77.711	111.631	126.824
Dark Web Interest	53.991	12.784	30.270	100.000	41.747	45.436	51.575	61.438	69.760
Legal Recreational State	0.124	0.330	0.000	1.000	0.100	0.120	0.120	0.140	0.140
Medical Marijuana State	0.516	0.501	0.000	1.000	0.480	0.500	0.520	0.540	0.540
Population Density	198.334	261.990	1.267	1218.078	196.116	197.249	198.286	199.503	200.517
Median Household Income	54157.936	8904.695	38305.00 0	75847.000	53399.560	53368.680	53827.040	54172.060	56022.340
Income Inequality (Gini)	0.461	0.020	0.408	0.514	0.457	0.458	0.463	0.462	0.464
% Black	10.445	9.517	0.317	37.827	10.342	10.412	10.445	10.509	10.518
% Over 35 Years Old	46.419	2.914	39.121	58.584	46.686	46.566	46.479	46.296	46.069
% College Degree+	28.846	4.927	18.470	41.467	27.859	28.444	28.885	29.234	29.810
State Representative Ideology	41.855	30.739	0.000	92.360	42.254	41.477	41.228	41.795	42.519
State Citizen Ideology	50.306	14.798	13.482	91.852	48.232	48.495	49.874	51.836	53.096
Drug Arrest Rates (per 100,000)	385.488	156.379	4.537	822.161	388.974	390.989	385.865	387.036	374.579
% of Spending on Police Expenditures	0.670	0.144	0.305	1.066	0.638	0.670	0.673	0.682	0.690
Observations	250								

Table 2. Dark Web Interest & Cannabis Use in Past Year

	Model 1: Past Year Use 12+	Model 2: Past Year Use 12-17	Model 3: Past Year Use 18-25	Model 4: Past Year Use 26+
Dark Web Interest	22.35** (7.422)	0.785 (1.132)	2.594 (2.273)	19.16*** (5.642)
Recreational Legalization	2106.8*** (415.8)	179.6** (57.49)	410.8*** (89.59)	1627.8*** (434.6)
Medical Legalization	1043.6 (543.9)	58.41* (29.39)	195.4 (108.2)	842.9* (418.6)
Pop Density	-1.339 (2.360)	-0.0445 (0.136)	0.325 (0.638)	-1.401 (1.622)
Household Income	0.00759 (0.0627)	-0.00198 (0.00466)	-0.0121 (0.0151)	0.0114 (0.0475)
Income Inequality	-6629.2 (9254.8)	258.4 (1090.2)	-2708.8 (1830.3)	-4831.1 (7843.1)
% Black	-11.72 (24.32)	-2.395 (1.887)	-2.986 (6.125)	-6.356 (17.95)
% Over 35 Years Old	-225.3*** (68.45)	-1.276 (7.868)	-41.44 (24.68)	-172.0*** (51.73)
% College Degree+	174.9* (73.53)	15.18* (6.359)	66.27** (21.29)	92.24 (52.93)
Representative Ideology	5.872 (7.808)	-0.789 (0.661)	0.148 (1.756)	6.515 (5.960)
Citizen Ideology	18.02 (13.56)	2.106 (1.443)	5.858 (3.084)	10.13 (11.05)
Drug Arrest Rates (per 100,000)	-0.595 (0.668)	0.0785 (0.0692)	-0.0486 (0.166)	-0.715 (0.623)
Police Expenditure	-1433.7	-211.6	-473.7	-796.5

	(1597.1)	(112.7)	(409.5)	(1243.2)
Year 2011	0	0	0	0
	(.)	(.)	(.)	(.)
Year 2012	-37.17	-39.45***	-42.76	44.33
	(96.52)	(9.865)	(24.19)	(77.22)
Year 2013	-100.7	-82.19***	-76.15	63.19
	(145.2)	(20.03)	(44.16)	(111.4)
Year 2014	393.1	-156.2***	-58.59	614.0***
	(224.3)	(33.79)	(74.63)	(167.7)
Year 2015	153.9	-183.6***	-130.3	499.3*
	(286.0)	(42.14)	(90.79)	(222.0)
Constant	17093.7**	737.9	5189.3***	11524.2*
	(5709.0)	(580.7)	(1542.6)	(4515.1)
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Constant	7.272***	4.738***	5.984***	6.951***
	(0.177)	(0.111)	(0.160)	(0.176)
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Constant	6.454***	4.268***	4.970***	6.260***
	(0.105)	(0.0697)	(0.0592)	(0.108)
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Observations	250	250	250	250
Adjusted R^2				

Mixed Effects Estimations with Robust Standard Errors

* p<0.05, ** p<0.01, *** p<0.001

Table 3. Dark Web Interest & First Time Cannabis Use

	Model 5: First Time Use 18+	Model 6: First Time Use 12-17	Model 7: First Time Use 18-25	Model 8: First Time Use 26+
Dark Web Interest	-0.112 (0.554)	-0.000573 (0.399)	-0.0770 (0.443)	-0.361 (0.403)
Recreational Legalization	79.75*** (21.17)	28.15* (11.26)	37.95* (16.75)	9.249 (7.648)
Medical Legalization	-0.648 (15.91)	-5.306 (12.07)	3.010 (9.760)	8.510 (4.686)
Pop Density	0.0377 (0.0688)	0.0117 (0.0219)	0.0298 (0.0480)	-0.0140 (0.0118)
Household Income	0.00195 (0.00241)	-0.000667 (0.00116)	0.000313 (0.00173)	0.00163** (0.000604)
Income Inequality	239.5 (541.9)	145.1 (320.2)	108.2 (417.4)	174.8 (142.8)
% Black	-1.283 (0.699)	-0.612 (0.513)	-0.396 (0.605)	-0.316 (0.196)
% Over 35 Years Old	-2.871 (4.830)	-1.331 (2.391)	0.910 (3.451)	0.295 (1.151)
% College Degree+	4.224 (3.068)	3.170 (1.669)	3.119 (1.987)	-1.682 (0.972)
Representative Ideology	-0.621 (0.337)	-0.271 (0.225)	-0.314 (0.227)	0.0138 (0.0818)
Citizen Ideology	0.741 (0.729)	0.288 (0.531)	0.684 (0.484)	0.318 (0.412)
Drug Arrest Rates (per 100,000)	-0.0331 (0.0504)	-0.00755 (0.0270)	0.0110 (0.0413)	-0.000230 (0.0115)
Police Expenditure	-66.79	-21.74	-12.18	-2.013

	(56.32)	(36.88)	(55.34)	(13.30)
Year 2011	0	0	0	0
	(.)	(.)	(.)	(.)
Year 2012	-8.470	-10.09**	-2.858	8.739**
	(5.645)	(3.478)	(4.453)	(2.750)
Year 2013	-18.93	-20.17**	-5.873	16.15**
	(10.29)	(6.907)	(7.914)	(5.475)
Year 2014	5.971	-47.25***	17.19	52.84***
	(17.02)	(11.54)	(11.67)	(12.04)
Year 2015	11.01	-54.62***	14.79	68.37***
	(20.53)	(13.85)	(14.94)	(14.42)
Constant	758.5*	377.9*	201.5	-68.00
	(304.5)	(188.0)	(242.7)	(75.14)
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lns1_1_1				
Constant	3.875***	3.444***	3.652***	2.060***
	(0.142)	(0.144)	(0.144)	(0.248)
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Constant	3.808***	3.217***	3.471***	3.034***
	(0.101)	(0.0896)	(0.0883)	(0.134)
<hr/>				
Observations	250	250	250	250
Adjusted R^2				

Mixed Effects Estimations with Robust Standard Errors

* p<0.05, ** p<0.01, *** p<0.001

Figure 1.1 Dark Web Interest in U.S. States, 2011-2015

Figure 1.2 Past Year Cannabis Use, 12+ in U.S. States, 2011-2015

Figure 2.1 Dark Web and Past Year Use 12+

Figure 2.2 Dark Web and Past Year Use 26+

Figure 3. Plotted Coefficients of Infrequent Use vs. Past Month Use

Figure 4.1 Dark Web and Past Month Use 12+

Figure 4.2 Dark Web and Past Month Use 26+