NTNU
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Master's thesis

Department of Industrial Economics and
Technology Management
Faculty of Economics and Management

Longitudinal data gathering and analysis of Dark web marketplaces

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Analysis of cannabis retail on the Dark web and market impact of legalization

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Preface

This report is part of a master's thesis at the Department of Industrial Economics and Technology Management and Faculty of Economics at the Norwegian University of Science and Technology (NTNU). It is delivered alongside a companion paper, *Analysis of cannabis retail on the Dark web and market impact of legalization*, where both papers combinedly constitute the thesis. While this paper focuses on data collection methods and general analysis across the entirety of our material, the aforementioned paper focuses on aspects of cannabis retail in particular.

The study was done over a span of eight months. Both Hjelstuen and Longva have formal program specializations in financial engineering with minors in data analytics and computer science respectively. Hjelstuen is employed as an equity analyst at Danske Bank. Longva is working as a penetration tester at Bouvet, an IT consultancy.

The focuses of this paper are on data gathering and data analysis. The data analysis was originally envisioned as the primary task, but the data gathering process eventuated as the more demanding part of the project. It was not a trivial task to implement the technical requirements and design goals of our project, and it required extensive knowledge of computer networking, programming, infrastructure and databases.

We appreciate the help, data and guidance in completing this report, both from our industry contacts and from academics at NTNU and abroad. We would especially like to thank our supervisor, professor Peter Molnar at the University of Stavanger, professor Nicolas Christin and Kyle Soska at Carnegie Mellon University, professor David Décary-Hétu and Rasmus Munksgaard at Université de Montréal, and Torbjørn Bull Jenssen at Arcane Crypto.

Håkon Hjelstuen and Magnus Longva

Trondheim, July 2, 2020

Abstract

Dark Web marketplaces have been in operation for more than a decade, and they are host to a vast number of retailers and customers who exchange illegal goods and services. Leveraging the anonymity of the Tor network and the resilience of cryptocurrencies against censorship and audit, these marketplaces have remained an enduring nuisance for law enforcement and prosecutors. Trends and metrics on these marketplaces are a novel source of information, but it is a non-trivial undertaking to access, retrieve and systematize this data.

Firstly, this paper documents our design, implementation and operation of a scraping software which accomplishes this task. The software consistently scraped marketplaces within 24 hours and reliably subverted marketplace measures designed to evict bots. We scraped three marketplaces, Empire Market, Cryptonia Market and Apollon Market, and parsed data from ca. 180 000 unique listings over a period of 150 days. Additionally, we parsed another 260 000 listings from offline crawls of Dream Market with data from January 2014 to November 2019. Secondly, based on our collected data, we present quantitative analyses which characterize economic aspects of the Dark Web marketplaces. We examine product types, vendors, prices, quantities and more, and cross-aggregate these entities by time, geography and other attributes, revealing many trends and metrics for both individual marketplaces and the industry of Dark web retail at large.

Contents

Chapter 1

Introduction

The Internet (World Wide Web) has become a global platform available to everyone, interconnecting people and ideas from all around the world. Internet is a medium bringing billions of people together without physical and geographical boundaries. The web has created opportunities and advantages, and revolutionized the way humans act and live. Despite the many positives, it has also facilitated crime. Misuse of the Internet has become a matter of concern, and sometimes gravely so. Terrorist organizations, extremist groups, hate groups, and racial supremacy groups are using the web to promote their ideology, to facilitate internal communications, to attack their enemies, and to conduct criminal activities (Chen et al., 2008).

The Internet can be divided into *Surface web*, *Deep web* and *Dark web*. The Surface web (also called the visible web, indexed web or Lightnet) is the part of the World Wide Web accessible to the general public by standard search engines like Google. As of September 2019 the Surface web is estimated to contain 6 billion webpages, although good estimates of the web and especially the Deep web is basically impossible (Liang, 2008). The Deep web is not indexed by convectional search engines, but accessed via query interfaces. Some early measurements estimated the size of the Deep web to be 4000-5000 times larger than the Surface web. Later estimates are in the range of 400-550 times the surface Internet, and can be visualized as an iceberg with the Surface web as the part above the surface of the ocean (Bergman, 2001). The Deep web includes by example government resources, academic information, medical records, online banking and cloud storage. The content is ”hidden”, i.e. only accessed by queries that dynamically generate web documents for the context of each user's session. The size of the Deep web is growing faster than the Surface web (Bergman, 2001).

A portion of the Deep web, consisting of an estimated 6% of the world wide web, is the dark web. The dark web is encrypted and only accessed by specific browsers, such as TOR (The Onion Router) and I2P (Invisible Internet Project). The TOR browser establish an anonymous connection to the Tor network, protecting against tracking and surveillance.

A new generation of cyber criminals has risen with the advent of the Internet, transferring old enterprises like drug trade to a digital format. Online drug trade began as the World

Wide Web was first introduced in the 90s. However, customers and retailers alike were easily thwarted by law enforcement while operating on the Clear Web with traditional, transparent network routing. Futhermore, currency transactions from drug purchases, mediated through the traditional banking system, could easily be traced and investigated by authorities. The Dark Web got its real beginning with the release of Freenet in March 2000. This provided a peer-to-peer platform that facilitated unfiltered communication between customers and retailers while obfuscating the IP-addresses of participants. However, Freenet did nothing to solve the issue of traceable currency transactions, and was (and still is) primarily used for other purposes than illegal retail.

With the gradual launch of the Tor network in the 2000s, it became possible, for the first time, for customers and drug retailers to effectively mitigate efforts by law enforcement to deanonymize their IP addresses. A few years later, with the advent of Bitcoin in 2009, the problem of traceable currency transactions was resolved, and the last major obstacle for online illegal retail was vanquished.

The new-found anonymity both within network routing and currency transactions culminated in the first major Dark Web marketplace, The Silk Road, in 2011 (Martin, 2014). More marketplaces have since emerged, especially after the original Silk Road was seized by the FBI in October 2013. Silk Road 2.0, run by former administrators of Silk Road (Greenberg, 2013), went online in November 2013, and closed down after one year of operations. See Figure 1.1 for a timeline summary of these events. In recent years, the Dark Web has been under major scrutiny from law enforcement. Despite shutting down multiple marketplaces, the combined efforts of police around the globe have not been able to significantly impede the trade of drugs and illegal goods and services. Attempts to combat the global drug market have produced infinitesimal results, sometimes even counteractive of their purpose (Wisotsky, 1986; Baum, 1996; Carpenter, 2014).

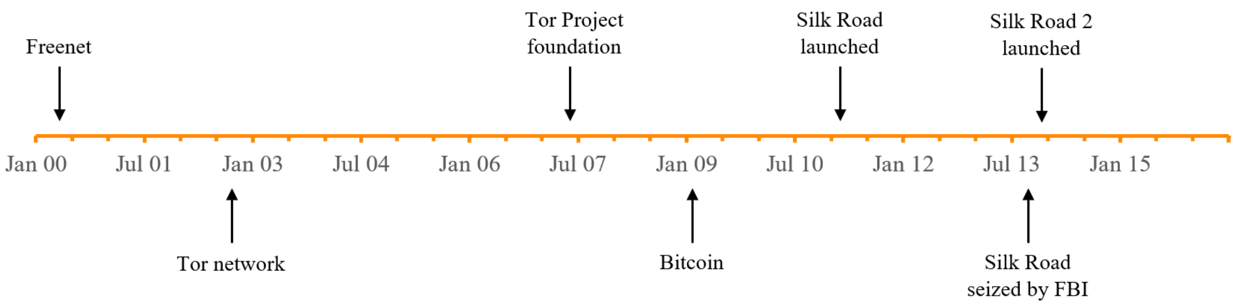
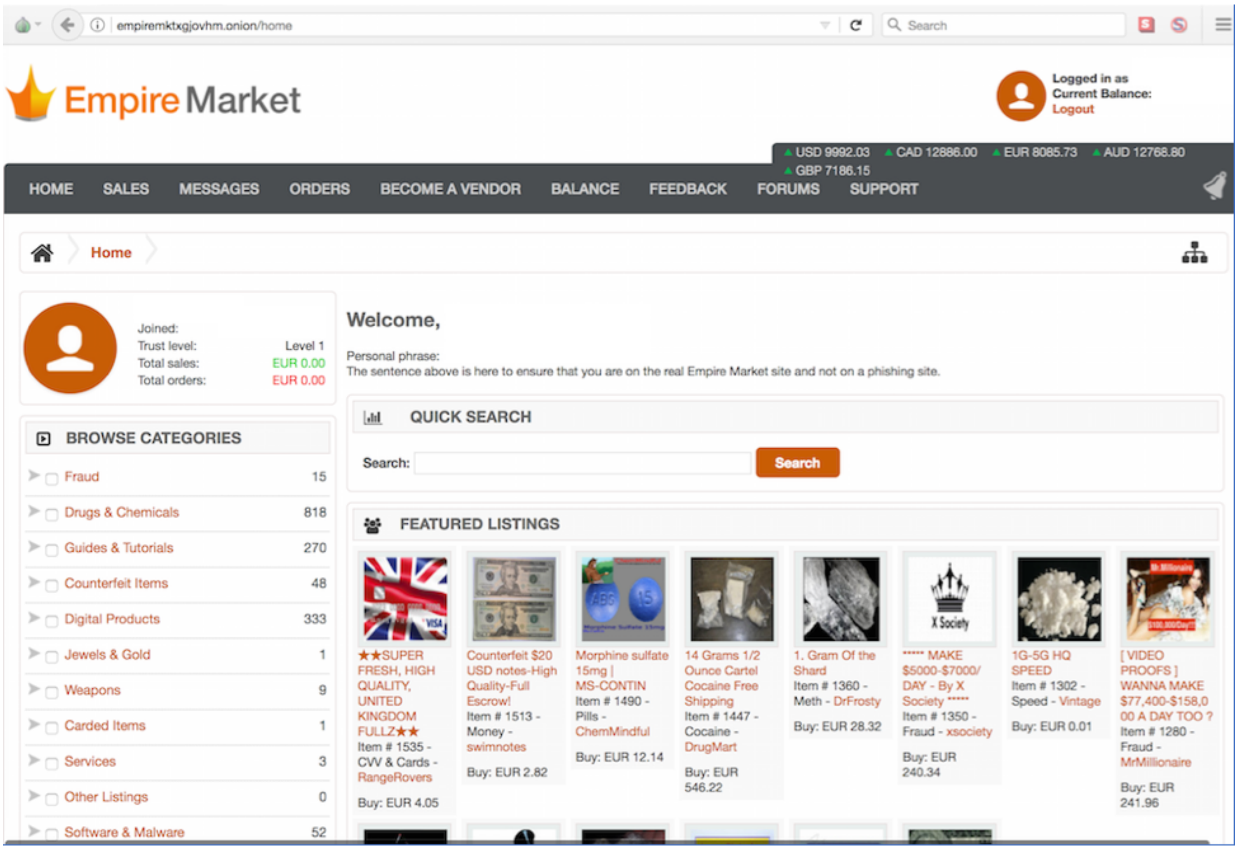


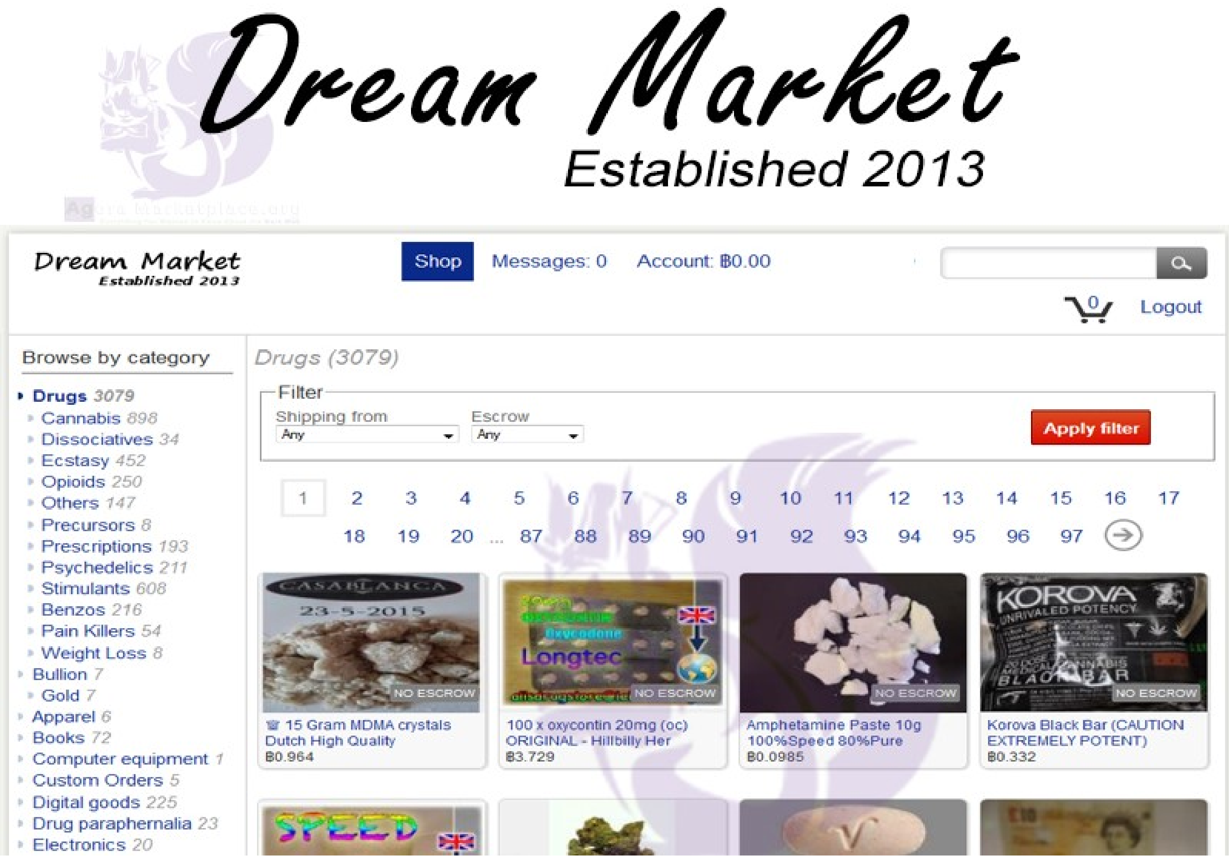
Figure 1.1: A timeline of notable events in the history of Dark Web markets.

Today, the majority of illegal activities are happening at several marketplaces on the Dark web. The information on these marketplaces is not easy for researchers to obtain and systematize, and the administrators of the marketplaces make no effort to remedy this. On the contrary, they zealously implement measures to undermine efforts to collect their data. In this paper, we (1) document our process of designing a web scraping software that subverts these measures, and (2) examine the resulting data from our scraping, making time series, geographical aggregations, currency analyses and more. The motivation behind our work is to compile an extensive and versatile database of Dark web marketplace data for future research, and to provide empirical, quantitative analysis on one of the most elusive business sectors in the world.

The rest of this paper is structured as follows. Section 2 provides a background and presents research related to analysing and scraping Dark web marketplaces. Section 3 describes our scraping methodology, its framework and technical details of how we solved challenges during development. Section 4 describe what data the marketplaces expose, and section 5 explains our measures to systematize and infer extra information from selected portions of the data. Section 6 presents the results, and we discuss the significance of our findings in section 7. We summarize our work and make concluding remarks in section 8.



(a) Empire Market



(b) Dream Market

Figure 1.2: Screenshots of two of the Dark web marketplaces scraped in this study

Chapter 2

Literature review

2.1 Work by Christin, Soska and Thomas

Upon review of existing literature about automated scraping and quantitative analysis of Dark web markets, we note three papers with pronounced similarities to our work with regard to both topic and methodology. The papers are titled *Traveling the Silk Road: A measurement analysis of a large anonymous online marketplace* by Christin, 2012, *Measuring the Longitudinal Evolution of the Online Anonymous Marketplace Ecosystem* by Christin & Soska, 2015 and *Analysis of the supply of drugs and new psychoactive substances by Europe-based vendors via darknet markets in 2017-18* by Christin & Thomas, 2019.

In the first paper, the author has used automated scraping software to collect web documents from Silk Road, and parsed data from these documents for analysis. The author produced a number of statistical aggregations to characterize the products, vendors and customers on the marketplace. Some notable findings are that (1) cannabis was the most popular category on the now-defunct marketplace, (2) the monthly transaction volume was estimated to a lower bound of 1.22 million USD and (3) customers and vendors were internationally distributed.

In the second paper, the authors reuse the data from the former paper and gather additional data on another 15 unique marketplaces. The data collection methods are conceptually similar to those in the 2012 paper, but were developed to greater sophistication in order to accommodate the technical and functional requirements of routinely scraping 16 websites. While the Silk Road marketplace was singularly characterised in *Traveling the Silk Road: A measurement analysis of a large anonymous online marketplace*, the authors of *Measuring the Longitudinal Evolution of the Online Anonymous Marketplace Ecosystem* make data aggregations to characterize and generalize all the Dark Web marketplaces, interpreting them to comprise a single market in the microeconomic sense of the term. Notable findings from this paper include, but are not limited to, that (1) cannabis is the most popular product category, (2) sellers are usually specialized in a particular niche, (3) the top 1 % of vendors constitute more than 50 % of transacted revenue and (4) monthly transaction volumes peaked at around 20 million USD during the observation period.

In *Analysis of the supply of drugs and new psychoactive substances by Europe-based vendors via darknet markets in 2017-18*, the authors expand upon the methods of the 2015 paper. Sales volumes are aggregated by geographical areas, producing similar metrics as from from earlier research, but providing data that is sufficiently granular for application to individual countries and political confederations. Furthermore, the authors use natural language processing to infer the *mass* of drugs offered by individual listings, enabling aggregations of traded drug mass by product category and geography. One notable finding from the study is that the trade volume for the marketplaces have stabilized in recent years; while the volume of Silk Road increased exponentially during 2012, the current marketplaces exhibit a more linear growth.

2.2 Other related work

The data used in several research papers on Darknet marketplaces stems from an archive of scraped data from over 80 marketplaces in the period from 7 July 2013 to 20 December 2015. The archive is made available by Gwern Branwen, an independent researcher. The data set contains not only data scraped by the researcher, but several other contributors. Most of the data was scraped at random times. Using this data, Cherqi et al., 2018 did an exploratory analysis on four large marketplaces on the Dark web: Silkroad 2, Agora, AlphaBay and Nucleus, and characterised the nature and prevalence of hacking related services. Norbutas (2018) explored the behaviour of users on Abraxas Market, making a particular effort to measure geographical consumer preferences. Bhaskar et al. (2017) studied the behaviour of marketplace users on Silk Road 1, Silk Road 2 and Evolution Market from a game theory perspective, examining whether moral hazards impede the function and viability of Dark web markets in lieu of lawful arbitration and consumer protection services.

Décary-Hétu et al. (2016) independently scraped web pages from Silk Road, parsed the data, and examined various types of risks for marketplace vendors and their significance for decision making. Using similar data collection methods, Barrera et al. (2019) parsed information from 6 marketplaces and aggregated it to characterize and quantify the scope and extent of tobacco trade on the Dark web. Many other publications, also co-authored by David Décary-Hétu, explore various other topics related to Dark Web marketplaces, and they typically contain original data collection and a cross-disciplinary approach to the subject matter.

Ubbink (2019) characterized and described the arms trade on Berlusconi Market in a MSc thesis, using self-written software for scraping and parsing.

Chapter 3

Obtaining Data

This section documents the process of obtaining and systematizing data from Empire Market, Cryptonia Market, Apollon Market and Dream Market. We present some general background on web scraping and a brief chronicle of its use cases in Section 3.1. In section 3.2, we explain some special considerations that apply to Dark web marketplaces. In section 3.3, we explain our design process, whereas in section 3.3.1, we elaborate on a selection of engineering challenges we had to solve in order to achieve our secondary design goals.

Unlike the other three markets studied in our paper, Dream Market ceased its operations before we started our work, so we have naturally not been able to retrieve web documents from that marketplace ourselves. We obtained the raw documents from D. Décary-Hétu and R. Munksgaard at Université de Montréal and a publicly available dump hosted by Gwern Branwen on his eponymous website `gwern.net`. Parsing and systematizing these offline documents posed problems and considerations which did not apply to the other marketplaces, and our solutions and workarounds to these issues are documented in section 3.3.2.

3.1 General background on scraping

Web scraping is the process of systematically gathering data from human-readable web documents. While this may be done manually, the term typically refers to a fully automated process handled by software (Glez-Peña et al., 2013). To retrieve formatted data from a web-accessible API would typically fall outside the definition of web scraping. (Mitchell, 2018).

The concept has been used in various forms all the way back to when the Internet was launched. As the popularity of the Internet developed and people shared ever increasing amounts of data, so did the need for scraping. Search engines (like Google and Bing) were among the first known automated web scrapers. They scanned every web page on the Surface web, extracting information and building indexes in order to organize it for efficient search.

Although the practice of scraping the web has become widespread for the purpose of facilitating easy access to data, it has drawn a lot of concerns and controversy. Some are worried about malicious use of information, especially private and protected information, violating the rights of privacy. Some website owners prohibit scraping in their legal terms of use, but there is no technical approach that can enforce such a prohibition in a reliable manner. In a capacity as researchers, there are three relevant considerations that should be made when scraping a website: copyright, trespassing, and whether the information can be obtained from existing archives (Boeing & Waddell, 2017). While not given further elaboration in this paper, it can be stated that our views and concerns are similar to those of Christin & Soska (2015): we seek neither to enhance nor diminish the Quality of Service (QoS) of the Dark web marketplaces we target for scraping, and our software is designed with appropriate considerations.

From the technical perspective of a developer, the challenges of web scraping differ significantly between websites. While not an exhaustive list, major obstacles can include (1) complex and inconsistently structured web documents, (2) asynchronous content loading, particularly in the case of RESTless (REpresentational State Transfer), stateful APIs, (3) *honeypot* URLs with payloads designed to corrupt scrapers (cedriczirtacic@github.com, 2017) and (4) anti-scraping mechanisms like HTTP request limits, IP bans, frequently rotating URLs and CAPTCHAs (Completely Automated Public Turing Test to Tell Computers and Humans Apart). As stated, no technical measures can reliably evict web scrapers as of July 2020, but several of the aforementioned issues necessitate a certain level of sophistication for the web scraping software.

3.2 Special considerations for Dark web scraping

Websites on the Dark web have an idiosyncratic set of technical properties in the context of web scraping. Some of these properties are abating qualities, whereas other properties pose technical challenges.

As stated in section 3.1, the practice of asynchronous content loading, a ubiquitous feature in modern web frameworks, can pose a non-trivial obstacle for automated web scraping. However, for reasons that relate to end-user security against deanonymization attacks, Dark web marketplaces are typically designed entirely without JavaScript, and this precludes asynchronous content loading. This simplifies the process of parsing web documents, because the scraping software will not require a JavaScript engine in order to load content to web documents *after* the initial fetch from the web server.

Dark Web marketplaces have one more agreeable property inherent for all web servers on the Tor network. As a consequence of the opaque routing paths that provide anonymity for clients and servers, it is impossible for any hidden service to reliably determine whether any two network connections originate from the same client machine. This makes it impractical to ban or limit request rates from IP addresses as an anti-scraping mechanism, because such a measure would indiscriminately evict any client which bounces through that particular Tor node, and it would be of little to no cost for the adversarial web scraper to resume the efforts through a different Tor node.

While the aforementioned properties are abating qualities, the Dark web marketplaces are uncooperative scraping targets in most other respects. Operating outside the protection of the law, they are subject to unceasing Distributed Denial of Service (DDoS) attacks. As of March 2020, all online marketplaces seem to implement some mechanism to mitigate this, and these mitigating measures will typically pose obstacles for web scrapers and DoS-agents alike. CAPTCHA challenges are a ubiquitous and relentless annoyance for users on the marketplaces. It can also be observed that at least one market, Empire Market, implements request rate throttling despite the inherent detriment for QoS.

CAPTCHA challenges were not prevalent on the marketplaces back in 2015 (N. Christin, email, 20 November 2019). It can be assumed that DDoS attacks have gotten more pervasive since 2015, and that this necessitated the current CAPTCHA regimen.

3.3 Design of our scraping software

From a high level of abstraction, our design process may be interpreted as a list of eight sequential steps, each of which is explained below.

Step 1 **Deciding technology stack**

Our first consideration was what programming language and technologies we should use in our project. We considered it would be preferable to use a language with well developed frameworks for HTTP messaging, web document parsing, DBMS communication and multithreading. We also decided that a high-level language with concise syntax would best serve our needs, optimizing for development time over execution speed. This is in large part because we estimated web latency would constitute the main bottleneck and render CPU and memory efficiency nearly irrelevant. The choice landed on Python 3.6, offering `requests` for HTTP, `BeautifulSoup` for web document parsing, `SQLAlchemy` for DBMS management and `threading` and `multiprocessing` for multithreading.

Step 2 **Setting the premises**

We considered what data and information was needed for our study, ranked from most important to least important. What data do we need, how frequently do we need to retrieve it, and what benefit would it serve us? While we *did* have some initial hypotheses we were eager to investigate – XMR adoption trends, correlations between marketplace activity and cryptocurrency prices – the overarching goal for our study was to obtain a versatile data set with a variety of applications. Accordingly, we elected to scrape every type of data we could observe, within reasonable limits of effort. This included all product listings, user profiles of all sellers (but not customers) and product reviews left by customers, as well as all available metadata for all these three entities. This metadata included product discount rates, external marketplace verifications, shipping alternatives etc. As for how frequently we should scrape, we decided early on that daily snapshots of each marketplace would be advantageous. This would give us granular data on marketplace evolution and provide us a good basis for correlation with other time series.

Step 3 **Deciding which marketplaces to target**

There are numerous marketplaces on the deep web, ranging from hundreds of thousands of listings to just a few. The largest marketplaces with the highest transaction volumes were identified and given extra consideration as scraping targets. A more popular marketplace will yield a greater data set, but will not necessarily pose a greater technical challenge to scrape. We observed the layout and structure of the candidate marketplaces, and for each marketplace, we gauged whether the information seemed structured in a sufficiently deterministic manner in order to be reliably parsed. We also consulted discussion forums, web articles etc. in order to get a rough impression of which marketplaces were considered most available. Whenever a marketplace is offline, it would impair our data set, especially with regard to time series analysis.

Empire Market, Cryptonia Market and Apollon Market were selected for scraping. The first of the three marketplaces had the Dark web's largest user base at the time, and the second was reputed to have a high rate of availability. The third marketplace, which was the last we scraped, was chosen because it had high traffic and was superficially similar to Empire Market in terms of structure and layout. All websites organized data in a HTML structure which seemed tractable for parsing, and for all three sites, we were able to devise a strategy to selectively crawl all their relevant web pages. While more marketplaces would have added greater utility to our data set, we had to limit the scope of our endeavour. See Figure 1.2a for a screenshot of Empire Market's front page.

Step 4 **Constructing a framework and data storage**

We decided to store our data in a relational database, enabling us to aggregate and retrieve our data in a single step. Our first design iterations used PostgreSQL, but we eventually landed on MySQL. After deciding which marketplaces to scrape, we identified – in a precise, technical sense – which data fields should be parsed from the web documents. E.g., should we store dates as `DateTime` objects or as `VARCHAR`, should we store currency units as `Enum` or as `CHAR`, and should we restrict to 3 characters and save storage space, or should we allow more characters for future flexibility? After making such considerations, we designed a schema to store our data which is shown in Figure 3.3. In order to tune performance for querying and aggregating data, we added appropriate table indexes across our schema. One may note that our schema is not 3NF normalized; while this increased data redundancy and susceptibility to anomalies, it made our SQL queries as well as our development process less complicated.

Step 5 **HTML structure**

We thoroughly scrutinized the structure of the web documents in each marketplace, and saved multiple samples of each type of web page. We created functions to parse individual data fields from all these pages, and implemented automated unit tests to verify their correctness.

Step 6 **Identify obstacles in website message flow**

Empire Market, Cryptonia Market and Apollon Market required logged in sessions in order to browse their contents, as well as other, more subtle HTTP protocol requirements. The technical details of our efforts to comply with these requirements and maintain our sessions are documented in section 3.3.1.

Step 7 **Write the program**

After identifying obstacles in the previous step, we could start writing the core logic of our program. We implemented routines for logging in, instantiating task queues for each scraping run, delegating tasks to individual threads, subverting anti-bot measures, writing and reading parsed data to the database, avoiding overlap in tasks, recovering from transaction errors and much more. We used an objected oriented programming (OOP) design. Table 3.1 shows a list of methods for the superclass `BaseScraper`, arguably the core component of our program. By studying the names of the methods, one might get an overview of our implementation and design pattern, and get a rough appreciation of the scope of the task. The entirety of our code base is hosted in a Git repository at `https://git.sikkerhetshull.no/magnus-longva/msc`, available from NTNU's campus network or VPN.

Step 8 **Set up environment for convenient analysis**

In order to simplify the continuous error diagnosis and data observation and visualization, we set up an instance of PHPMyAdmin, a web interface for managing MySQL databases. We also set up an instance of Grafana, enabling us to observe live updated time series analysis of our data. Figures 3.1 and 3.2 show screenshots of some of our dashboards.

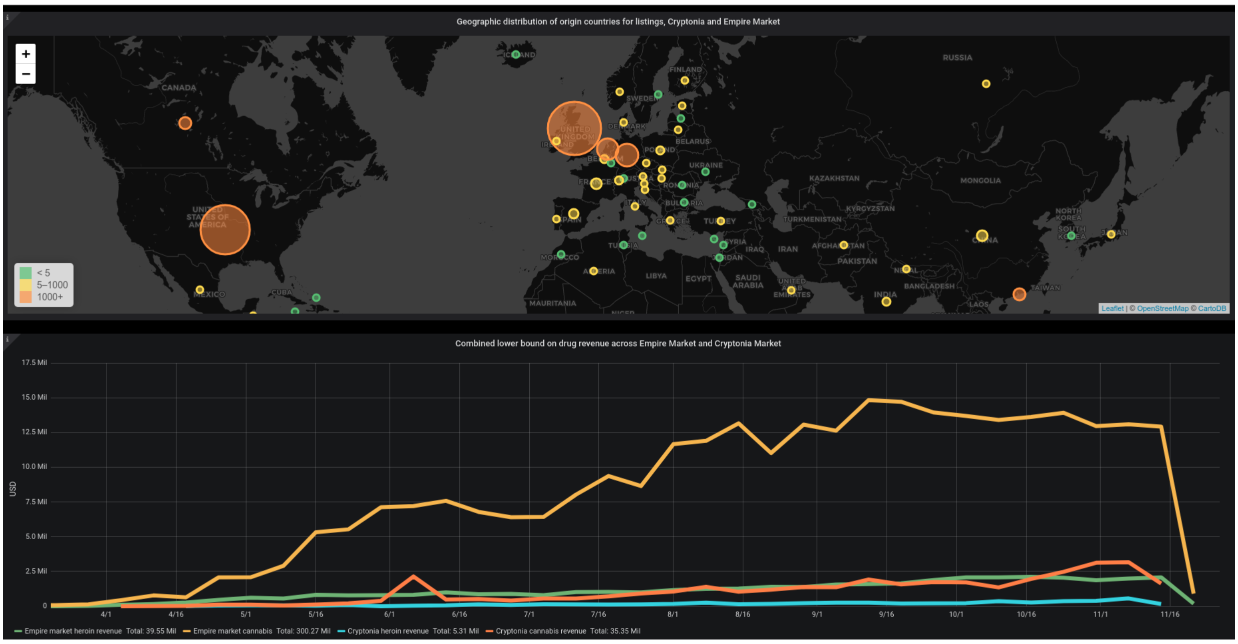


Figure 3.1: Screenshot of two Grafana dashboards, plotting listings counts by country and weekly heroin and cannabis revenue for Empire Market and Cryptonia Market. The data is from December 8 2019. The suddenly downward sloping graphs are largely due to missing data points because of recent marketplace downtime.

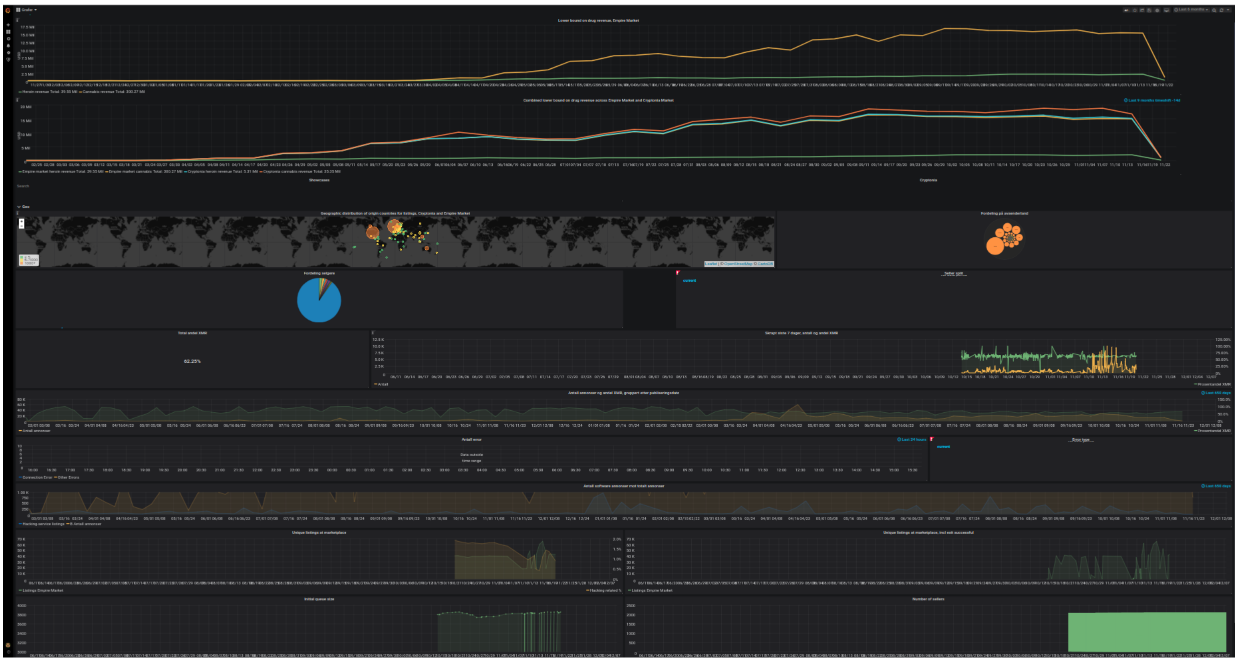


Figure 3.2: Screenshot of a Grafana dashboard. The various graphs give us live updated information on parsed data, runtime errors in our software and resource usage in our cloud based hardware.

Table 3.1: List of scraping methods

List of methods for the `BaseScraper` superclass, parent to the market specific scraper classes of Empire Market and Cryptonia Market. Methods prefixed with an underscore are internal methods, and are not designed to be accessed from external components.

__init__(self, queue: Queue, nr_of_threads: int, thread_id: int, proxy: dict, session_id: int):
scrape(self):
_initiate_session(self) -> int:
_log_and_print_error(self, db_session: Session, error_object, error_string, updated_date=None, print_error=True) -> None:
_wrap_up_session(self, db_session: Session, exited_gracefully: bool = False, fail_count: int = 0) -> None:
_get_cookie_string(self, web_session: requests.Session) -> str:
_get_wait_interval(self, error_data) -> int:
_get_seller(self, seller_name: str) -> Tuple[Seller, bool]:
_get_listing_observation(self, title: str, seller_id: int) -> Tuple[ListingObservation, bool]:
_exists_seller_observation_from_this_session(self, seller_id: int) -> bool:
_add_category_junctions(self, listing_observation_id: int, listing_categories: Tuple[Tuple[str, Optional[int], Optional[str], Optional[int]]]) -> None:
_add_country_junctions(self, destination_country_ids: Tuple[int], listing_observation_id: int) -> None:
_add_countries(self, *countries: str) -> Tuple[int]:
_add_shipping_methods(self, listing_observation_id: int, shipping_methods: Tuple[Tuple[str, Optional[float], str, float, Optional[str], Optional[bool]]]) -> None:
_add_bulk_prices(self, listing_observation_id: int, bulk_prices: Tuple[Tuple[int, Optional[int], float, float, Optional[float]]]) -> None:
_add_text(self, text: Optional[str]) -> int:
_should_scrape_pgp_key_this_session(self, seller: Seller, is_new_seller: bool) -> bool:
_add_pgp_key(self, seller: Seller, pgp_key_content: str) -> None:
print_crawling_debug_message(self, url=None, existing_listing_observation=None) -> None:
_get_logged_in_web_response(self, url_path: str, post_data: dict = None, web_session: requests.Session = None) -> Response:
_login_and_set_cookie(self, web_session: requests.Session, web_response: Response) -> requests.Session:
_add_captcha_solution(self, image: str, solution: str, correct: bool, website: str = None, username: str = None):
_add_web_session_cookie_to_db(self, cookie_jar: RequestsCookieJar) -> None:
_set_cookie_on_web_sessions(self) -> None:
_get_cookie_from_db(self, username: str) -> Union[dict, None]:
_process_generic_error(self, e: BaseException) -> None:
_get_web_response_with_error_catch(self, web_session, http_verb, url_path, *args, **kwargs) -> Response:
_db_error_catch_wrapper(self, db_session: Session, *args, func: Callable, error_data: List[Tuple[object, str, datetime]] = None, rollback: bool = True) -> Any:
_generic_error_catch_wrapper(self, *args, func: Callable) -> any:
_format_logger_message(self, msg: str) -> str:
_is_logged_out(self, response: Response, login_url: str, login_page_phrase: str) -> bool:
get_temporary_server_error(self, response) -> Optional[HTTPError]:
_handle_custom_server_error(self) -> None:
_get_market_id(self) -> str:
_get_working_dir(self) -> str:
_get_headers(self) -> dict:
_get_login_url(self) -> str:
_get_is_logged_out_phrase(self) -> str:
populate_queue(self) -> None:
_get_web_session_object(self) -> requests.Session:
_scrape_queue_item(self, *args) -> None:
_get_scraping_funcs(self) -> Type[BaseFunctions]:
_get_anti_captcha_kwargs(self):
_get_schemaed_url_from_path(self, url_path: str) -> str:
_is_meta_refresh(text) -> bool:
_wait_out_meta_refresh_and_get_redirect_url(self, web_response: Response) -> str:
_has_successful_login_phrase(self) -> bool:
_get_successful_login_phrase(self) -> str:
_get_min_credentials_per_thread(self) -> int:
_is_successful_login_response(response: Response) -> bool:
_get_mirror_db_lock(self) -> Lock:
_get_user_credentials_db_lock(self) -> Lock:
_get_mirror_failure_lock(self) -> Lock:
_is_custom_server_error(self, response) -> bool:
_get_captcha_solution_from_base64_image(self, base64_image: str, anti_captcha_kwargs: Dict[str, int] = None) -> Tuple[str, dict]:
_get_web_session(self, order_rand: bool) -> requests.Session:
_get_web_sessions(self, order_rand: bool = False) -> Tuple[requests.Session]:
_rotate_web_session(self) -> requests.Session:
_log_web_request(self, session, verb, *args, **kwargs) -> None:
_create_or_fetch_country(self, legit_country_name: str, alpha_2: str, alpha_3: str, is_continent: bool) -> int:
_release_user_credentials(self):
_clear_all_cookies(self) -> None:
_server_error_seems_permanent(self, temporary_server_error, url_path) -> bool:

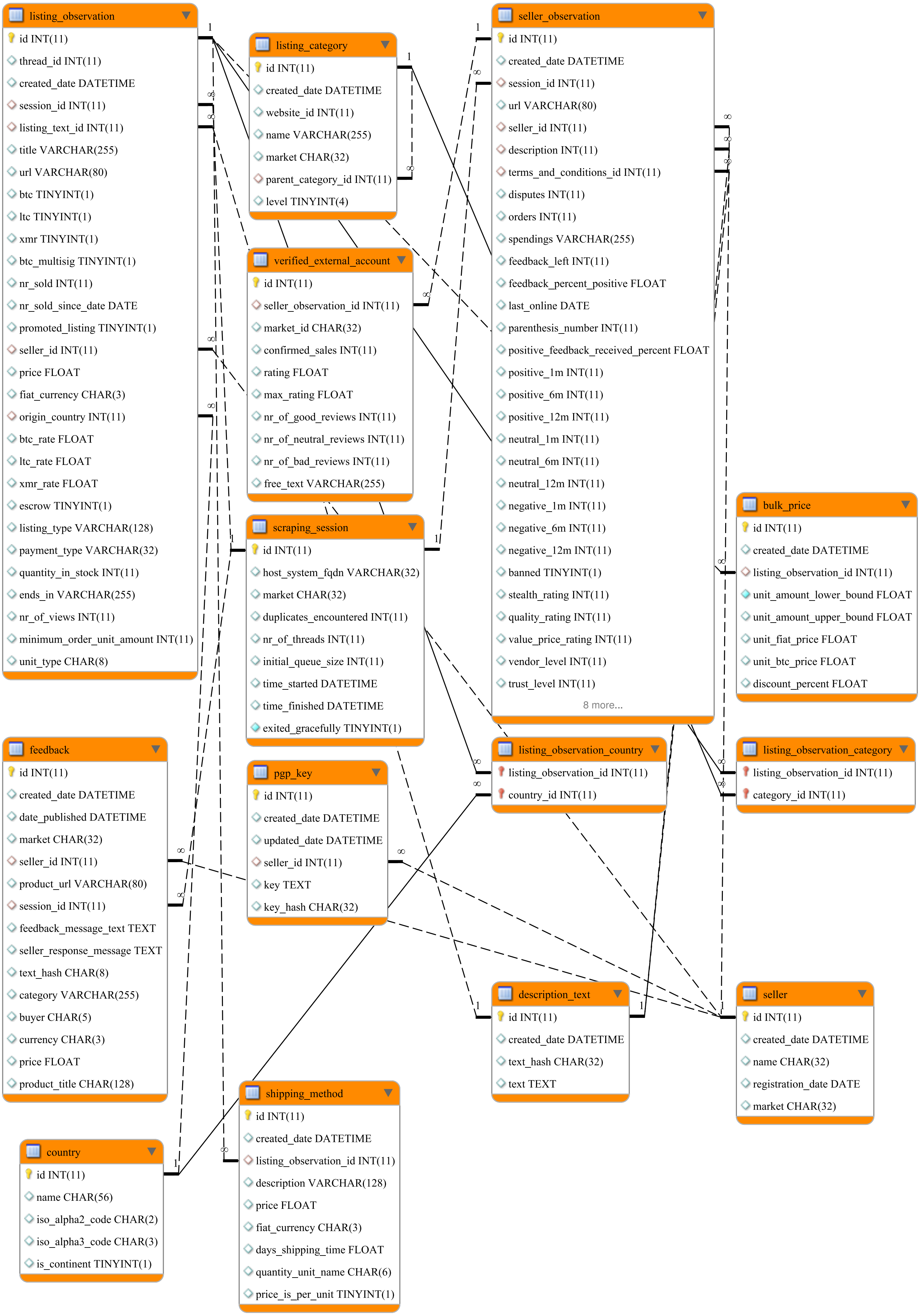


Figure 3.3: Schema structure of the tables containing marketplace data, as of December 2019. The final iteration of our schema has grown too large for tractable presentation in this paper. Lines between columns indicate a foreign key relationship, and the cardinality of each relationship is indicated on the ends of the line.

3.3.1 Technical optimizations and secondary design goals

Beyond the mere basics of automatically parsing web content, we had several secondary design goals for our scraping software. In the following subsections, for each design goal, we explain (1) what the goal is, (2) why it is justified and (3) how we achieved it.

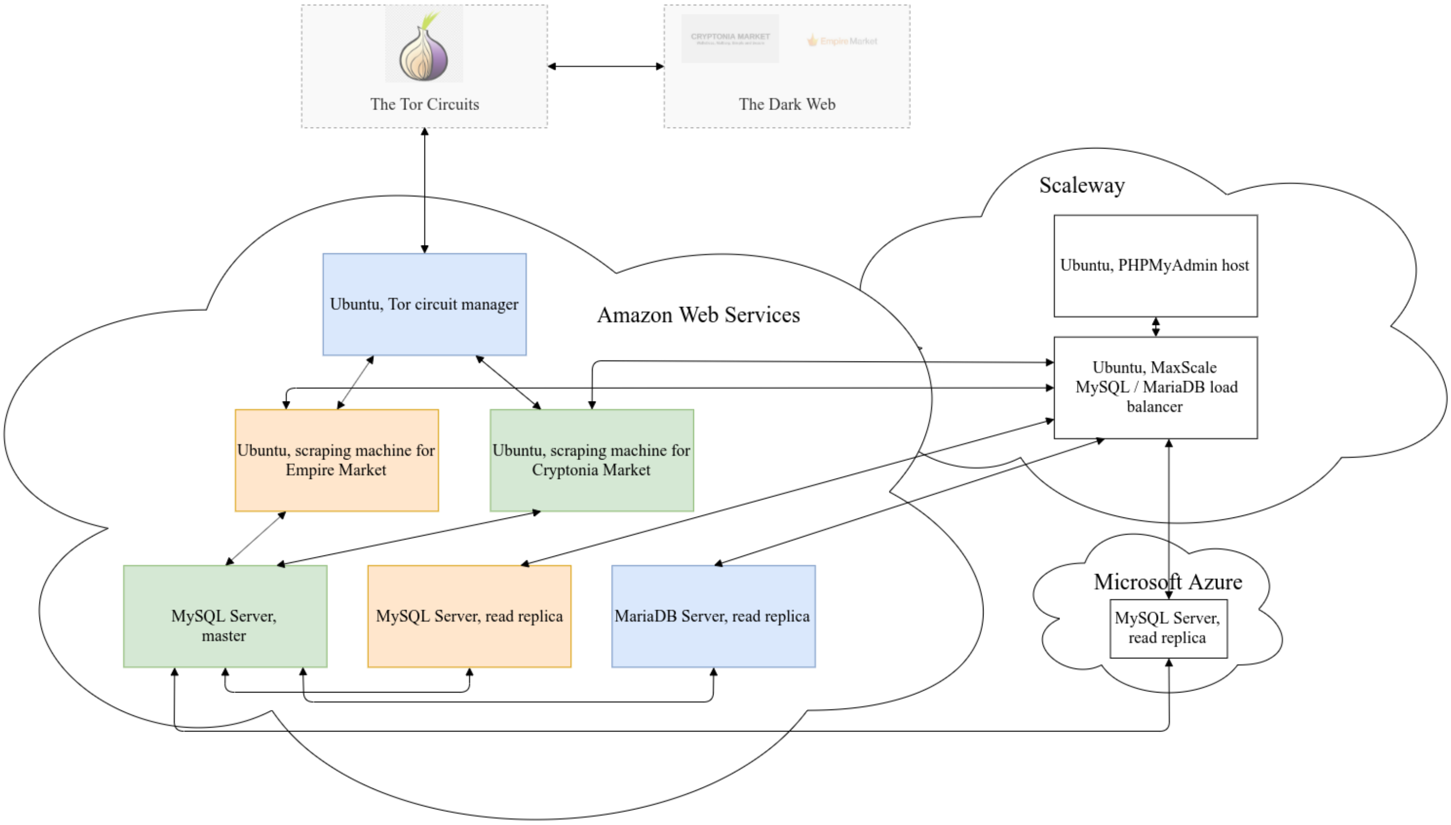


Figure 3.4: Diagram of the infrastructure architecture in our project. A total of nine different VPSs hosted across AWS, Scaleway and MS Azure were part of our setup. Same-colored squares inside the AWS cloud belong to the same virtual network.

Speed and frequency

We wanted our scraping runs to be **fast**. If we could minimize the time delay between the first observation and the last observation within a single scraping run, we could make a more meaningful comparison of data points within each snapshot. Furthermore, a speedy completion of each run would make our scraping process more resilient against marketplace downtime. E.g., if we could make our scripts finish a complete sweep of each site in 1 hour, we would get all necessary data even if the marketplace is down for 23 hours on a particular day. Another closely related design goal, is that we wanted our snapshots to be **frequent**. With a daily snapshot frequency, we would be better positioned to correlate our data with external time series, e.g. cryptocurrency day rates, social media trends or keyword popularity in search engines. If we have missing days in our data set, this would add uncertainty to any such model.

We made four design choices that optimized the execution speed, but which also added much project complexity and greater susceptibility to runtime errors. The first choice was to tight-couple the process of fetching web documents and the process of parsing their contents. This approach offered two advantages. Firstly, it saved hard drive space, because we did not need to store and persist web documents during and between scraping sessions. Secondly, it enabled our scraping software to intelligently disregard certain URLs that would not contain new information. E.g., in the case of Empire Market, each seller page displayed the number of positive, negative and neutral reviews received by customers. The seller page also had URL links to web pages that contained the actual reviews of the seller in question. In each scraping run and for each seller profile, our scraper could look up the previously recorded number of reviews, and then determine whether a new review had been posted since the last run. If not, our scraper would not fetch the URL. 98 % of the execution time across all threads in our software is to wait for HTTP requests, taking about 6 seconds on average, and this largely because of latency in the Tor network. Accordingly, there is a great performance benefit by skipping redundant requests. We were able to reduce our total number of requests by about 40 %.

The second design choice was to run the scraping of each individual marketplace in parallel threads instead of a single synchronous process. This makes the program much more complicated and harder to diagnose – the details of which are not elaborated on in this paper – but it also enables the program to fetch and parse multiple web pages simultaneously, as opposed to sequentially waiting for each web request between parsing. With the hardware limitations on our free-tier machines on Amazon Web Services (AWS), we could run 50 threads in parallel without exhausting our memory (indirectly), but not more. This did, in turn, make our program run close to 50 times faster. See Figure 3.5 for a screenshot of terminal output from our software, displaying state information for various threads.

The third design choice was to separate management of Tor circuits to a dedicated machine, and this was in turn necessitated by the second design choice. To maintain a proxy interface to a Tor circuit carries a memory overhead of about 50 MB, and due to lock-out mechanisms explained in section 3.3.1, it was some times necessary to maintain no less than 13 such interfaces simultaneously. With tight memory bottlenecks on our cloud hardware, it was pertinent to reduce this memory usage by moving it all to a dedicated instance. This freed up about 850 MB of RAM across our two scraping machines, and while we were initially bottlenecked to only run 5 stable threads in the beginning, we successfully increased this count to 25, then 50 after further improvements.

The fourth and final design choice in the context of performance optimization, was to configure our infrastructure for minimal network latency between master DBMS instance, the Tor circuit manager and the scraping machines. Our scrapers would need to run a varying number of SQL queries between each request, and each query carries a latency

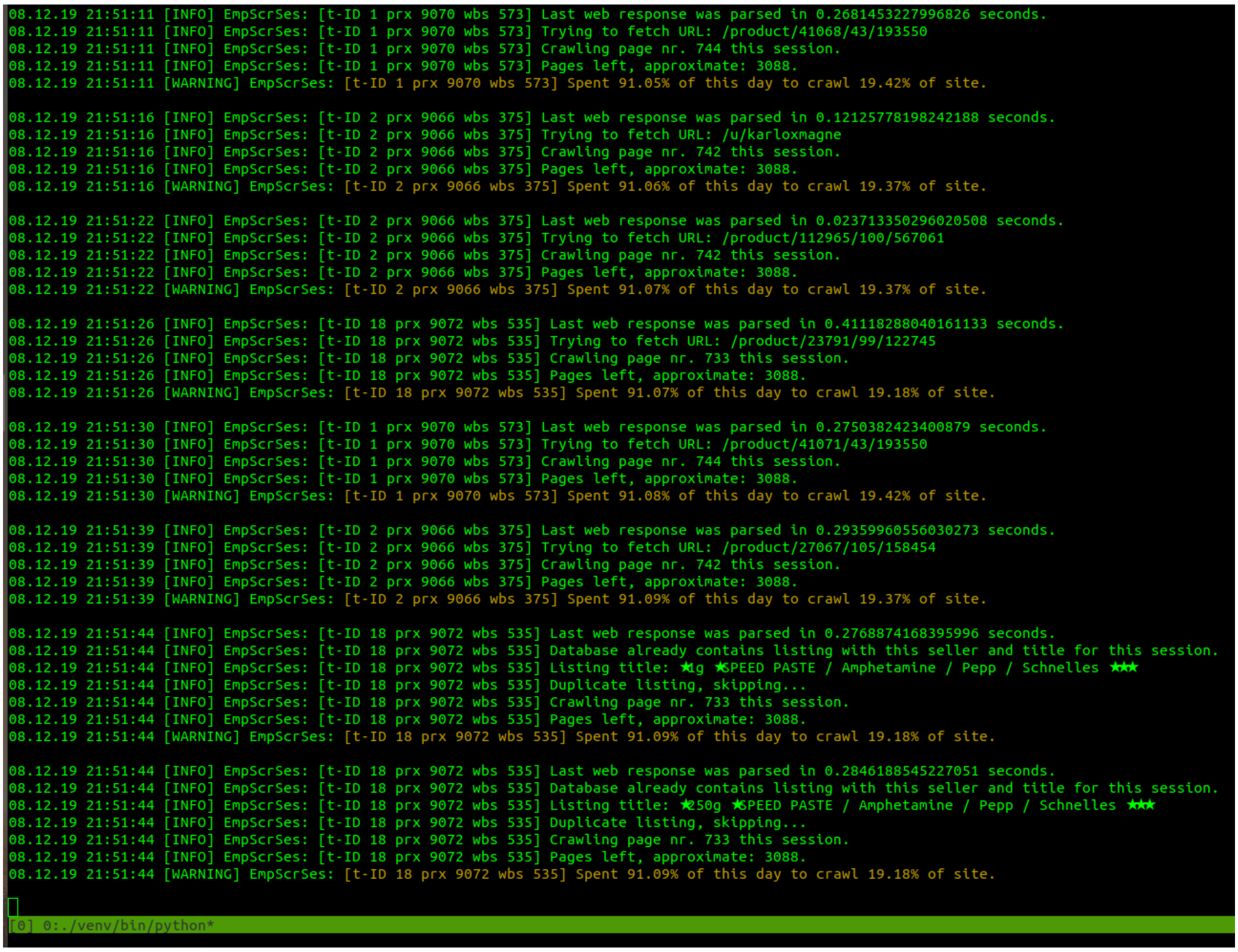


Figure 3.5: Screenshot of terminal output from our scraping software.

overhead. Our initial prototypes on infrastructure architecture carried a query latency per HTTP request which could go as high as 7 seconds. We have been unable to reliably determine the latency overhead to the circuit manager, but we estimate it was about 1.5 seconds. In order to remedy this, we configured our DBMSs and VPSs hosted on Amazon Web Services to be deployed as geographically close to each other as possible. Furthermore, we needed to configure the machines to communicate on a single virtual private cloud (VPC). This required some network engineering efforts, as our machines were registered on multiple user accounts with initially isolated networks. After the reconfiguration, latency was reduced to less than 20 ms between all machines. See Figure 3.4 for a diagram of our final setup.

The combined effect of all our optimization efforts have increased execution speed from our initial prototype by a factor of more than 200. Without any one of these optimizations, and with our hardware limitations, it would not have been possible to reliably complete a single scraping during the span of 24 hours. The benefits from the implementations made, create a unique set of panel data. Other efforts to scrape Dark net marketplaces have been limited to just a handful of crawls, and the sessions are often incomplete due to the challenges mentioned.

Client emulation and countermeasure circumvention

We needed our software to emulate the client side state of a web browser. This is necessary in order to manage authorization tokens in cookies, maintain logged-in user sessions and context-dependent headers in HTTP requests. Failure to comply with any of this would make the marketplace web server invalidate our session. It was also necessary to circumvent any countermeasures specially designed to lock out bots sending HTTP requests, such as our web scraper. Empire Market and Cryptonia Market would automatically invalidate a web session if too many requests were sent within a certain time interval, and at regular intervals, it would be invalidated for no apparent reason at all. Furthermore, Empire Market would drop the TCP connection entirely if it received too many handshakes from a single Tor exit node. In the event of session invalidation, the web scraper needs to log back in, and this will in turn require it to solve a CAPTCHA. On top of all this, the marketplaces would frequently go offline at one URL and reappear instantaneously at some other URL. This is a defense strategy against DDoS attacks, interrupting any current attacks and forcing the adversaries to update their parameters. Similarly, this is an obstacle for automatic scraping, as each thread needs to have their state updated with the new URL.

The emulation of client state was in large part managed by the Python `requests` library, and it successfully automated every aspect of cookie validation. However, it required some manual effort to send the correct HTTP headers from each web page to the next. It appeared, e.g., that Cryptonia Market would not accept a login request unless the `Origin` and `Referer` headers had expected values. We also encountered a situation where the style sheet returned a `Set-Cookie` header. A normal client browser would automatically retrieve this style sheet and set the cookie, but the Python `requests` library will not follow style sheet URLs automatically, and this required manual design efforts on our part.

The HTTP request rates were not a relevant problem with Empire Market or Apollon Market, as those websites would tolerate any request rate where only one request was sent in parallel. However, Cryptonia Market was much more restrictive in this regard, and would aggressively evict visitors who exceeded the request limit. In order to not trigger session invalidation, we decided make each thread rotate between multiple web sessions, i.e. multiple sets of usernames and passwords, for each request. In our final iterations, the scraper uses five different web sessions per thread for Cryptonia Market. This added much complexity to our design, but increased our average session length by an order of magnitude.

In order to solve Empire Market's TCP connection limit, it was necessary to divide our requests over multiple Tor circuits. We chose a simple design where each thread is assigned a proxy interface upon instantiation. We subjectively observed that the number of dropped TCP handshakes would increase if more than two threads shared a single Tor circuit.

Accordingly, we created 13 different Tor circuits, so that no more than 2 of the 25 threads would share a single circuit.

While we made efforts to avoid session invalidation as far as possible, it still remained an inescapable hazard. Without a method of automatically solving CAPTCHAs, our scrapers would require 24-hour attention in order to meet our speed and frequency requirements. Our solution was the commercial `anti-captcha` HTTP API, and we designed our program to communicate with this service. When confronted with a CAPTCHA, this API enables our program to provide a solution in less than 30 seconds.

The problem of randomly changing URLs was solved by emulating what a human would do: consult some external website that keeps track of Dark web URLs. We used `dark.fail` for this purpose. See Figure 3.6 for a screenshot of its layout. For all major Dark web marketplaces, that site keeps a continuously updated record of which URLs are online and which are offline. We designed our scraper to, whenever necessary, but never more frequently than every 1800 seconds, send a single request to that website and parse its content. The `dark.fail` site itself features a set of rare HTTP headers, a strong CAPTCHA and several hidden cookies, and accordingly, it posed a significant technical challenge to automatically scrape.

Resilience

We wanted our scraping software to be resilient against external failures, e.g. downtime on the marketplaces we scrape, the `anti-captcha` API, `dark.fail`, or failures in our remote cloud based DBMS instances. Such external failures are frequent events, and we wanted our software to resolve such obstacles by pausing execution, using a fallback strategy or doing some other appropriate action.

In the case of marketplace downtime and DBMS or `anti-captcha` failure, the strategy is generally to (1) pause execution, (2) periodically diagnose the status of whichever external service has failed, and (3) resume execution when external service recovers. In the case of downtime on `dark.fail`, the fallback strategy is to retry connections to URLs that have been online at some earlier point in time.

3.3.2 Technical challenges particular to Dream Market

While Empire Market, Cryptonia Market and Apollon Market have been online during the time span of our study, Dream Market ceased its operations on 30 April 2018, more than one year before we started. In order to analyze the now-defunct marketplace in a similar fashion as the other three, we have relied on downloaded web documents compiled by other

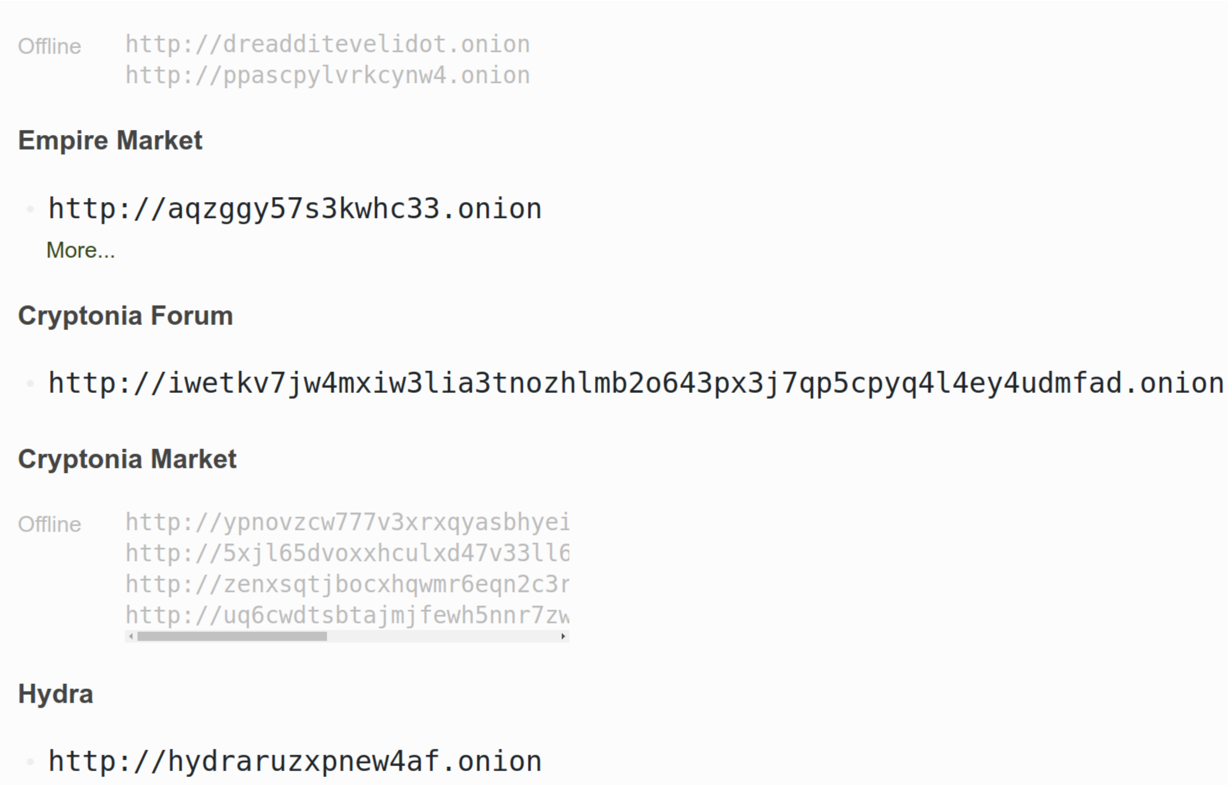


Figure 3.6: Screenshot of the `dark.fail` website. The greyed out button prefixing the Empire Market link indicates that the marketplace was temporarily offline at the time of the screenshot. The greyed-out text of the Cryptonia Market links indicate that the site might be permanently offline.

researchers. The bulk of our documents, numbering 673 871, were generously provided to us by David Décary-Hétu and Rasmus Munksgaard at Université de Montréal. Another 201 791 documents were obtained from an archive compiled by Gwern Branwen, shared via BitTorrent with a torrent file hosted on his eponymous website `gwern.net` (gwern, 2019).

Categorizing page types

When conducting live scraping of online marketplaces, our software has relied on the context of web URLs to make assumptions about which type of page they point to. E.g., if our software followed a URL with an anchor text like Seller:<some seller name>, and this link originated from certain fields in a listing, then it was a very safe assumption that you would indeed get the HTML document of a seller profile page upon downloading the URL resource. Because of this, it was rarely necessary to analyze the document type after retrieving a resource. See Figure 3.7 for an example of an URL on Apollon Market which can be inferred from its context to be a seller profile URL.

When parsing the offline documents of Dream Market, there was little to any such context, so no similar assumptions could be made. For each single document, the structure and contents of it had to be rigorously analyzed in order to categorize it appropriately. Many

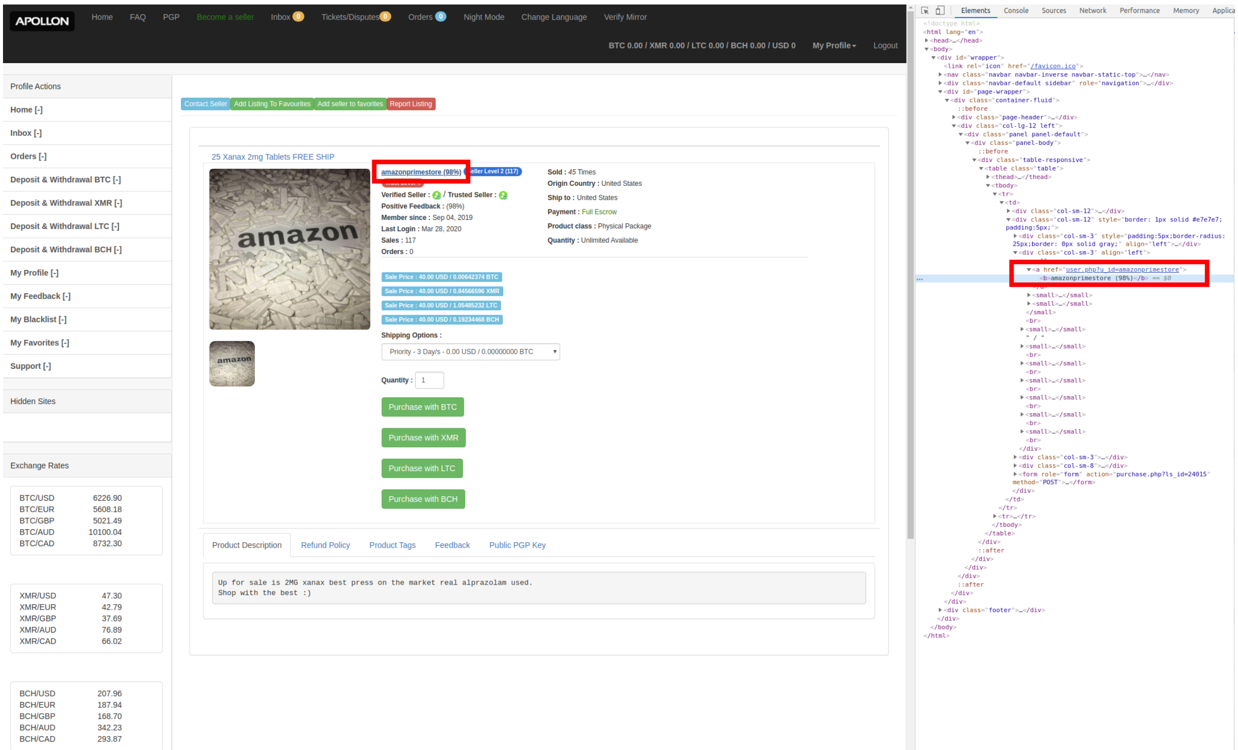


Figure 3.7: Each listing has a seller, and for each listing page, a URL link to the seller's profile is predictably positioned in a particular node of the HTML tree. When retrieving this URL, our scraping software expects from context that a seller profile page will be downloaded (as would any human). The URL in the rendered web page and its corresponding node in the HTML tree are highlighted with red rectangles on the left and right hand side respectively.

types of irrelevant documents needed to be filtered out, including, but not limited to, 40x and 50x errors, wiki pages and profile administration panels.

Inferring entity associations

In addition to knowing *what type* of web page to expect, our software could also assume *the associations* of the downloaded entity. I.e., for the listing in Figure 3.7, it can be safely assumed that the seller who's profile is linked to in the URL, is also the *owner* of the listing, and we could associate the entities accordingly in our database schema.

In the case of Dream Market, such associations had to be inferred and mapped from available information on a best-effort basis. E.g., the name of the seller for each listing could be reliably determined from each listing page, but there was no guarantee of ever obtaining an actual observation of this seller's profile with attributes like rating, feedbacks, registration date, last online date etc. Similarly, there were cases of feedback belonging to a listing with some particular title, but we lacked record of any such listing in the entirety of our material. The lack of such associations are detrimental, because much of our analysis relies on these mappings. E.g., if a feedback is not associated with a listing, we don't know what product category it represents. Fortunately, these cases were not frequent, and they do not significantly impair the completeness of our data.

3.3.3 Incompleteness of Dream Market data

Five crawls of Dream Market were provided by David Décary-Hétu and Rasmus Munksgaard at Université de Montréal. The crawls were conducted between 1 March 2018 to 23 November 2018. The crawls are known to *not* be individual, complete snapshots of Dream Market. *"Some of the crawls might be partial and missing some pages"* (R. Munksgaard, email, 1 March 2020). The sum of transactions made each day on Dream Market is visualized in Figure 3.8. One may note that the graph exhibits a wave-looking shape, with sudden drops and subsequent surges in marketplace trade volume. We hypothesize three reasons, or a combination thereof, to create this abnormal pattern.

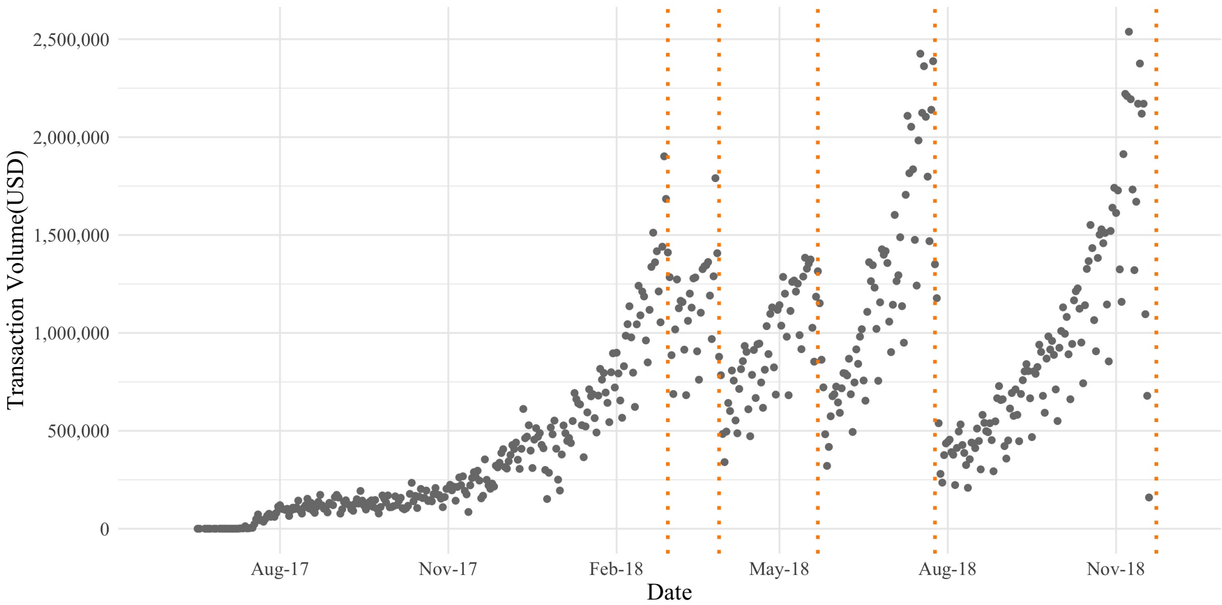


Figure 3.8: Historical transaction volume of Dream Market from provided snapshots. The dates of the five individual snaphots are indicated in orange.

1. Time limit on storage of feedback

Dream Market may or may not have pruned feedback comments beyond some particular age, or otherwise used some design that made old feedback comments less represented in our data. We subjectively observe that "old" feedbacks – published more than 180 days before observation – are rare in our Dream Market material, but we have not quantified their relative prevalence.

2. Paginated feedback was not scraped

Feedback on Dream Market would, for the most part of the site's history, appear as a panel on the bottom part of the corresponding seller's profile page. If the panel contained more feedback than it could fit, there would be pagination buttons to view additional feedback. Feedback would be sorted by publication date, where the most recent feedback was displayed first. In our web pages from Dream Market, the pagination buttons have invariably been toggled to the first page only. We hypothesize that significant numbers of feedback may have gone unobserved as a result of this, and it will disproportionately affect feedback with a publication date long before the observation date.

3. Varying uptime

If Dream Market had extended periods of downtime or otherwise impaired service, we would expect that fewer transactions would be made during those periods. We have searched for old forum posts during the periods of decreased activity to find mentions of marketplace downtime, but with negative results. Our efforts were, however, not exhaustive, and this explanation cannot be ruled out entirely.

3.3.4 Potential incompleteness of Empire Market data

Our scraping software browses through Empire Market in a systematic manner, crawling through ca. 4000 *result pages* each scraping session, where each result page contains links to 25 listings. However, it happens frequently that a listing is observed more than once during a single session. I.e., while a single listing may be observed on result page nr. 54, it may happen that the same listing appears again when the scraper browses to page nr. 55. We believe this can be accounted for by Empire Market's feature of *promoting listings*, enabling retailers to temporarily boost the visibility of their listings. With this feature turned on, a listing may appear in arbitrary result pages.

However, even when taking this explanation into account, it is disconcerting that the number of observed duplicates within a single scraping session does not remain consistent across sequential sessions. E.g., for the scraping sessions conducted on 14, 15 and 16 November, the number of observed duplicates are 14 593, 13 728 and 15 333 respectively, but the size of the initial task queues are nearly identical. This would indicate that the number of unique listings scraped for each these sessions differ by thousands. We have been unable to comfortably determine why this is, the specifics of the potential incompleteness, and how it affects our data set and analysis thereof.

As a general mitigation strategy against the detrimental effects of incomplete scrapes, our software scrapes through the result pages in a stochastic order, attempting to make each snapshot represent a uniform distribution of the contents of the marketplace, *even* in the case of an incomplete run. Taking this into account, we feel somewhat reassured that the incompleteness does not significantly impact the correctness of our results and analysis.

Chapter 4

Selected entities and features of our data

The three most important entities in our data set are *listings*, *sellers* and *feedbacks*. Our data stems from four different marketplaces, but the relationships between the entities, as well as certain core attributes, are consistent and largely similar across the marketplaces. In this section, we describe some properties of our listings, sellers and feedbacks, and we also point out some limitations about what information we *can* and *can not* extract from them.

4.1 Listings

Listings on the Dark Web marketplaces are essentially similar to product listings on legal marketplaces like Amazon or Ebay. For all four marketplaces studied in this paper, they contain a description, the price of the product, the shipping origin country, available destination countries, a list of supported payment currencies, the name of the seller and a weighted rating of reviews (referred to as 'feedbacks'). Other attributes, which are listed on some marketplaces, but not all, are listing publication dates, number of items sold, minimum order amount, quantity in stock and available payment options (Bitcoin multisig, marketplace escrow etc.). Some notes on selected attributes are elaborated below.

Product prices

Product prices are displayed in currencies determined by user submitted preferences in marketplace account settings. We hypothesize that sellers set the prices of their products by entering a fixed amount in their currency of choice. We believe this to be the case because product prices on Empire, Apollon and Cryptonia Market were updated in tandem with the currency exchange rates table on each marketplace. E.g., while the Empire Market listing on Figure 4.1 was priced to 5.46 USD at the time of capture, and we assume the seller has set the price in EUR, we would observe that the price would adjust to 5.51 USD if the EUR gained 1 % on the USD in the marketplace's exchange rate table. Empire Market state *"The* [exchange rates] *are updated every 15 minutes and taken using a weighted average of major exchange platforms"*.

Shipping origin country

One might assume that a self-interested seller is best served by not disclosing her true geographical location, as this would aid a police investigation in discovering her identity. However, a buyer of illegal goods may be concerned about the source location of the shipment. Customs agencies are apt to more thoroughly scrutinize shipments from countries that are common origins of illegal parcels. E.g., the Norwegian Customs pay extra attention to parcels from the Netherlands (FriFagbevegelse, 2015). Accordingly, sellers have significant incentive to be upfront about the real origin of their goods.

Listing rating

Listings are scored with an average of individual feedback ratings. The numeric scales vary between marketplaces, but all scores have been normalized to 0-100 in our data.

4.2 Sellers

All the marketplaces in this study have profile pages associated with individual sellers (or 'vendors', a term used interchangeably in this paper). Profile pages display the registration date, last online date, internal market rating and imported ratings from external marketplaces, if any. All profile pages also contain links to any listings offered by the seller, as well as a complete list of feedbacks submitted to all listing offered by the seller.

For Apollon Market and Empire Market, each seller has a *Vendor Level* and *Trust Level*, indicating how much experience and how many positive feedback the seller has received, respectively (see Figure 4.2). Inexperienced and unknown sellers have *Vendor Level* and *Trust Level* of 1. 21.2 % of the sellers have a vendor level above 3, and 23.6 % trust level above 3. The median trust level and vendor level is 1. The highest level found on Empire Market is 10, although there is only one seller, `HumboldtGrower`, who has earned this rank.

4.3 Feedback

After a product purchase, a user may leave feedback about the product. For Dark Web marketplaces analysed in the past, like the original Silk Road, users were strongly encouraged to leave feedback. Upon submitting feedback, the payment from buyer is released from the marketplace's escrow to the seller. A buyer who does not submit feedback would make the seller wait an extended period of time before receiving payment (Christin, 2012, p. 4). One may note that this does not give personal incentive for buyers to leave feedback, and we are not at liberty to assume all, or even most, of buyers do leave feedback. The volumes of many of our metrics are therefore underestimates of the true volumes.

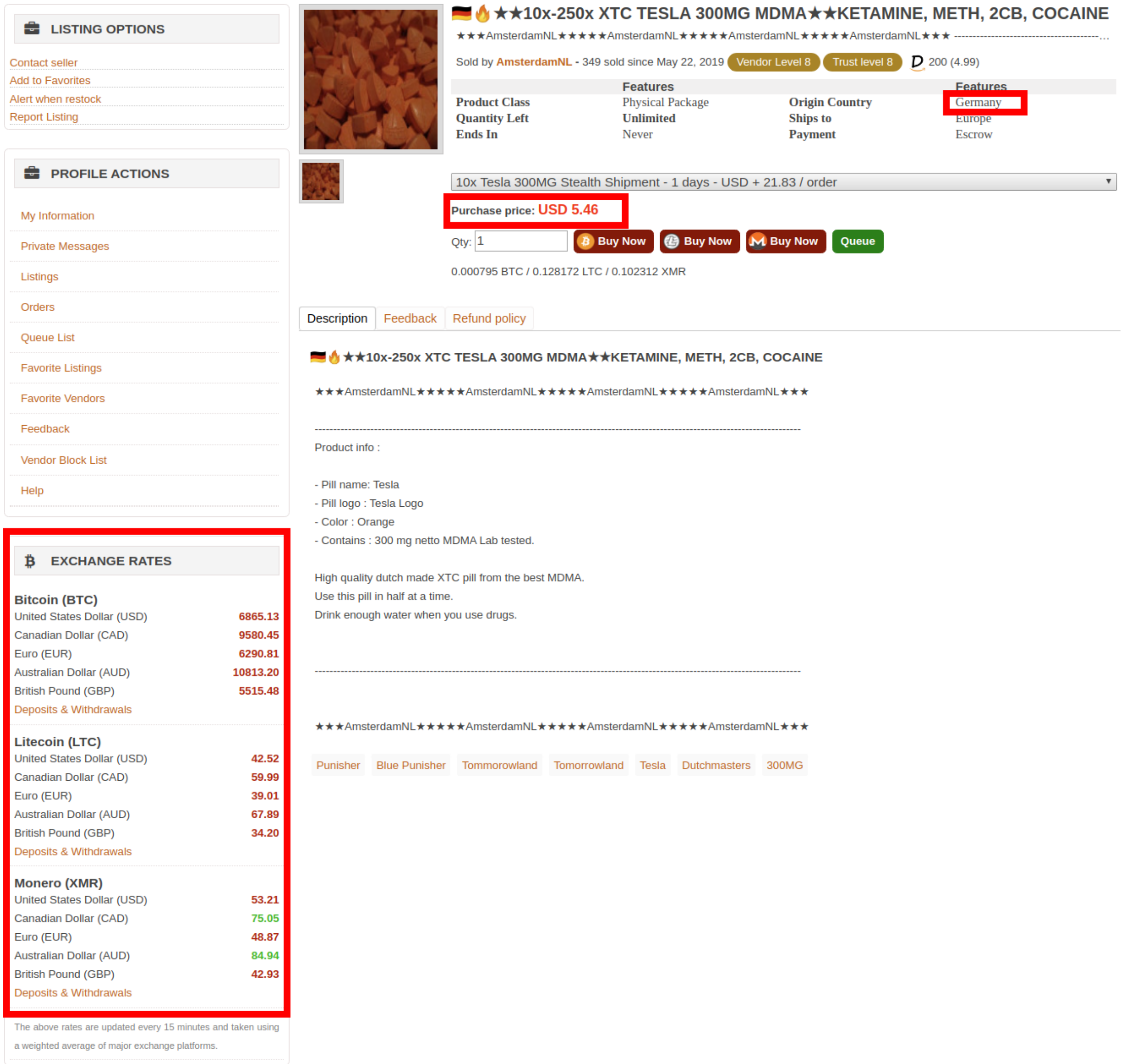


Figure 4.1: A listing on Empire Market. The momentary exchange rates, the momentary USD product price and the shipping country of origin are highlighted with red rectangles.

Feedback rating

The feedback on Empire Market, Apollon and Cryptonia have a threefold scoring; positive, neutral and negative. Dream Market used a five-star rating system, with 1 as the lowest possible score, and 5 as the highest. Figure 4.3 shows an example of a single listing on Empire Market with the three types of feedback.

Purchase amounts

Each feedback contains the purchase amount of the associated transaction. Note that the feedbacks left for the listing in Figure 4.3 are associated with purchases involving 6.25, 15.00 and 20.00 USD respectively. We infer that the purchase amounts are in all likelihood denominated in fixed currency pegged to exchange rates of the purchase date. We believe

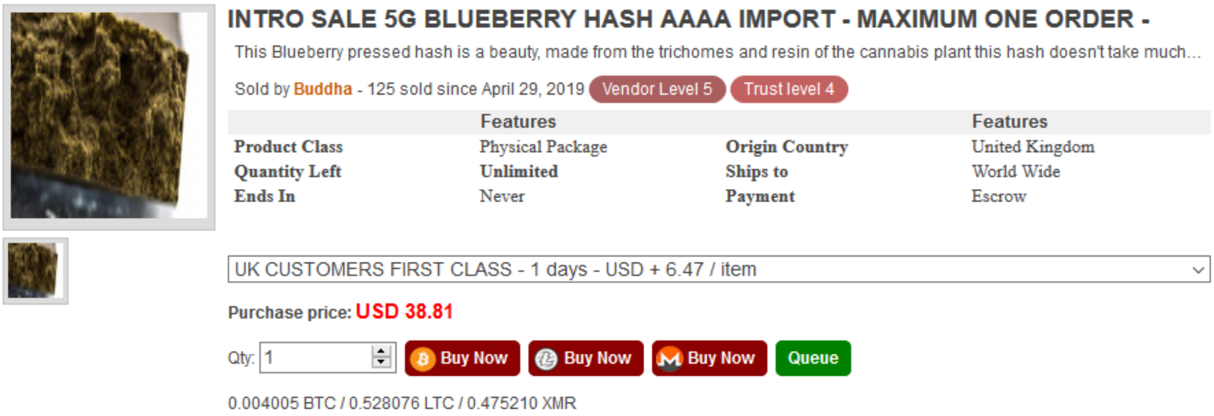


Figure 4.2: Example of listing on Empire Market. This listing is offered by Buddha and has 125 units sold since April 29 2019. Buddha has Vendor Level 5 and Trust Level 4. The listing's origin shipping origin is the United Kingdom, and is shipped to any destination in the world. The seller offers payment in BTC, LTC or XMR, and the current USD price of the item (5g hash) is 38.81.

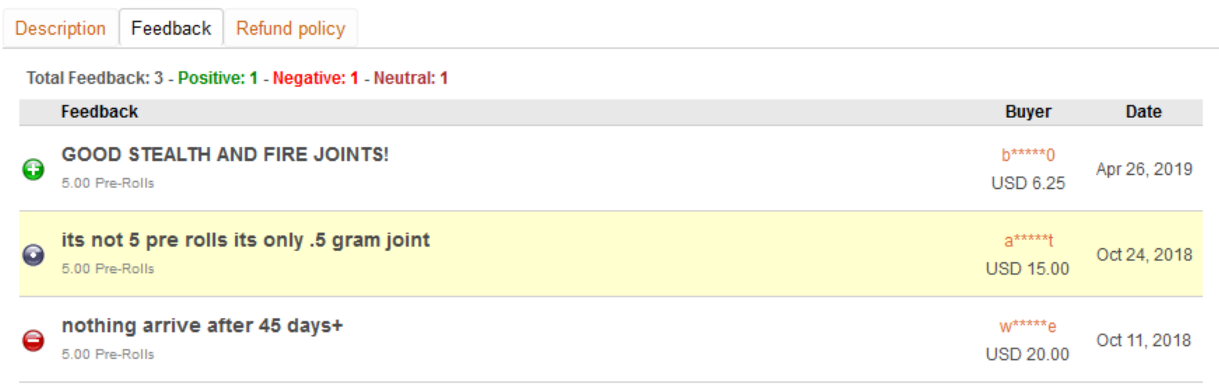


Figure 4.3: Example of listing feedback on Empire Market (GoEmpireMarket, 2020)

this to be the case because amounts are static when observing the same feedback over time. E.g., if a product was purchased for 0.0167 XMR at some point in time when this equaled 1.0 USD, then the corresponding feedback would be published with 1.0 USD as the permanent amount. Even if 0.0167 XMR would trade to 5.0 USD at some later date, the stated amount on the marketplace will still be 1.0 USD.

Exactly which currency the amounts are denominated in, is determined by user submitted account preferences in the case of Empire Market, Apollon Market and Dream Market. In the case of Cryptonia Market, however, the amounts were denominated in *the actual currency which the transaction was made in*, which was invariably either BTC or XMR. This was valuable information for research purposes, as it made it possible to determine the relative transaction volumes and popularity of the two cryptocurrencies, the analysis of which is detailed in section 6.4.

Publication dates

Each listing is stamped with a *publication date*. During our scraping, we have consistently observed that most feedback – but not all – is made visible with a delay of about two weeks. E.g., the feedback with publication date April 26 2019 in Figure 4.3, was likely made visible on the market around May 10. This phenomenon has been consistent across all three marketplaces we have scraped. As a consequence, the two most recent weeks of data analysed in section 6 can be assumed as incomplete, and real marketplace activity was almost certainly higher in that period than indicated by our data.

Chapter 5

Refining the data

This section documents our process of inferring data attributes from natural language by heuristic methods. On two occasions during our work, it was necessary to use such methods. One occasion was inferring the origin countries of listings on Dream Market, and the other occasion was inferring the metric quantity of mass for drug listings on all marketplaces.

5.1 Origin countries

Listings on Empire, Apollon and Cryptonia market used consistent names for countries in the origin country field. Listings on Dream Market did also have this field, but it appears that sellers could submit any arbitrary text to it. E.g., a country could be misspelled as ”Uinted Kingdom” and colloquial names and slang term were occasionally used. It was not entirely trivial to map country names to their proper names even on the three former marketplaces, and it posed a significant challenge on the latter. In order to automatically map fuzzy terms to proper country names and corresponding ISO 3166-1 alpha-3 codes, we devised an algorithm, utilizing third party libraries `pycountry`, `hdx-python-country`, `pyspellchecker` and `googletrans`.

`pycountry` and `hdx-python-country` feature a ”fuzzy search” feature, enabling us to match terms like ”The US” to ”The United States of America” and alpha-3 code USA. `googletrans` offers a programmatic API to the Google Translate service, enabling us to e.g. match ”Deutschland” to ”Germany”. `pyspellchecker` produces a list of candidate words if supplied with a misspelled word, enabling us to convert mangled names like ”Uinted Kingdom” to ”United Kingdom”.

5.2 Units

No marketplace in our study have designated fields in listings to denote what quantity of product is being sold. E.g., a listing may be titled *2 KILO Meth CORONA VIRUS UPDATE USA to USA 95%+ Pure Large Shards*, where the product presumably constitutes 2.0 kilograms of methamphetamine. Inconveniently, the listing does not contain a fixed, machine-readable field stating something like `Metric quantity: 2000 grams`. As researchers, the metric quantities are interesting pieces of information, allowing us to calculate standardized drug prices, estimate metric trade volumes and much more. Accordingly, we considered it worthwhile to devise an algorithm for inferring this attribute for all listings.

Our approach to this problem is similar as the one used by Christin & Soska (2015), which is regular expression matching. The authors of the aforementioned paper used a sequence of 17 expressions to infer the mass. We have used two regular expressions, one for inferring the unit mass of the product, and one for inferring the number of units. E.g., in the title *2 KILO Meth CORONA VIRUS UPDATE USA to USA 95%+ Pure Large Shards*, the unit of mass is kilogram – 1000 grams – and the number of units is 2 (because 2 kilograms are being sold). By multiplying these two quantities, we get the total mass of the product. Table 5.1 shows a random sample of 30 drug listing from our data set for which our algorithm inferred the metric quantity. 89 % of all listings have been labeled with a mass. The remaining 11 % mostly constitute listings with (1) a quantity denoted in volume instead of mass and (2) listings without explicit quantity at all.

Table 5.1: A random sample of product titles from our data set and inferred metric quantity for each title. Quantities are inferred by an algorithm relying on regular expressions.

Product title	**Grams**
250 x 180 mg Blue Tesla xtc Pills	45
1.7 grams Caviar Crack Cocaine	1.7
1gr. High-Quality Cocane	1
Pregabalin 150 mg Lyrica - 42 caps	6.3
28 tablets ZOPICLONE 7.5MG	0.21
X40 Diazepam/Valium 10mg	0.4
1g STARDAWG COFFEESHOP TOP SHELF AAA+	1
KETAMINE - 0,5 KG - R or S - 88%	500
238x*_*Europe Oxycontin 80mg*_*	19.04
4oz Crumble	113.398
Ritalin fr 40mg x 10 caps	0.4
1oz Girl Scout Cookies (GSC)	28.3495
2 gram OG KUSH ——HOLLAND—— AAAA++++	2
1 Gram Hashish - HIYA - FRANK	1
@@AMPHETAMINE SPEED PASTE 56g @@ 160 @@	56
25x GammaGoblin 100mcg LSD — SHIP WW	0.0025
7 grams of China White Heroin	7
28g of Cooked S+ Ketamine [free P+P UK]	28
1000 XTC PILLS 220 mg HIGH QUALITY + TRACK AND TRACE	220
10 x **BRAND NEW** 1.1g DANK VAPES, Fruit Pack, 6 New Flavours In Stock.	11
- 100 pieces Route 66 XTC 220mg MDMA -	22
1 KILO AAAA BIKER METH DELIVERY TO AUS/NZ	1000
25x Hello Kitty XTC pills 180mg mdma	4.5
1.5g ACAPULCO GOLD MEDICAL CBD STRAIN - CBD 12.4%	1.5
7g WHOLE P. Cubensis Cambodians. Organic, Cracker Dry USA	7
The Finest Bruce Banner #3 Shatter California Import 3.5 Grams	3.5
50x Petch's Kesey Acid 150ug LSD blotters	0.0075
-Liquidation Sale- 2oz Unstable Nug Run BHO	56.699
0.2g Crystal Meth straight from Mexico / Best quality / Clean and intense	0.2
3.5 GRAMS of HIGH HEAT COCAINE- Peruvian RAW	3.5

Chapter 6

Results

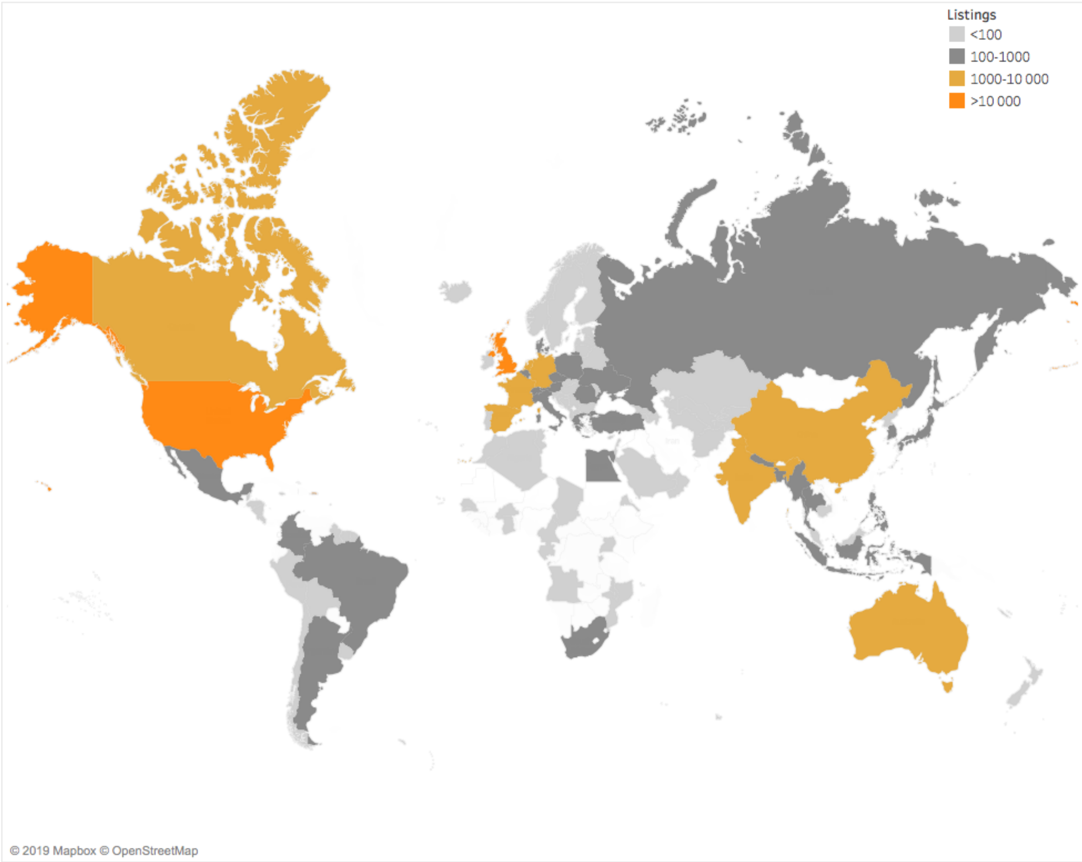
This chapter contains analysis of selected portions of our data set, especially related to cannabis. We examine the popularity of the marketplaces over time and intraweek activity in 6.2 and the price distribution of listings in section 6.3. In section 6.4, we examine popularity trends of XMR and BTC, and we also use a statistical approach to deduce which currencies sellers lock their product prices to. In section 6.5, we examine seller ratings based on feedback submitted by buyers. Our data set was obtained by daily scraping several marketplaces. Empire Market was the first, started 13 October 2019 and is still active. Cryptonia Market was scraped from 9 November 2019 to 19 November the same year. Cryptonia Market went offline on the 19 November, and has not come back online as of July 2020 (see Appendix A.1). Scraping of Apollon was initiated 3 February 2020 and lasted until 12 March 2020. We were provided ca. 650 000 web documents from Dream Market, spanning from 9 January 2014 to 12 November 2018.

Table 6.1: Marketplaces Database Summary

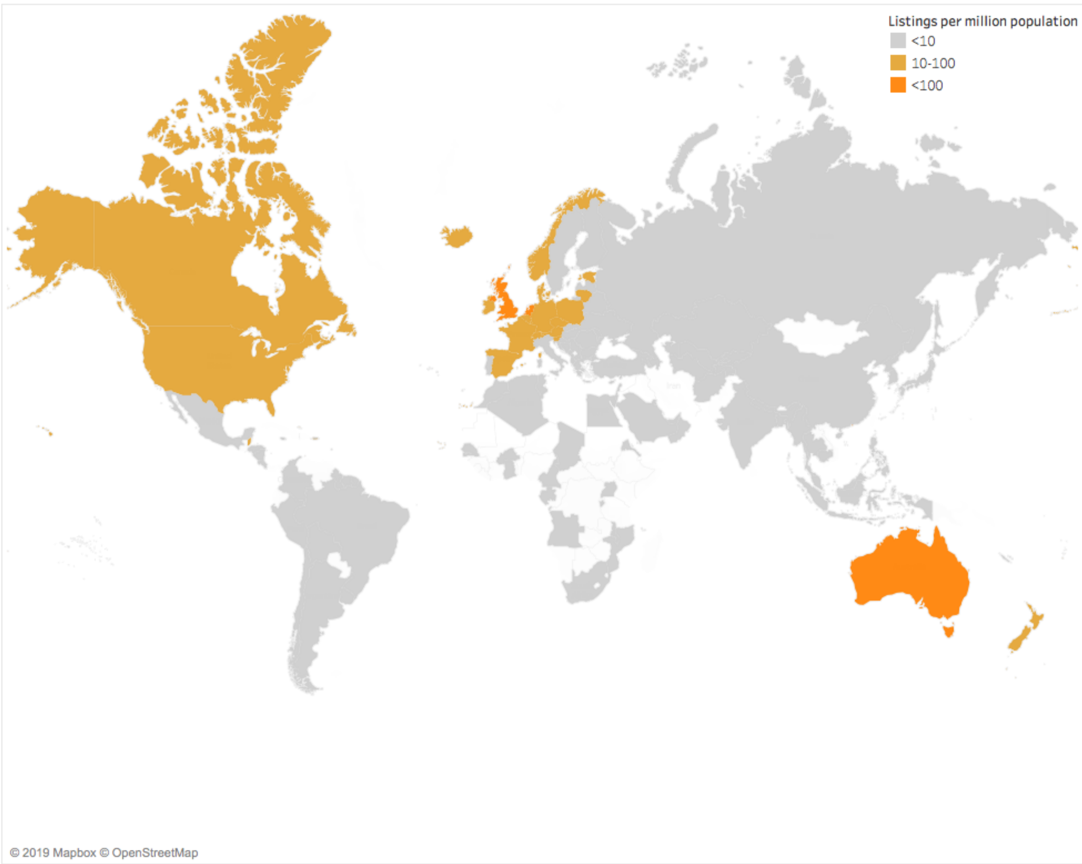
	Listings	**Sellers**	**Value (USD)**
Empire	95 899	3315	130.9 M
Cryptonia	22 495	951	11.2 M
Apollon	64 897	1841	5.8 M
Dream	258 286	4582	148.5 M

6.1 Listing Distribution

The listings have self-reported origins mainly in the US, UK, Europe, Australia, China and India as seen in Figure 6.1a. By dividing number of listings of each country by the total population of the respective country, the per capita distribution in 6.1b is formed. By examining the latter distribution, it appears that Dark web vendors are most prevalent in the Anglosphere and Western and Eastern Europe.



(a) Listings by country, based on origin country as stated in each listing description



(b) Listings per capita by country, based on origin country as stated in each listing description

Figure 6.1: Heatmap of listings

6.2 Market Distribution

As of April 1st 2020, the data set has accumulated 3 386 279 observations of listings spread over 441 577 unique listings. Similar to most known marketplaces on the surface web, the marketplaces on the dark web are divided into several categories and subcategories.

Table 6.2: Marketplace overview

Marketplace	Total listings scraped	Unique listings	Sellers	Feedback given
Empire	1.86 M	95 899	3315	1.01 M
Cryptonia	228 967	22 495	951	56 607
Apollon	728 507	64 897	1841	61 664
Dream	568 805	258 286	4582	2.36 M
Total	3.39 M	441 577	10 689	3.49 M

6.2.1 Marketplace development

Dream Market was founded a couple of months after the close of Silk Road, growing to be the biggest marketplace during operation (*Dream Market* n.d.). The authors have been provided scrapes with transaction recordings between 24th March 2015 and 19 November 2018. Dream Market announced 26 April 2019 that it was going to close down the web page on 30 April.

Empire Market was launched in February 2018. We can observe from our data that the first transaction was 14 February 2018, with frequent transactions from beginning of March 2018. The growth of Empire was slow and steady until start of April 2019, when the transaction volume increased exponentially within the first two weeks. The biggest marketplaces at the time, Dream Market, announced on 26 April 2019. When observing Figure 6.2 in light of the closure of Dream Market, a conclusion can be drawn that a large amount of the users of Dream Market moved to Empire Market.

A month after the establishment of Empire Market, Apollon Market was opened. The first transaction recording in the obtained data set is dated 3 April 2019, about a year after the stated opening. In the end of 2019, a a surge in user activity happened in the period while Empire Market was facing problems, as seen in Figure 6.2.

Cryptonia had the first transaction 5 January 2019. It was not until 1 April 2019 the second transactions took place, followed by multiple transactions daily. In a similar fashion as Empire Market, Apollon experienced a rapid growth with the closure of Dream Market. It was, however, less pronounced in this case. We hypothesize that the administrators conducted a test in January while setting up the site, and made it public in beginning of April.

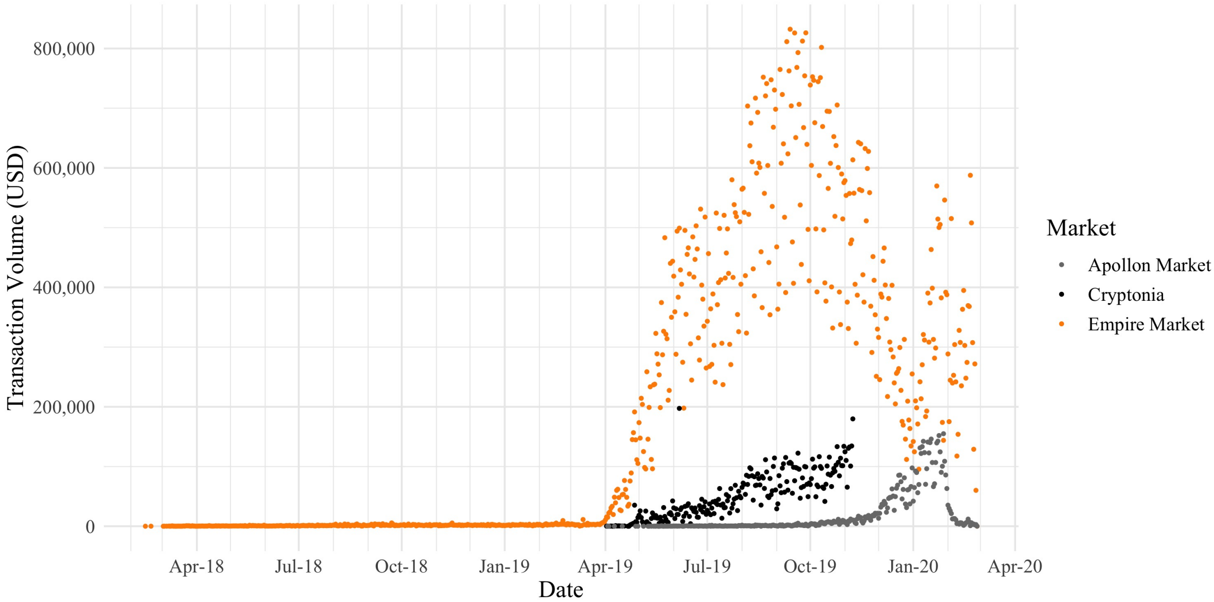


Figure 6.2: Historical Transaction Volume Empire Market, Apollon Market & Cryptonia

6.2.2 Weekday volume

Both Cryptonia and Empire have an increase in transaction volume from Monday, to the weekly high on Friday as Figure 6.3 present. Apollon Market and Dream Market have a somewhat different distribution with a leveled volume from Tuesday to Friday. The two marketplaces have a weekly high on Tuesday and weekly low on Sunday. This might indicate that most of the buyers on all marketplaces are somewhat professional. The authors hypothesise that non-professionals with a regular day-job use the weekends to a greater extent to buy illicit goods and services.

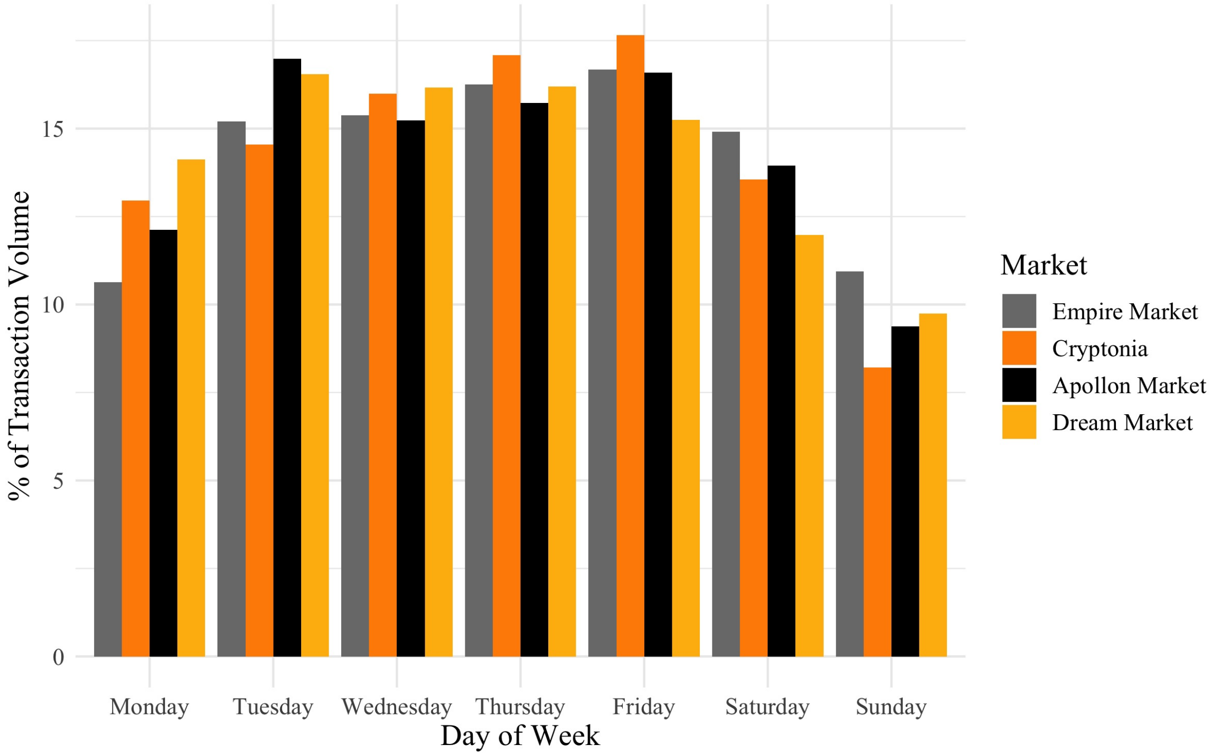


Figure 6.3: Transaction Volume Day of Week

6.3 Listing analysis

6.3.1 Price distribution

The price distribution of all listings in the observed time frame range from USD 0.01 to USD 150 000. The largest transactions in terms of dollar value is two units of *HONEST COCAINE - 1 kg Premium 90% Fire Cocaine* listed to a price of USD 25 000. The transaction of USD 50 020 made by G***r was made 1 July 2019. Most of the listings of a price close to zero have a way higher transaction price, indicating that the price is negotiated later when contact is established between buyer and seller. This is mainly seen in listings offering services, but samples of a great difference between listing price and transaction price are seen in all kind of categories.

6.3.2 Quantity

By running an algorithm searching for information about the unit size as described in section 5.2, grams per unit for drug related listings were calculated. Figure 6.4 visualize the distribution of listing sizes. The median size is 14.0 grams per unit. The listing with the most grams per listed unit is *100kg Premier Gelato* cannabis based in Germany, although there is no record of an actual purchase of this product. Using the price of transactions, calculations of price per gram of all these drugs can be made. Longitudinal prices of different kinds of drugs can be analysed by category, location and vendor.

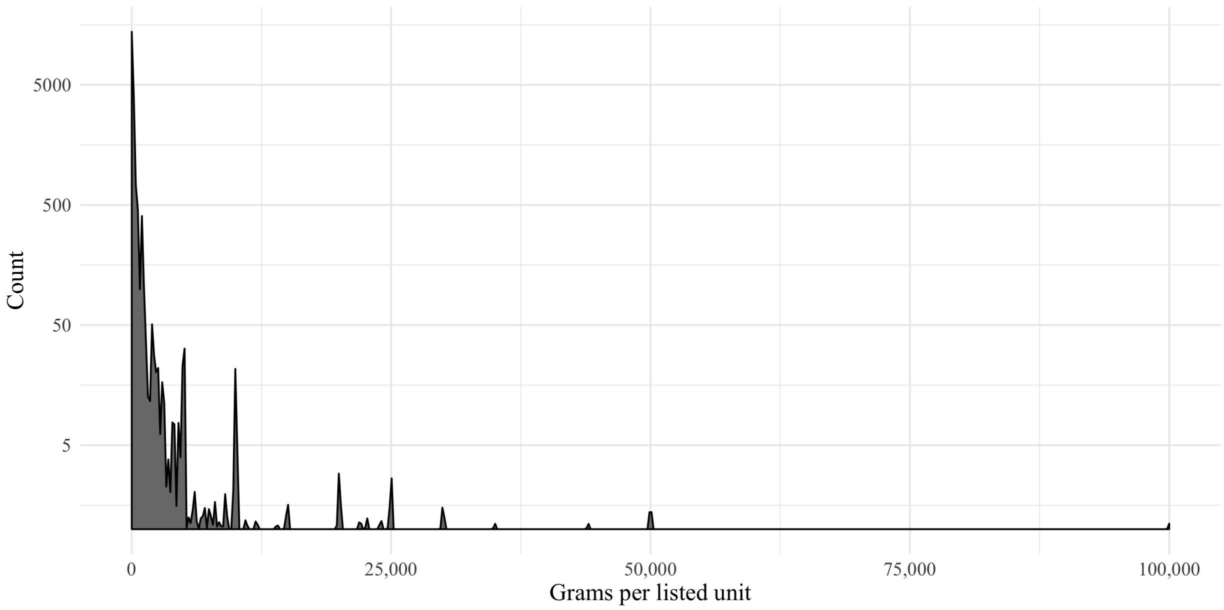


Figure 6.4: Size distribution of drug listings

6.4 Currency analysis

6.4.1 Comparing adoption of Bitcoin and Monero

Bitcoin is a decentralized digital currency, not associated with any central bank. Bitcoins are mined by solving computationally difficult puzzles to discover new *blocks*. The incentive to the miner for creating a new block is the *block reward* (currently 12.5 bitcoins). After every 2016 blocks, the puzzle is made either harder or easier by the collective network in order to ensure the average time between each block is 10 minutes. The block contains a collection of the transactions done between the holders of bitcoins since the last block was mined. Each block has a reference to the last, forming a *blockchain*. The blockchain contains collections of all transactions done in the history of bitcoin and is available to all participants. Bitcoin holdings are identified by an *address* (public key); a long strings of numbers and letters. *Transactions* are transfer of coins from one address to another. The transaction needs to be authorized by the owner of the addresses, using a secret known as their *private keys*. According to Foley et al., 2019, 46 % of Bitcoin transactions are associated with illegal activity. Most of transactions on dark web marketplaces are done in Bitcoin, but other currencies are gaining market shares.

Monero (XMR) was launched in April 2014 and has become one of the biggest cryptocurrencies in terms of market capitalization. Monero obscures the digital addresses and value in all transactions, creating almost totally anonymous transactions. It has a dynamic limit to the size of individual blocks, making it more suitable than the Bitcoin network for handling large transaction volumes. An AlphaBay representative told *Bitcoin Magazine* that Monero accounts for 2% of AlphaBay's transactions (Torpey, 2016).

By the use of feedback on Cryptonia marketplace, it is possible to obtain information of what cryptocurrency was used as payment (Bitcoin and Monero are the options available on Cryptonia). By analysis of the scraped data, is it possible to gain a view of the trends in use of the two currencies.

As stated in section 6.4.1, Monero is a cryptocurrency which provides greater anonymity for users than Bitcoin, and would seem the natural choice for retailers and customers on Dark web marketplaces. However, according to AlphaBay in 2016 (the most widely used marketplace at the time), Monero only accounted for 2 % of their transactions (Torpey, 2016). Noting this, we hypothesized that Monero market share would, at the very least, be trending positively. We discover, somewhat surprisingly, that this is not the case.

The relation between the use of Bitcoin and Monero is calculated historically as a ratio by dividing total daily transaction volume of Monero by total daily transaction volume of Bitcoin. A hypothesis of a increase in use of Monero would result in a increasing ratio.

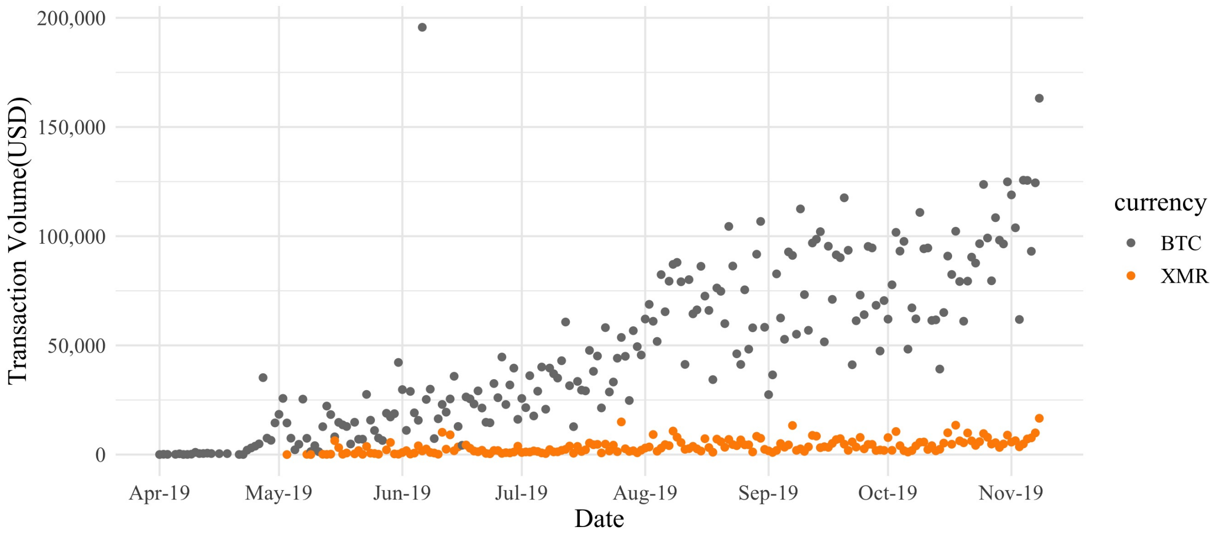


Figure 6.5: Historical Transaction Volume Cryptocurrency

Figure 6.5 shows a very slow and linear growth of Monero and a continuous high growth of Bitcoin. With a declining ratio of all transactions made on Cryptonia as Figure 6.6 shows, the hypothesis of increased use of Monero can be rejected. Doing a linear regression of the relation over time by ordinary least square method where X is date and $\hat{Y}$ is the ratio of total transaction volume of XMR to total transaction volume of BTC:

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X + \hat{\epsilon}_i \tag{6.1}$$

The relation between Monero and Bitcoin gives a $\hat{\beta}_0$ of 0.085 and $\hat{\beta}_1$ of -1.4081×10^{-4} with a p-value of 0.12. A null hypothesis of flat trend can not be rejected. Although not significant at the 0.05 level, the trendline indicates a decrease in use of XMR compared to BTC of 31.4% during the six months studied.

6.4.2 Underlying currency

The data set with daily data points makes it possible to analyse the daily changes in price of each listing. When listing a product, the seller chooses an underlying currency to denominate the product price. The possibilities at the marketplaces in focus are USD, EUR, CAD, AUD, GBP, BTC and XMR. From the perspective of a customer, the stated price for a listing is *not* necessarily denoted by the seller's currency, but a user-defined currency which is configurable in the settings of each marketplace web account. Therefore, if a listing has e.g. Euro as underlying currency, but is observed multiple times with a price denominated in US dollars, the listing price will fluctuate in tandem with the exchange rate between the underlying currency and US Dollars. The price seem to be updated every 15 minutes on average. We argue that for each individual listing, we can infer the underlying currency by (1) collecting all observations of the listing, (2) retroactively calculate the price in each available currency with historical exchange rates, (3) calculate the variance of prices

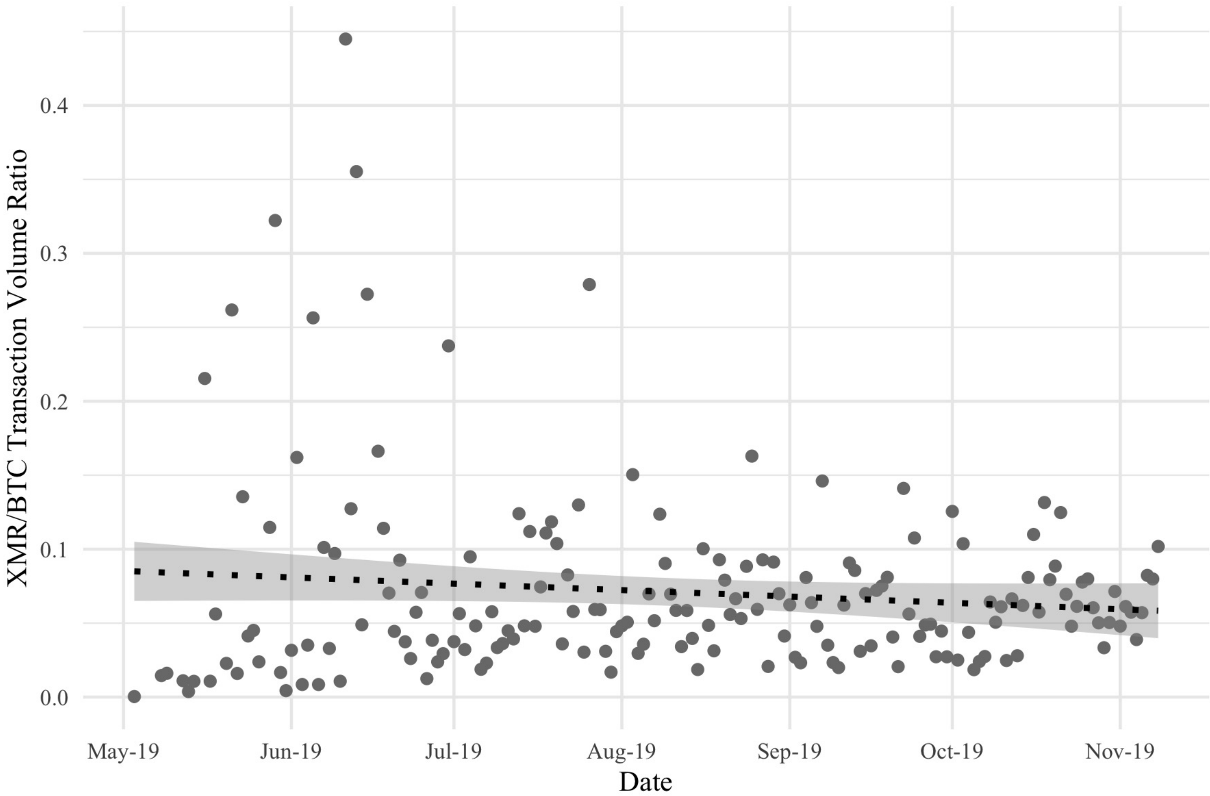


Figure 6.6: Historical relation between use of Bitcoin and Monero

in each currency, (4) select the currency which exhibits the lowest variance.

Formally, let $C_a = \{USD, EUR, GBP, CAD, AUD, BTC, LTC, XMR\}$, let p_{cl} be the set of retroactively calculated prices for listing l in currency c. The inferred underlying currency $\hat{c}_l$ for each listing l is defined as

$$\hat{c}_l = \min_{c \in C_a} \{\mathrm{Var}\left(p_{c_l}\right)\}, \quad l \in L \tag{6.2}$$

This analysis is done for all listings on both platforms. As seen in Figure 6.7, half of all listings have US Dollars as the underlying currency.

In order to minimize the hazards posed by law enforcement, it is in each seller's best interest to remain anonymous and limit public information of themselves. It is conceivable, e.g., that a seller's identity would be more easily unmasked by police if they knew the seller's country of operation. Conversely, a seller also has incentive to *do* disclose her true country of operation, for reasons explained in section 4.1. Considering these counteractive forces, we pose the hypothesis that risk averse sellers might choose to disclose a *false* origin country in their listings, and that for some sellers, the *true* origin country might be revealed by the underlying currency of their listings. E.g., a listing which is stated with a French shipping origin, but is inferred to have GBP as underlying currency, might be indicative of a UK based vendor who want law enforcement to believe she is based in France. If we compare the

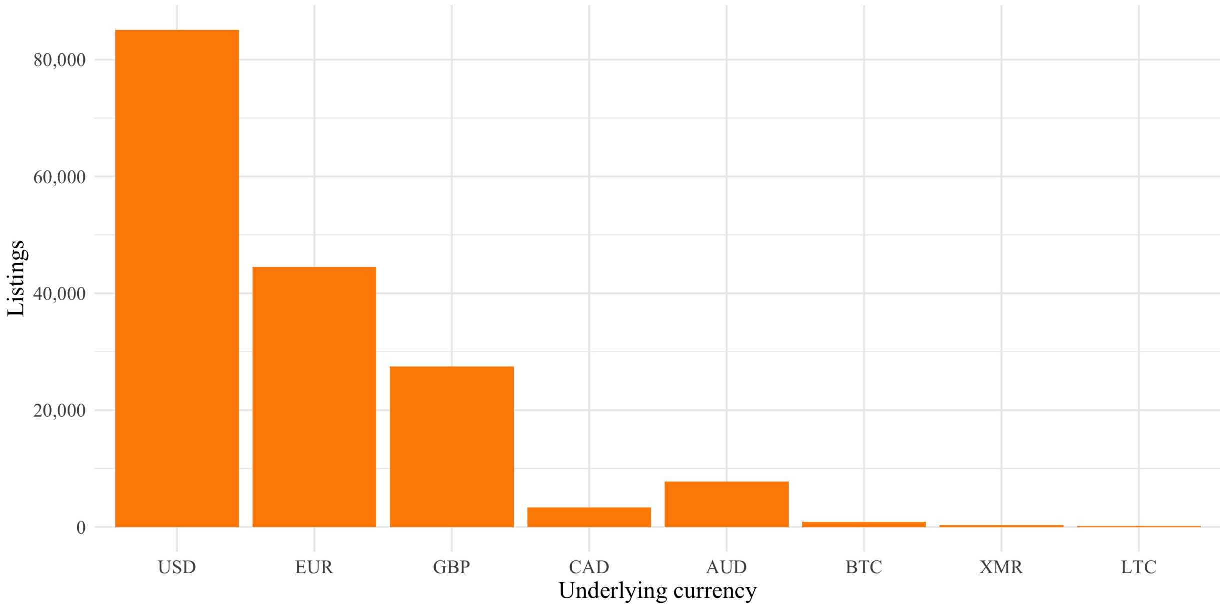


Figure 6.7: Listings sorted by currency

primary currency for the stated origin country of each listing (e.g. GBP is primary currency for UK), and compare this value with the inferred underlying currency of each listing, we can examine any disparities between the stated origin and the underlying currency.

Let $C = \{USD,\ EUR,\ GBP,\ CAD,\ AUD\}$, let M_c be the set of countries with official currency $c \in C$, let L be the set of all listings, let L_c be the set of listings with an origin country $m \in M_c$, let $L_{\hat{c}}$ be the set of listings with inferred underlying currency $\hat{c} \in C$. *Location coefficient* k_c is calculated as

$$k_c = \frac{|L_{\hat{c}} \cap L_c|}{|L_c|}, \qquad c \in C \tag{6.3}$$

Informally, this coefficient can be interpreted as *how large a percentage of listings with currency c originate from a country where c is the national currency.* E.g., if $k_{USD} = 0.5$, it means that 50% of all listings which have inferred underlying currency USD, also state the United States as their country of origin. See Table 6.3 for the calculated values.

Table 6.3: Location coefficient by currency

Underlying currency	Location coefficient	Nr. of listings
USD	0.699	44 163
EUR	0.798	33 499
GBP	0.885	25 392
AUD	0.630	7 304
CAD	0.372	30 32
Total	0.755	113 388

The location coefficients in table 6.3 would indicate that underlying currencies do, more often than not, coincide with the stated origin locations of products. An interesting observation is how the location coefficient of Canadian dollar deviates significantly from the average of all the listings (see further details in Table 6.4). We hypothesize this may be because Canadian vendors prefer to lock their prices to USD, even though this is not Canada's national currency. Interestingly, only 1.9% of listings with USD as underlying currency have Canada as the given location by the seller. For the hypothesis to be correct, Canadian sellers are listing both the United States as their location and US Dollars as their currency of choice.

By adjusting the original hypothesis that risk averse sellers state false origin countries, we can get another interpretation of the results. Suppose that (1) some vendors are organized in international enterprises, and (2) the underlying currency is *not* necessarily indicative of the physical origin of the products, but rather the nationality of the enterprise headquarters. Suppose, e.g., that a listing which is shipped from the Netherlands is determined to have underlying currency USD. One could interpret this as an indication of a US based enterprise with a subsidiary in the Netherlands. The US headquarters would dictate USD-denominated prices to the Dutch subsidiary, and individual parcels would be shipped from the Dutch location to European customers. We lack data to support the absence or prevalence of such enterprises, so it is ultimately difficult to test the hypothesis.

Table 6.4: Given location of listings with CAD as underlying currency

Given location	Count	% of total
Canada	1241	37.2
Germany	423	12.7
United Kingdom	301	9.0
United States	278	8.3
Netherlands	255	7.6
World	244	7.3
Europe	178	5.3
Australia	106	3.2
France	96	2.9
Others	153	4.6
Total	3336	

6.5 Seller analysis

6.5.1 Seller loyalty

A great part of the buyers leave feedback, both good and bad. Vendors on Dream Market got rated with a score from 1 to 5. Apollon, Empire Market and Cryptonia have a threefold scoring; positive, neutral and negative as described in section 4.3. However, although Cryptonia user guides explicitly state that neutral feedback is supported, we have never actually observed an instance of neutral feedback on Cryptonia. For all marketplaces, the profile page of each vendor publicly displays the average score of all feedback that vendor has received, comprising that vendor's *rating*. The distribution of vendor ratings are displayed in Figure 6.8. Most of the vendors are given positive feedback; the median feedback of all sellers is 99.35%, indicating a better business from selling a good product than scamming buyers. We note that this result supports the findings of Bhaskar et al. (2017), who ascertained that Dark Web marketplaces are resilient to the moral hazards which one might naively assume would plague them.

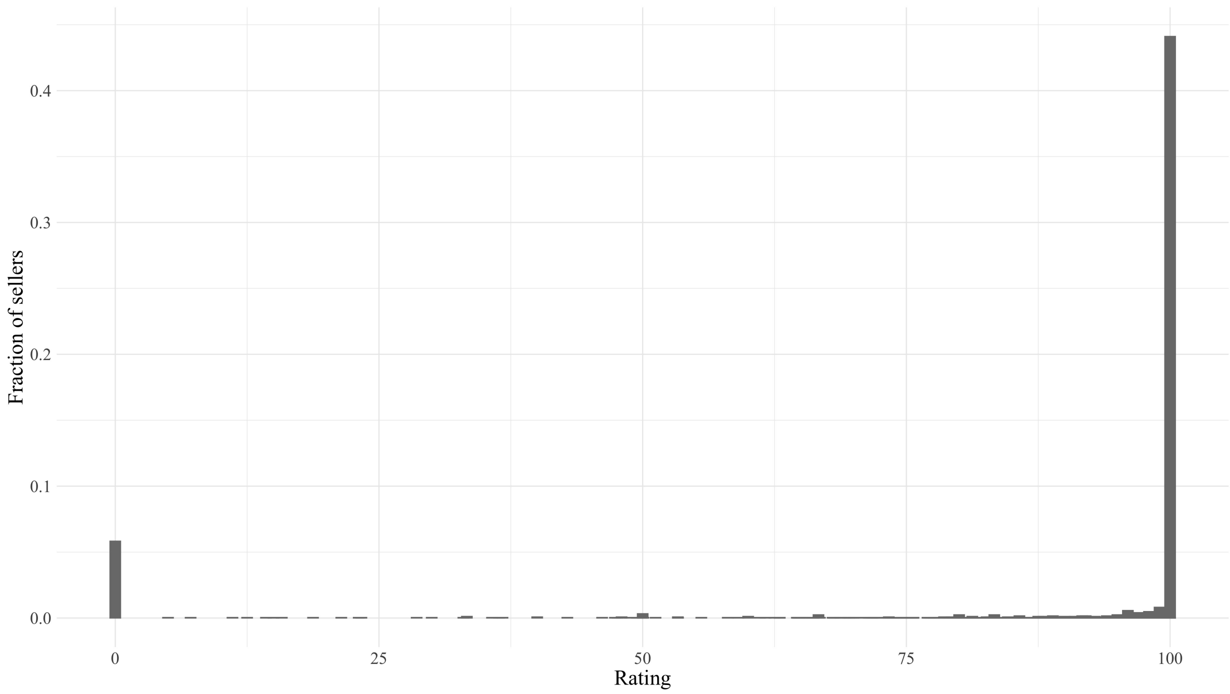


Figure 6.8: Rating Distribution, score 0-100

6.5.2 Vendor volume

To obtain better insight in the ecosystem of illegal activity, the total value of the transaction volume of each seller is calculated. Empire present the transaction value in US Dollars, and Cryptonia in the cryptocurrency used (either Bitcoin or Monero). The value is converted to Dollar-value by linking it to the exchange rate at the time the feedback was posted. Figure 6.9 plots the cumulative distribution of vendors by the entire value of their sale-transactions. On average, a seller has generated a total of just below USD 5000. Most sellers, 65%, have sold between USD 1000 and USD 100 000 worth of items. About 30% of all vendors at the marketplaces have made about USD 1000. The last 10% of the sellers have a total volume of above USD 100 000. 1% of them made more than half a million dollars, equaling 23.3% of the total transaction volume. Dream Market is the marketplace with the longest timeframe of observed feedback data, and as a result the top vendors in respect of revenue made are sellers from Dream Market. The most successful vendor is of all *HumboldtGrower*, who has made USD 1.8 million in the period between registration at Empire Market 25 April 2019 and 1 December 2019. He is fully specialized within the *Drug* category, particularly *Cannabis & Hashish*. The disparity in transaction volume shows the marketplaces consist of both professional sellers who operate a business and sellers who experiment in the market. 60% of all vendors have made less than USD 10 000 since the marketplaces were launched, and we label these sellers as *non-professional*. The vendors who have made above USD 10 000 are considered successful and labeled as *professionals* who operate a real business.

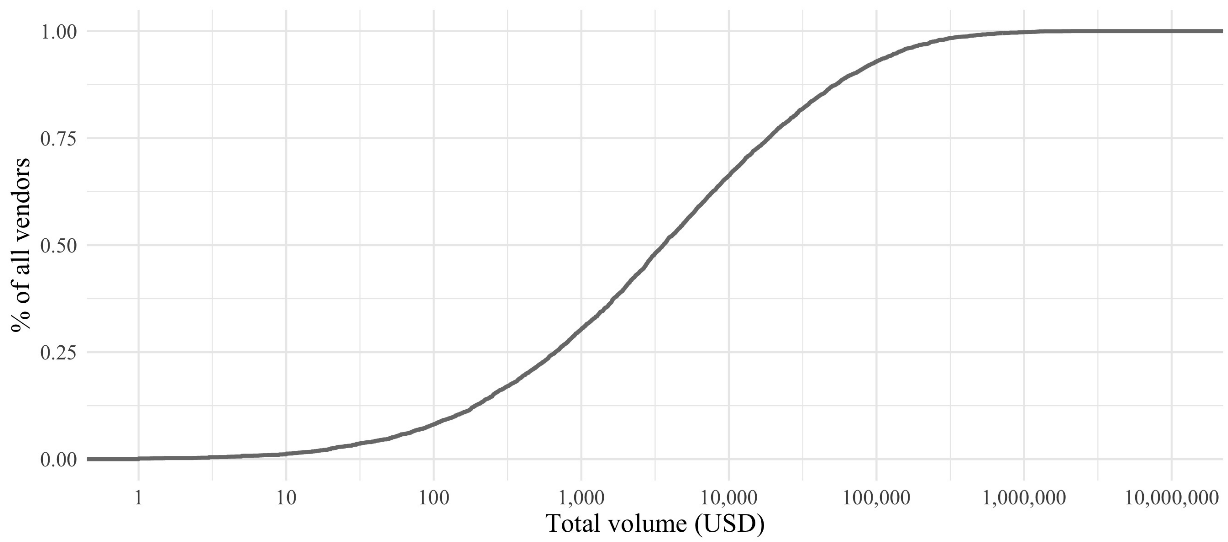


Figure 6.9: Cumulative distribution of total seller revenues. E.g., about 65% of sellers have sold products for less than 10 000 USD.

6.5.3 Diversification

To understand the business of the different types of sellers, analyses of the diversity of what each vendor is offering have been conducted, both for professionals and non-professionals. To see trends for the past, the present and possibly the future, analysis of diversification of both products offered and sold was done. By the use of the feedback information to get the transaction history and linking them to the data of all listings, the sold items are aggregated into categories. The marketplaces being scraped have multiple category levels. Empire is structured into 11 main categories, with two recursive levels of subcategories, i.e.

a main category may have a subcategory which in turn has more subcategories. Let α be the set of main categories on Empire Market. To obtain comparable result to Christin & Soska, 2015, the same method of calculating diversity for sellers is used. $\phi_i(s_j)$ is defined as the normalized value of the category $i \in \alpha$ for seller s_j, where $\sum_{i=1}^{|\alpha|} \phi_i(s_j) = 1$. The specialization of each seller s_j is measured by a coefficient of diversity c_j, defined as

$$c_j = (1 - \max_{i\in\alpha} \{\phi_i(s_j)))\} \frac{|\alpha|}{|\alpha| - 1} \tag{6.4}$$

Informally, this coefficient measures how specialized a seller is in the category of their "main" product, normalized so that a coefficient equal to zero means that seller is fully specialized. A low number equals a high degree of focus in one category. If a seller has 50% of the listings in one category, and 10% in seven other categories, this will equal a coefficient of diversity of 0.57.

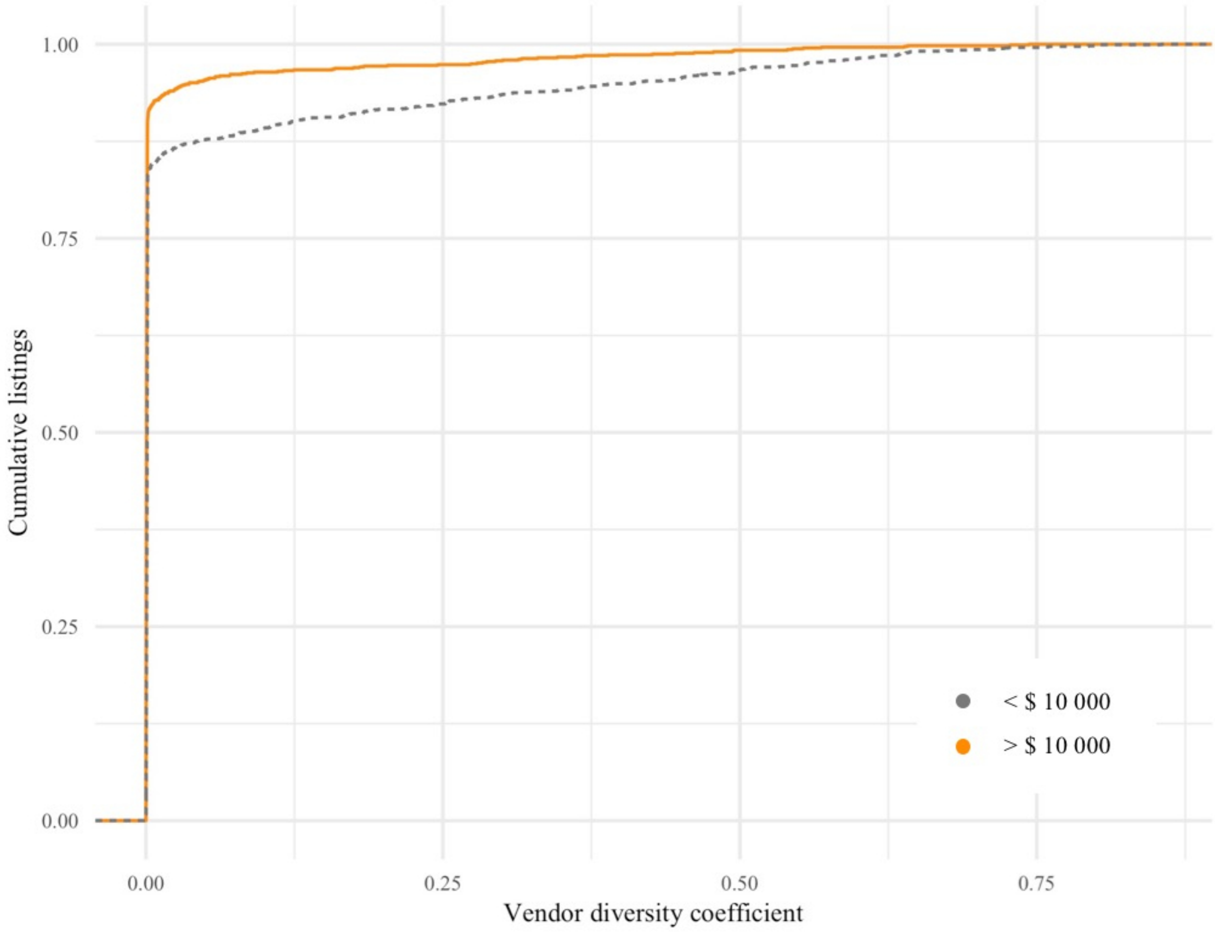


Figure 6.10: Vendor diversity

As seen in Figure 6.10, most sellers have a low diversity coefficient. As the *Drugs* category is by far the largest on the marketplaces, and the sellers offering this type of product are less likely to sell other type of products, a massive fraction of all sellers have a coefficient of 0 (equal to offering only products within the same category). To see the differences between the one doing a real business and the ones who do it for experimenting, the diversity coefficient were divided by their sellers status as professionals and non-professionals. Of vendors making above USD 10 000, just 0.77% have a coefficient above 0.5. 95.94% have a diversity below 0.1, i.e., more than 90% of their listings in the same category. Almost all of the professionals are highly specialized and sell only one type of product. Of the non-professional vendors, 3.36% have a diversity coefficient above 0.5 and 89.16% below 0.1. The Figure 6.10 clearly demonstrates that vendors with a low transaction volume are more diverse than the professionals.

Comparing the coefficient of diversity to the paper of Christin & Soska, 2015, it is indicated that the diversity of vendors have decreased. Their paper only looks at retailers with a transaction volume of more than USD 10 000, and found approximately 15% of them to have a diversity coefficient above 0.5, significantly higher than our results. The authors of the paper have generated their own categories. Although many are similar to the main categories used on the marketplaces, they have split drugs into specific groups. As a result, many of the drug listings get a coefficient between 0 and 0.1, instead of 0 as they do in our analysis. This explain some of the deviations between our results and theirs. Furthermore, it is worth noting that the marketplaces represented in our respective data sets have little overlap. Still, the data might suggest a trend of increasingly specialized sellers.

6.5.4 Rating

As seen in Figure 6.11, there is no relation between rating and price of scam records compared to genuine listings.

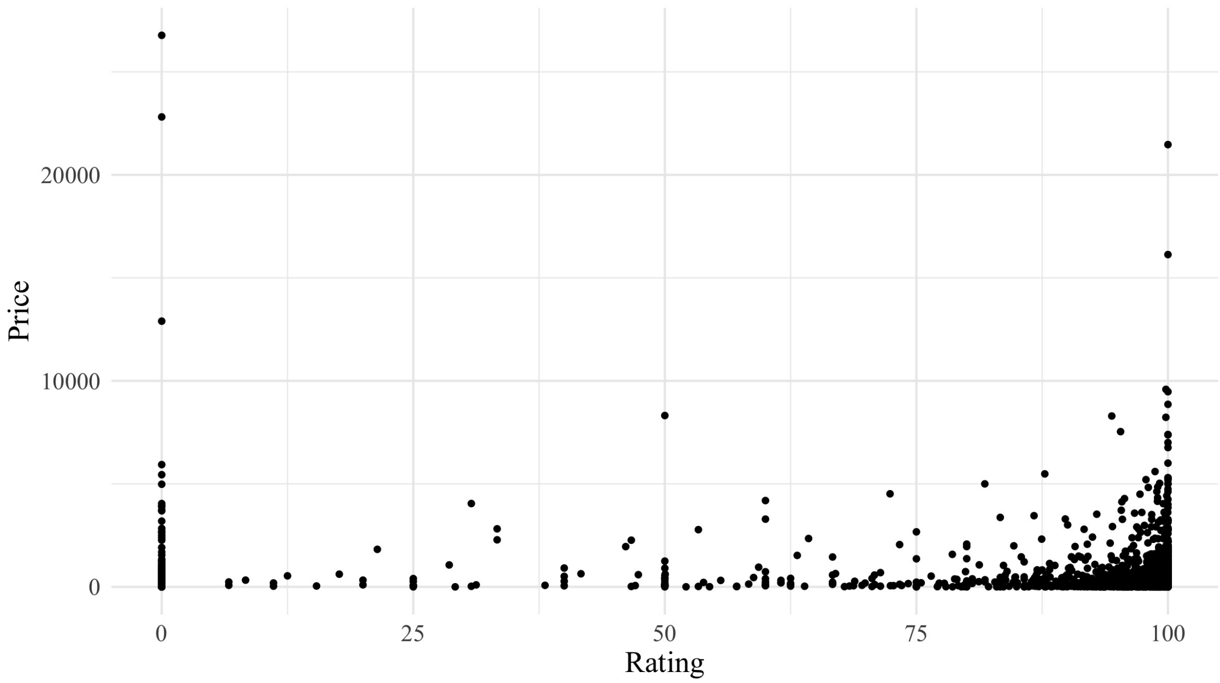


Figure 6.11: Price related to listings

In addition to estimating the distribution of rating and feedback given to the sellers, we strived to develop an understanding of what are the main variables affecting a good or bad rating. As a great amount of the feedback are positive, this causes a great clustering in the data set. As a result, a regression was not revealing.

More interestingly, the factors related to neutral or negative feedback was analysed. By removing all the ratings with a perfect score, a better study of the differences between a bad and a almost perfect score could be obtained. All different variables obtained in the data set were analysed in relation to the rating-score, a total of 41 parameters. Quantity of items sold, time since the seller joined the marketplace, number of feedback given to others, what cryptocurrencies the sellers offered and if the listing was a promoted listing, were some of the most significant variables related to rating score. In Table 6.5, the 11 most meaningful variables of the linear regression model is presented. Days since the vendor joined the marketplace is the most important variable of predicting rating, and gives a $\hat{\beta}_0$ of -0.05 per day from sign-up until 1 April 2020. This parameter has a p-value of 0 (where the coefficient having a value of zero is the null hypothesis). If the seller offer the buyer to pay in Monero, this creates a linear regression to higher rating score that is highly statistically significant and a $\hat{\beta}_1$ of 2.3. Close to every seller offers Bitcoin as a payment, only a few frivolous sellers with a bad rating does not have this option. Hence, a clear relation with the offering of Bitcoin and seller rating is seen. As is indicated in 6.11, no significant linearity is found of price related to rating. Interestingly, the listings that have been promoted has a $\hat{\beta}_2$ of -5.7 with p-value of 0.00006 (highly significant). We hypothesize that sellers with motivation of scamming buyers might promote the fake listings in the attempt of tricking more people into their scam. Given feedback, quantity, number of views and how many disputes the seller has been part of are significant variables, but not having any substantial impact on the rating. This model gives a total R^2 of 0.19.

$$\hat{Y} = \hat{\beta}_0 + \sum_{n=1}^{11} \hat{\beta}_n X_n + \hat{\epsilon} \tag{6.5}$$

Table 6.5: Linear regression calculation

	$\hat{\beta}$	P-value	Note
Constant	51.9	0.00004	
Days since seller registration	-0.05	0	
Price of listing	-0.00002	0.12	
Bitcoin (supported payment option)	47.5	0.0001	Binary
Monero (supported payment option)	2.3	0	Binary
Listing is promoted	-5.7	0.00006	Binary
Nr. of feedback given to others	0.07	0.006	
Nr. of sales for listing	0.003	0.0006	
Days since last day seller was online	-0.2	0	
Nr. of disputes raised against seller	0.4	0.01	
Nr. of views for listing	0.0004	0.00004	

Chapter 7

Discussion

7.1 Comparison to work by Christin, Soska and Thomas

The work most closely related to ours is the work by N. Christin, K. Soska and J. Thomas, detailed in section 2.2. Their methods are similar to ours, and some of their analyses, most notably the diversity coefficients discussed in section 6.10, overlaps with our work. However, of the four marketplaces studied in this paper, only Dream Market was examined in any of the aforementioned publications, and while their data was collected in the periods 2011-2015 and 2017-2018, all of our data was collected in the period 2018-2020. Therefore, our results are not directly comparable with their results.

7.2 Implications and significance of our results

We would like to highlight two important contributions in our paper. They are the currency analysis of listings in section 6.4.2 and the relative adoption trends of cryptocurrencies Bitcoin and Monero in section 6.4.1.

To our knowledge, the first of the two analyses has not been attempted in existing literature, and it provides a novel factual basis for ascertaining the origin location of Dark web products. This result may have utility and relevance for policy makers and law enforcement. We note, e.g. that the paper *Analysis of the supply of drugs and new psychoactive substances by Europe-based vendors via darknet markets in 2017-18* by Christin & Thomas (2019), commissioned by the European Monitoring Centre for Drugs and Drug Addiction, assumes that vendor-reported origin countries are accurate, and the authors do not explore alternative assumptions. By considering the hypotheses posed in section 6.4.2, the report could present alternative estimates of the prevalence of Dark Web drug trade in Europe and a larger factual basis for decision makers.

The latter of the two analyses was only possible by using data from the relatively recent Cryptonia Market, and it provides evidence that Monero, a much less traceable alternative to Bitcoin, is *not* gaining traction on the Dark Web, contrary to reasonable assumptions. Law enforcement agencies in many countries are building expertise and capabilities to combat criminals using cryptocurrencies like Monero (Chohan, 2018, p. 2). Our results may provide factual basis to decision makers in charge of such efforts, helping them allocate resources that are appropriately proportionate to the problem they are mitigating.

7.3 Reuse of our data

The information gathered from our scraping sessions adds to a growing body of public Dark Web marketplace data. Readers may note from section 3.3.1 that our software did not store and persist the web documents from our scraping sessions; the documents were parsed in-memory and immediately transformed to data fields. While convenient for our own data collection process, it may pose an obstacle for future researchers who want to adapt our data to their existing entity models or parse extra data which we never persisted to our database. As of July 2020, due to resource constraints, our database is not hosted on any publicly available server, but we welcome interested researchers to contact us.

Chapter 8

Concluding Remarks

We scraped three Dark web marketplaces, Empire Market, Cryptonia Market and Apollon Market, and parsed data from ca. 180 000 unique listings over a period of 150 days. Additionally, we parsed another 260 000 listings from offline crawls of Dream Market in the period from January 2014 to November 2019.

Our scraping software was designed to be fast and resilient against external failures and bot defenses. The implementation was written in `Python`, and it operated on an infrastructure of 9 cloud instances, hosting 4 Database Management Systems (DBMS), 2 scraping bots, 1 DBMS interface, 1 DBMS load balancer and 1 Tor circuit manager. In our final builds, the software was able to consistently scrape several marketplaces within 24 hours, and it reliably subverted marketplace measures designed to evict bots, such as request limits, esoteric cookie assignments and CAPTCHA challenges.

By analysing this data, we have made an assortment of findings. The retailers on these marketplaces are densely concentrated in Europe and the English-speaking world. When examining the longitudinal traffic of the marketplaces, both Crytponia and Empire Market experienced a dramatic surge of popularity in April 2019. Conversely, Cryptonia shut down its operations, perhaps permanently, in November 2019. All marketplaces analysis show a similar weekly distribution of transactions, with the greatest volume happening between Tuesday and Friday. A regex based algorithm was able to determine the mass of 89 % of the drug listings on all four marketplaces. Contrary to our expectations, the cryptocurrency Monero, designed for anonymity and fungibility, has *not* gotten more popular over time, even while seller rating is positively correlated with support for Monero payment. Sellers generally offer a homogeneous assortment of listings, sticking to a single main product category, indicating a great degree of professionalism. By applying statistical inference methods on our data set, it appears that USD is the currency of choice for most sellers, with EUR and GBP trailing behind. Seller ratings based on customer feedback are overwhelmingly distributed toward the upper limit of the scale. 1% of sellers constitute 23.3% of total transaction volume.

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Appendix A

A.1 Open Marketplaces

Table A.1: Illicit Dark web marketplaces as of July 2020

Market	Operational	Launch date	Closure reason
Agartha	Yes	March 2019	
Apollon	Yes	March 2018	
Cryptonia	No[1]	April 2019	Scam
Empire	Yes	March 2018	
Samsara	Yes	July 2019	
Silk Road 3.1	No	May 2017	Scam
Nightmare	No	January 2019	Scam
Dream	No	November 2013	Hacked
Tochka	Yes	January 2015	
Berlusconi	No	July 2017	Raided
The Majestic Garden	Yes	NA	
Cannazon	Yes	March 2018	

[1] Closed 19 November 2019. Plan to open in beginning of 2020

NTNU
Norwegian University of Science and Technology

Analysis of cannabis retail on the Dark web and market impact of legalization

by Håkon Hjelstuen and Magnus Longva

July 2, 2020

Department of Industrial Economics and Technology Management

Faculty of Economics

Preface

This report is part of a master's thesis at the Department of Industrial Economics and Technology Management and Faculty of Economics at the Norwegian University of Science and Technology (NTNU). It is delivered alongside a companion paper, *Longitudinal data gathering andanalysis of Dark web marketplaces*, where both papers combinedly constitute the thesis. While this paper focuses on aspects of cannabis retail in particular, the aforementioned paper focuses on data collection methods and general analysis across the entirety of our material.

The study was done over a span of eight months. Both Hjelstuen and Longva have formal program specializations in financial engineering with minors in data analytics and computer science respectively. Hjelstuen is employed as an equity analyst at Danske Bank. Longva is working as a penetration tester at Bouvet, an IT consultancy.

We appreciate the help, data and guidance in completing this report, both from our industry contacts and from academics at NTNU and abroad. We would especially like to thank our supervisor, professor Peter Molnar at the University of Stavanger, professor Nicolas Christin and Kyle Soska at Carnegie Mellon University, professor David Décary-Hétu and Rasmus Munksgaard at Université de Montréal, and Torbjørn Bull Jenssen at Arcane Crypto.

Håkon Hjelstuen and Magnus Longva

Trondheim, July 2, 2020

Abstract

Dark web marketplaces have been in operation for more than a decade, and they are host to a vast number of retailers and customers who exchange illegal goods and services. Cannabis is one of the most sold items on the Dark web marketplaces, and one of lawmakers' main goals of legalizing cannabis is to marginalize this illicit industry.

Using recently obtained data from the marketplaces, we explore characteristic properties of the cannabis market and analyze the effects of legalization. Using natural language processing techniques and leveraging geographical attributes in our data, we have been able to calculate unique average per-gram prices of cannabis by country, enabling a comparative, quantitative evaluation of individual cannabis markets.

We have studied the impact of the Canadian *Cannabis Act* and the Australian *Drugs of Dependence (Personal Cannabis Use) Amendment Bill 2018* on the Dark web cannabis market. During the first 18 months after the Canadian law was enacted in October 2018, Canadian prices dropped by 57 % and relative sales volume of cannabis increased by 26 %. We did not observe any significant impact of the Australian law, probably because this law was relevant only for Australian Capitol Territory, and our data does not allow us to study this area separately from the rest of Australia.

Contents

Chapter 1

Introduction

Cannabis (or 'marijuana', a term used interchangeably in this paper) is a psychoactive drug from the Cannabis plant. Cannabis is mainly used for recreational purposes because of its mood-altering effects. Consuming cannabis can create effects of relaxation and euphoria, alteration of conscious perception and distortions in the perception of time and space. Marijuana is used for medical purposes to treat diseases or improve symptoms. The FDA (Food and Drug Administration) have only approved medical cannabis for treatment of Dravet syndrome and Lennox-Gastraut syndrome, two rare forms of epilepsy (FDA, n.d.).

The United Nations Office on Drugs and Crime estimated that 3.8 % of the global population between the age of 15 and 64 used cannabis at least once during the year 2017 (*World Drug Report* 2019). Many debates have been held around the world about marijuana legalization as many countries have legalized or decriminalized cannabis for medical or recreational use the last decade. Two of the main arguments from proponents of cannabis legalization are to get better control of the use patterns and to stifle the illegal market.

A new generation of cyber criminals has risen with the advent of the Internet, transferring old enterprises like drug trade to a digital format. With the development of the Tor network in the 2000s and the launch of Bitcoin in 2009, it became possible for retailers and customers of illegal drugs to sustainably evade law enforcement while conducting business online. The new-found anonymity both within network routing and currency transactions culminated in the first major Dark web marketplace, The Silk Road, in 2011 (Martin, 2014). Many similar marketplaces have were established in subsequent years.

As researchers, the Dark web is a more agreeable subject of analysis than the analog underworld. After parsing the online data, one can make quantitative statistics and aggregate trade data across geography, time periods and other attributes. The paper *Longitudinal data gathering and analysis of Dark web marketplaces* documents our process of obtaining, processing and systematizing such data.

We hypothesize that legalization or decriminalization of cannabis causes observable price drops in Dark Web cannabis prices, and using our collected data, we aim to test this hypothesis. Our results fail to demonstrate any significant relationship between the recent cannabis legislation in Australia and observed market price of cannabis, but our similar analysis of Canada indicates that legalization had a detrimental impact on the illegal part of the country's cannabis industry.

The rest of this paper is structured as follows. Section 2 contains a synopsis of past and ongoing legalization of cannabis in selected countries. Section 3 contains analysis of our data regarding aspects that are of particular relevance to cannabis, while section 4 summarizes our work with some concluding remarks.

Chapter 2

Literature review

2.1 Effect of police crackdowns on dark web marketplaces

While the Internet was initially framed as a platform solely for exchange of information, it opened the possibility to buy and sell illicit goods and services. The possibilities this new distribution channel created, together with the growing use of online illicit markets, hold the potential of disrupting illicit trading. “EU law enforcement, Europol included, has not fully conceptualised how to integrate this cyber dimension into all relevant aspects of police work, let alone devise a strategy and implementation plan to make this happen” Europol (2014). In the last decade, there has been a proliferation of Dark web marketplaces. Law enforcements have closed down several individual marketplaces, though the Dark web markets in general have been able to recover. Décary-Hétu & Giommoni (2017) studied the effects of Operation Onymous, a large-scale international police operation in 2014 that targeted many illicit marketplaces and hidden services operating on the TOR network. The operation had 17 vendors and administrators arrested, 410 hidden services taken down, USD 1 million worth of Bitcoins and EUR 180 000 in cash, drugs, gold and silver seized (Europol, September 21, 2019). The results show that users of Dark web marketplaces and illicit trade participants adapt to operations and crackdowns, and the Operation Onymous in particular had limited effect. Another interesting finding was that even though supply and consumption of drugs were impacted as many dealers decided to retire in the period after the operation in 2014, prices appeared to be unchanged.

Soska & Christin (2015) found that Dark web markets are controlled by a small set of highly influential vendors responsible for a large fraction of the sales. The illicit marketplace ecosystem have shown to be extremely resilient to take-downs and scam, with the buyers simply changing to another marketplace. The great demand results in a low barrier of moving to a different channel. Soska & Christin (2015) argue that focus should be shifted to reducing consumer demand by targeting the key participants and disruption of trust rather than marketplace take-downs.

2.2 Legal status of cannabis in selected countries

The legal status of Cannabis varies around the world, from complete prohibition on one end, to legalized recreational use on the other end. Many countries also permit Cannabis as a prescription drug, were the medical indications are different from country to country. The legality varies similarly in terms of possession, distribution, cultivation and consumption. Cannabis is illegal in the majority of countries and nearly all developing countries. Today, the most restrictive regions are Asia and the Middle East. A significant number of countries allow medical use of cannabis, although some only allow specified cannabis-derived pharmaceuticals. The first country to legalize cannabis was Uruguay in December 2013.

2.2.1 United States

In the United States, use and possession of Cannabis is illegal under federal law by the Controlled Substances Act of 1970. However, many state laws are in significant conflict with the federal law, both for medical and recreational use of marijuana. Medical use of cannabis is legalized in 33 states and recreational use is legal in another 11 states (National Conference of State Legislatures, 2020). Washington and Colorado were the first states to legalize marijuana for non-medical sale and possession in November 2012 by Washington Initiative 502 and Colorado Amendment 64.

Coley et al., 2019 conducted research on 861 082 high school students in 45 different states to study teens who smoke cannabis. The authors found that the number of youth cannabis smokers was 1.1% lower in states where cannabis is legal for medical use compared to states with overall prohibition, even when accounting for variables such as tobacco and alcohol policies, economic trends, youth characteristics and state demographics.

The annual report by the Rocky Mountain High Intensity Drug Trafficking Area program in 2019 documents the effects on some of the main issues debated in legalizing marijuana for medical and recreational use. *"Colorado serves as an experimental lab for the nation to determine the impact of legalizing marijuana."* Since legalization of recreational marijuana in Colorado, the authors note that traffic deaths from 2013 to 2018 involving drivers who tested positive for marijuana doubled, from 55 to 115.

2.2.2 Canada

In October 2018 Canada became the second country to legalise recreational use of cannabis at the federal level. At the day the *Cannabis Act* came to effect, 17 private retailers opened in Alberta. In Quebec, long lines of customers formed outside the 12 stores in operation. The main motivation of the government to legalize cannabis was to drive the illegal vendors out of business. *"It's by displacing the black market that we can control sales and put cannabis out of reach of our children"* said Ginette Petitpas Taylor, federal health minister in Canada. Both Petitpas and the prime minister of Canada, Justin Trudeau, have referred to a declining illegal market in Colorado after the legalization (Dyer, 2018).

A year after the legalization, Rotermann, 2020 estimated that about 70% of cannabis was bought illegally. The three main causes were lower prices, bad product variety and a limited access to stores. However, accessibility is significantly increasing. As of July 2019, 407 marijuana shops were open with 45% of Canadians living within 10 kilometers of a store. Canadians have the possibility to buy the cannabis online, an offer remarkably less popular than brick and mortar stores. The legal providers have had problems with supply and quality of their products. The president of the industry research firm Business of Cannabis, Jay Rosenthal, said a year after legalization that the legal sector was still not able to provide the same kind of high-end product the most sophisticated consumers demand (McClintock, 2019).

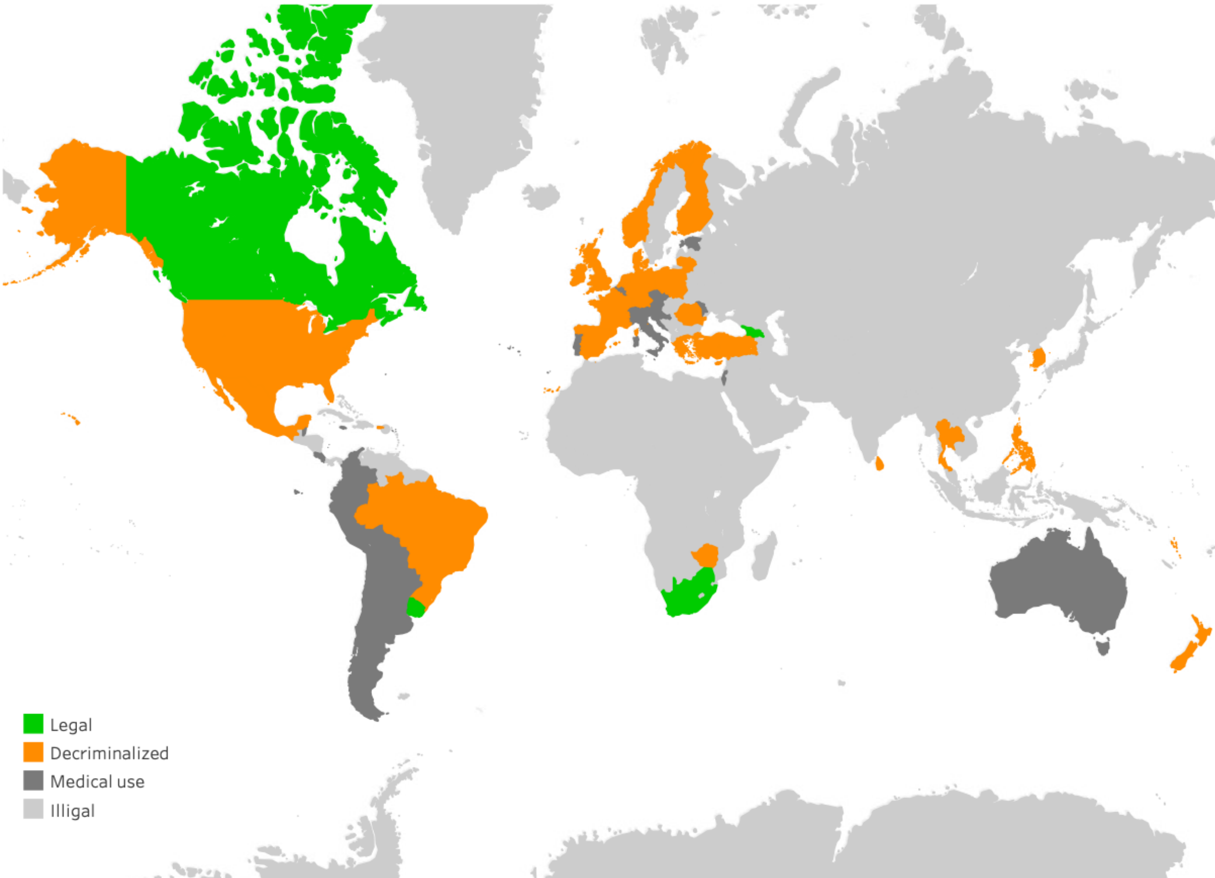


Figure 2.1: Global legality of cannabis

2.2.3 Australia

The Drugs of Dependence (Personal Cannabis Use) Amendment Bill 2018, legalizes cultivation of two cannabis plants per individual and possession of up to 50 grams of dried cannabis for citizens aged 18 year or older. It applies only to the ACT (Australian Capitol Territory), and it came into effect 31 January 2020 (Legislative Assembly for the Australian Capital Territory, 2018). This is the first region in Australia making marijuana legal for personal use, conflicting with the federal prohibition and strict regulations of medical use. Supply remains illegal, including seeds, creating questions of how the home-growers are supposed to obtain the necessities. There is some uncertainty as to how local law enforcement will react to the conflict between federal and territorial laws. The coming time will indicate if this ACT legalization is the start of changing the federal law and a pathway to commercialising cannabis. “I think it reflects the values of this community that we want our law enforcement to focus on organised crime and large scale production of illicit drugs and that we don’t want to penalise or stigmatise users, particularly small scale recreational users” said ACT Chief Minister Andrew Barr (Vinales, 2020).

According to *National Drug Strategy Household Survey,* 2017, 35% (33.1% in 2001) of Australians of age 14 years old or older have used cannabis in their lifetime, 10.4% in the last 12 months. Findings show little or no impact of a person’s socioeconomic status or education on the use of cannabis.

2.3 Societal costs of cannabis prohibition

Commenting on the general prohibition of recreational drugs, Becker & Murphy, 2013 state that *”the cost has been large in terms of lives, money and the well-being of many”*. Arrests, prosecution and incarceration of drug offenders result in direct monetary cost in the US due to spending on police, court and penitentiaries, estimated at over $40 billion USD per year according to the authors. President Richard Nixon declared the ”war on drugs” in 1971. In 1980, a total of 330 000 people were imprisoned, growing to 1.6 million in 2013. Half of the inmates in federal prison are convicted of selling or using drugs (Becker & Murphy, 2013).

Research made by Dragone et al., 2019 indicates a decrease in crime following legalization of marijuana in Oregon and and Washington. Rapes were reduced by about 30% between the two years before and after legalization, and thefts went down by 10% to 20%. The consumption of cannabis rose by 2.5% in the period, while usage of other drugs decreased by 0.5% and alcohol by 2%. The authors speculate the reason behind the drop in crimes being cannabis as a substitution for violence-inducing substances or the psychotropic effects of marijuana.

Research by Lenton et al., 2000 shows that convicting people in possession of small quantities of cannabis to be more harmful than the drug itself. The authors studied the difference between South Australians issued with an infringement notice and West Australians receiving a criminal conviction, both groups for possession of a minor amount of cannabis. The individuals in both groups were largely law-abiding and had respect for the law in general. Results show one third of the convicted group reported negative employment consequences, compared to 2% in the infringement notice group. Findings also show that many have further problems with the law (32% vs. 0%).

Chapter 3

Results

Our data set was obtained by daily scraping several marketplaces. Empire Market was the first, started 13 October 2019 and is still active. Cryptonia Market was scraped from 9 November 2019 to 19 November the same year. Cryptonia Market went offline on the 19 November, and has not come back online as of July 2020 (see Appendix A.1). Scraping of Apollon was initiated 3 February 2020 and lasted until 12 March 2020. We were provided ca. 650 000 web documents from Dream Market, spanning from 9 January 2014 to 12 November 2018. A thorough documentation of our data entities and collection methods can be read in *Longitudinal data gathering and analysis of Dark web marketplaces* (Hjelstuen & Longva, 2020).

Table 3.1: Summary of contents in our database.

	Listings		**Sellers**	**Value (USD)**	
	Tot.	Cannabis	Tot.	Tot.	Cannabis
Empire	95 899	22 279	3315	130.9 M	30.3 M
Cryptonia	22 495	5 431	951	11.2 M	3.1 M
Apollon	64 897	12 525	1841	5.8 M	0.9 M
Dream	258 286	48 186	4582	148.5 M	41.3 M

We examine the popularity of the marketplaces over time and intraweek activity in section 3.2 and the price distribution of listings in section 3.3. In section 3.4, we use a statistical approach to deduce which currencies sellers lock their product prices to, and in section 3.5, we examine seller ratings based on feedback submitted by buyers. The impact to the Dark web market ecosystem of legalizing cannabis is presented in section 3.6.

3.1 Classifying listings

In order to make a suitable data set of cannabis listings, it has been necessary to discern listings of cannabis products to those that are not. We take note that other researchers, e.g. Soska & Christin (2015, p. 41), implemented a machine learning classifier for this purpose. In their case, it was necessary in order to overcome inadequacies and inconsistencies in the category regimens of the marketplaces they studied. Keeping their considerations in mind, we contemplated a similar approach in our own work, but discovered some features of our data that made this option seem less inviting. Of the dataset from Empire Market, analysis shows that 1669 listings (1.74% of total unique listings) in categories with no relation to cannabis have the word "cannabis" included in the description text, see Table 3.2. These listings have included a large number of terms in their description (often bottom) to pop up at the list when buyers search for a specific term, many having the word cannabis listed several times in the text. The same is found for many other terms related to cannabis. Such noise in the data is inopportune for a machine learning approach. Conversely, we have *not* encountered obstacles with our four marketplaces similar to those encountered by Soska & Christin (2015), and we subjectively, albeit unscientifically, note that the marketplace categorization of cannabis products, as defined by the vendors themselves, is almost invariably accurate. Considering the pros and cons, we have opted to simply rely on the categories of the marketplace websites.

3.2 Market Distribution

As of April 1st 2020, the data set has accumulated 3 386 279 observations of listings spread over 441 577 unique listings. Similar to most known marketplaces on the surface web, the marketplaces on the dark web are divided into several categories and subcategories. For all marketplaces in study, cannabis is a large fraction of the total listing volume, as seen in Table 3.1. It is one of the major subgroups, further divided into sub-subcategories with further specifications (i.e. edibles, weed, concentrate, hash). From the data set, 22 279 are distinct listings within categories related to cannabis (23.2% of total distinct listings). Similar fractions are found at Cryptonia marketplace (24.1%), Apollon Market (19.2%) and Dream Market (18.7%).

In the time frame studied, the number of cannabis-related observations is steady and well correlated with the total number of marketplace listings. No conclusion can be made towards a growing amount of cannabis listings, as total listings often show similar trend. Some variations in the ratio of the marketplaces are seen, though the most significant differences occur between the marketplaces itself; Dream (6.73 % of total listings), Empire (8.46 %), Apollon (8.14 %), Cryptonia (17.22 %).

Table 3.2: Top five categories with listings not related to cannabis with ”cannabis” in description

Category	Count
Digital Products	220
Fraud	218
Guides & Tutorials	177
Services	56
Software & Malware	50

3.3 Listing analysis

3.3.1 Price distribution

The price distribution of all listings in the observed time frame range from USD 0.01 to USD 999 999. The largest transactions in terms of dollar value is nine units of *High Grade Platinum Kush 224g Indoor Weed*. The transaction of USD 15 905 made by l***k was done 28 January 2020. Most of the listings of a price close to zero have a much greater transaction price, indicating that the price is negotiated later when contact is established between buyer and seller.

3.3.2 Cannabis quantity

The data set contain all descriptive information for each listing, as well as associated transactions. A listing selling a specific amount of an item (like drugs) will disclose the size and unit in the title or description. By running an algorithm scanning through these strings and standardizing the amounts, information of units per gram of the respective listings have been calculated. Figure 3.1 visualize the distribution of metric quantities in listings. The median mass is 14.0 grams per unit. The listing with the most grams per unit of product is *100kg Premier Gelato* cannabis, shipped from Germany. We do note, however, that there is no record of an actual purchase of this product.

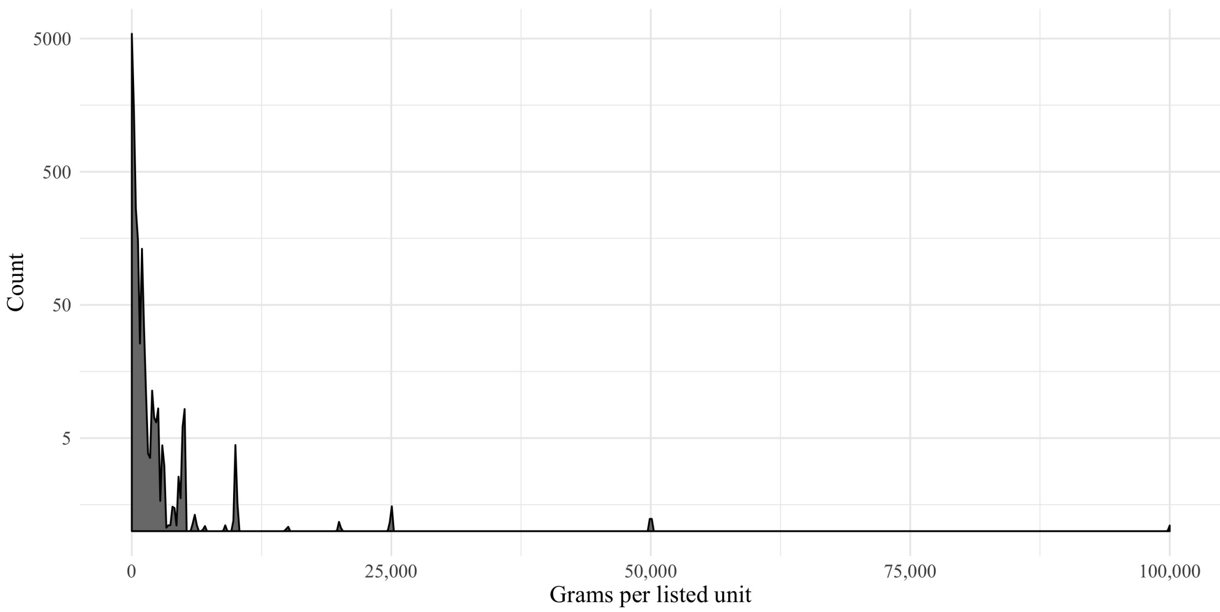


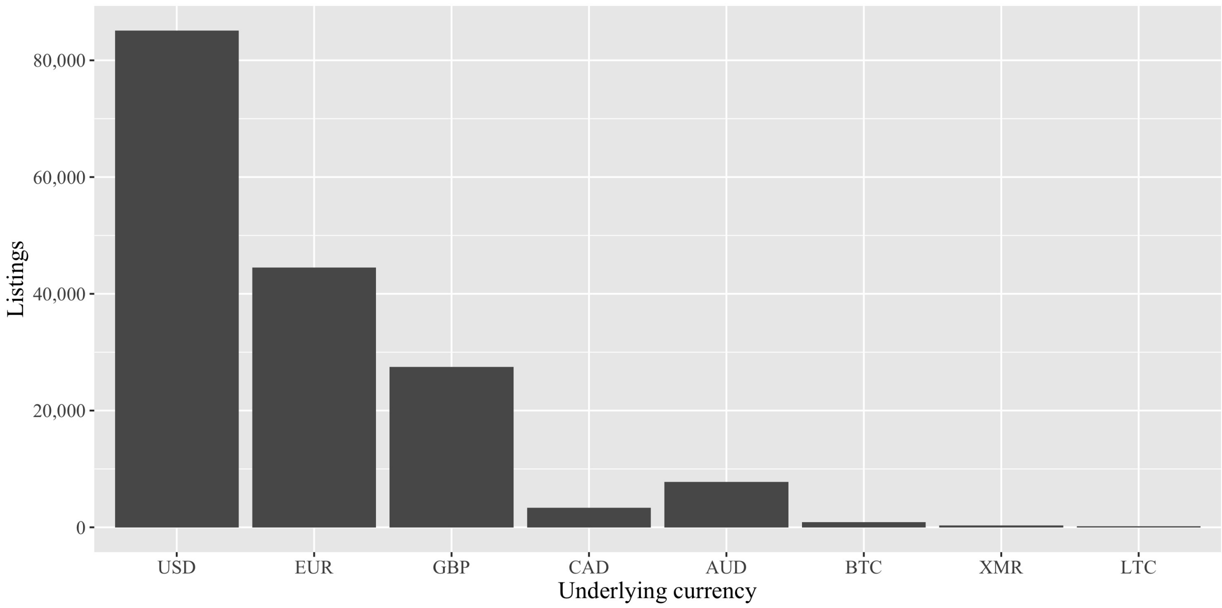
Figure 3.1: Size distribution of cannabis listings

3.4 Currency analysis

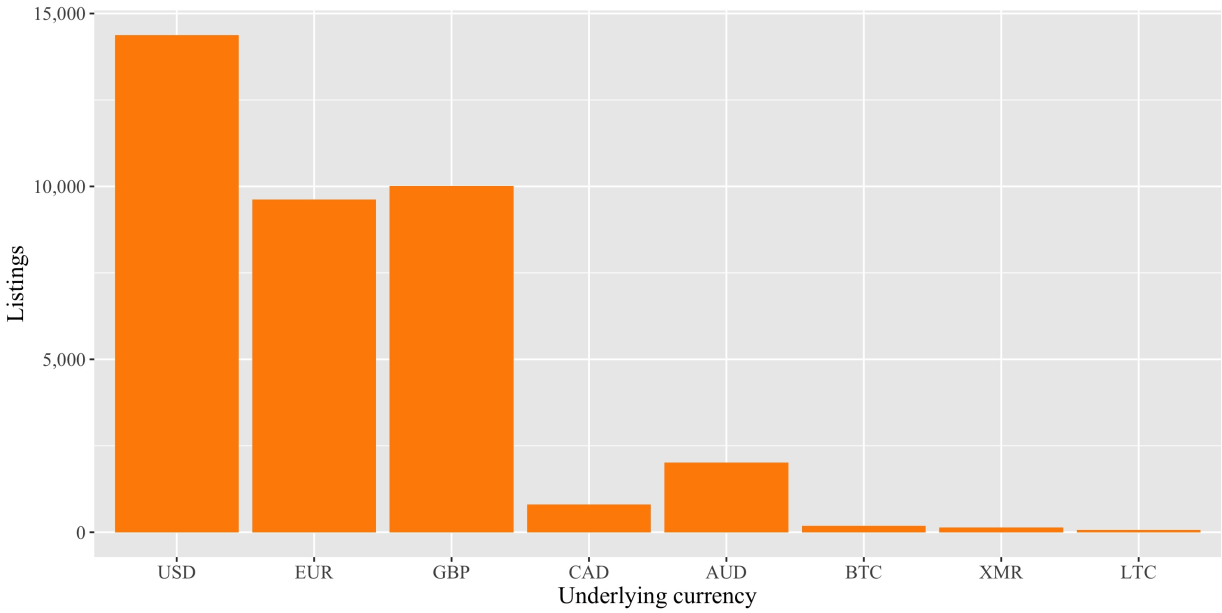
3.4.1 Underlying currency

The data set with daily data points makes it possible to analyse the daily changes in price of each listing. When listing a product, the seller chooses an underlying currency to denominate the product price. The alternatives at the marketplaces in focus are USD, EUR, CAD, AUD, GBP, BTC and XMR. Therefore, if a listing has e.g. Euro as underlying currency, but is observed multiple times with a price denominated in US dollars, the listing price will fluctuate in tandem with the exchange rate between the underlying currency and US Dollars. Taking advantage of this, it possible to infer which currency the seller has actually chosen to denominate a product price. The method of calculating the underlying currency is more thoroughly documented in *Longitudinal data gathering and analysis of Dark web marketplaces*.

As seen in Figure 3.2a, more than fifty percent of listings have US Dollars as the underlying currency. For listings related to marijuana, the American dollar is not as dominant, with a relative larger fraction of listings priced with a European currency, as seen in Figure 3.2b.



(a) Overall



(b) Related to cannabis

Figure 3.2: Listings sorted on currency

3.5 Seller analysis

3.5.1 Seller loyalty

A great part of the buyers leave feedback, both good and bad. For all the marketplaces we have studied, a seller's profile page will be labeled with the average rating of all feedbacks submitted to the seller. The distribution of seller ratings is displayed in Figure 3.3.

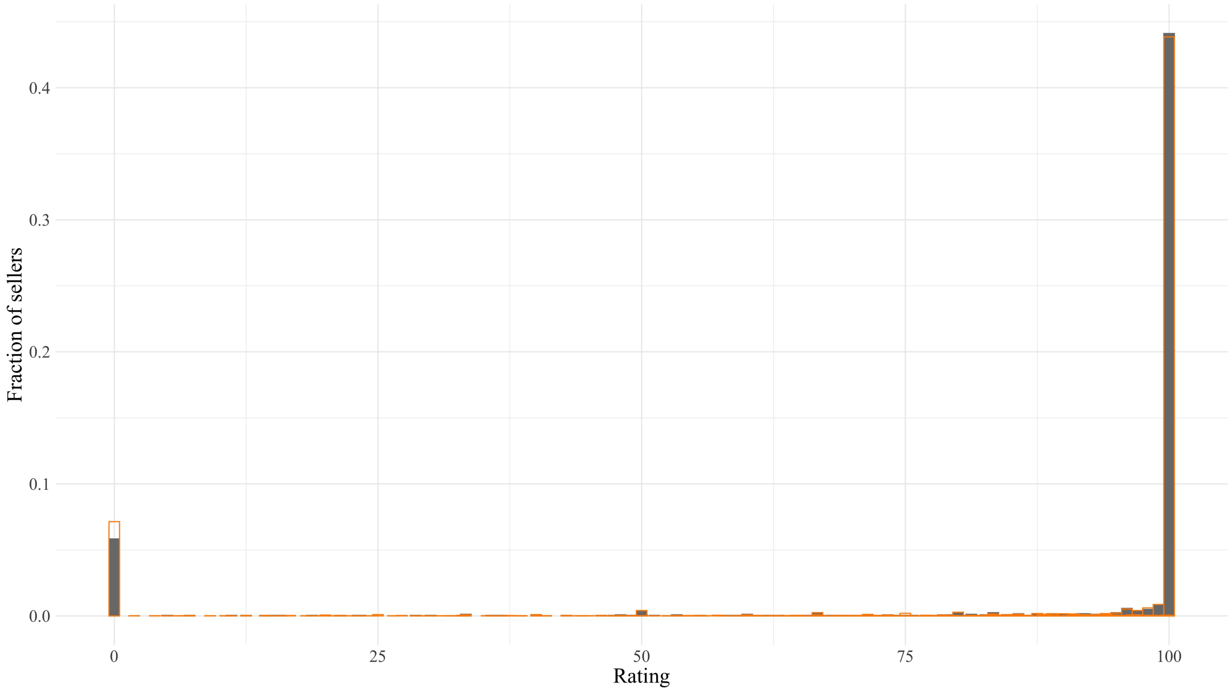


Figure 3.3: Rating Distribution, score 0-100

Sellers offering products related to cannabis are 40% of all sellers on the marketplaces. Analysis of the scraped data indicates almost identical rating distribution for these sellers. As the Figure 3.3 indicates, fewer cannabis sellers have a low rating than for the marketplaces in total. In the category of marijuana listings, 15.8% of the sellers have a rating below 90 and only 5.9% have a rating below 10. Similarly, for all listings 18.0% of the sellers have a score below 90 and 7.2% below 10.

3.5.2 Vendor volume

The total value of the transaction volume of each seller is calculated. Figure 3.4 plots the cumulative distribution of vendors by the summed up value of their transactions. On average, a seller has sold products for just below USD 5000. Most sellers, 65%, have sold between USD 1000 and USD 100 000 worth of items. About 30% of all vendors at the marketplaces have made about USD 1000, while similar revenue is obtained by 40% of cannabis sellers. The shift to the left in Figure 3.4 for sellers of cannabis disclose that most sellers of non-cannabis related listings make more, although the largest vendors in terms of total revenue are within cannabis.

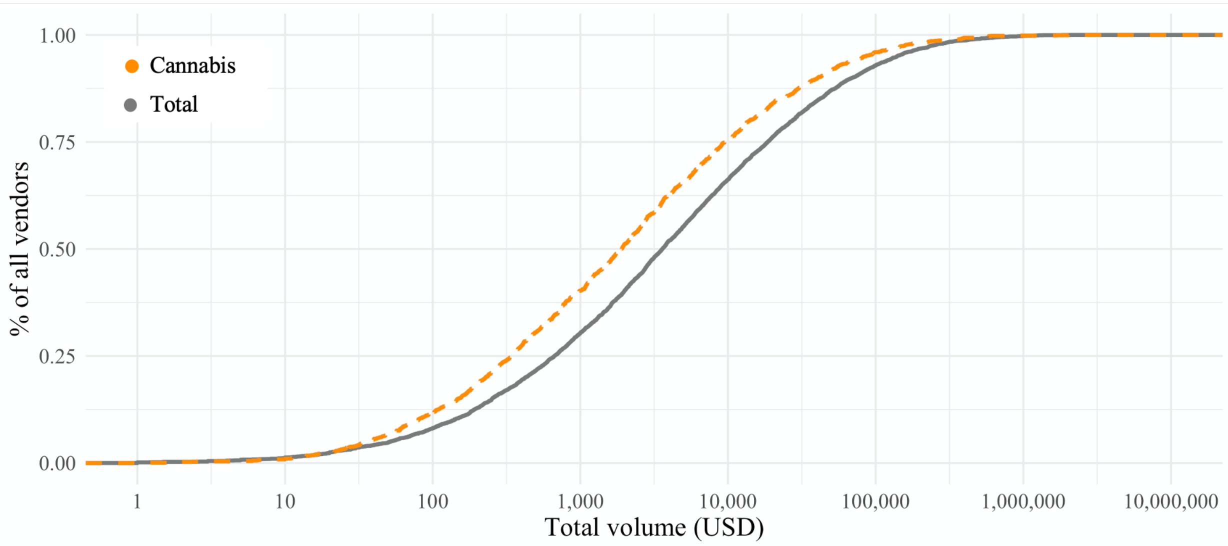


Figure 3.4: Cumulative distribution of total and cannbis seller revenues. E.g., about 65% of sellers have sold products for less than 10 000 USD.

3.6 Cannabis

High accuracy of analysing changes in cannabis sale due to local legalization was made possible by knowing the sellers location using the method of finding the underlying currency (section 3.4.1). Canada and Australia are two of the major locations on the Dark web marketplaces in terms of cannabis related listings, as seen in Figure 3.2b. Both Canada and Australia have legalized marijuana in recent time, and several metrics have been analysed to see the effects on the Dark web marketplaces before and after.

3.6.1 Validity of data from Apollon Market

Apollon Market is still up and running as of March 2020. However, in January 2020, the webmasters of both `dnstats.net` and `dark.fail` served visitors with notices that they believe Apollon Market was conducting a drawn-out exit scam, and even surmised that the owners of Apollon Market were besieging their business rivals on the Dark web with DDoS attacks (dark.fail, 2020) (DNStats, 2020). The notice on `dnstats.net` is still online as of 22 March 2020, while `dark.fail` has since erased any mention of Apollon Market on their site. Concurrently, we can observe from our data that the total revenue between 1 February and 1 March on Apollon Market was only 0.6% of the preceding months' revenue. Without making conclusions about the true state of Apollon Market, we deem it probable that the most recent data from that marketplace is affected by extraordinary circumstances and is not suitable for threshold modeling or difference in difference analysis. We have thus excluded this data from such models in this paper.

3.6.2 Global price of cannabis

By observing all cannabis listings and averaging their price per gram, we compute the *listing average price*. By analyzing all feedbacks which correspond to purchases of cannabis, and averaging their per-gram purchase amounts, we get the *purchase average price*. Analysis of all data since the first scrape shows a disparity between the former metric and the latter. The listing average price of cannabis is 12.40 USD per gram. The purchase average price, i.e. the actual average price at which cannabis has been retailed during the same period, is 11.90 USD per gram. This would indicate that the most successful sellers offer lower prices than the average seller. While trivial, one may interpret these findings as confirmation that *economy of scale*, the saving in marginal costs gained by an increased level of production, applies to cannabis retailers in a similar fashion as retailers of legal goods.

3.6.3 Price per gram and location

There are significant differences in prices per gram between locations (Table 3.4). This can be due to several reasons (supply/demand, local legislation etc.). The analysis was done by using the method of finding the listing's underlying currency to determine the location, then calculating price per gram using the listing observations and performing a regression by the use of dummy variables for each underlying currency. Dummy variables were made for *AUD*, *CAD*, *EUR*, *GBP* and *USD*. Locations not included in the dummy variables will result in a value of zero for all the dummy variables, and is the intercept of the regression:

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 D_{AUD} + \hat{\beta}_1 D_{CAD} + \hat{\beta}_1 D_{EUR} + \hat{\beta}_1 D_{GBP} + \hat{\beta}_1 D_{USD} + \hat{\epsilon}_i \tag{3.1}$$

The analysis is done on the listings observed from October 2019 to April 2020, and shows that the effect of location on price per gram of cannabis is statistically significant to the highest degree for all locations chosen. As expected because of the competition between legal and illegal vendors, the price in Canada is considerably lower than the average in the period. United Kingdom has a price well above the average price in the rest of the eurozone. Interestingly, the United States has the highest average price of cannabis, although 11 of the 50 states have legalized cannabis for recreational use.

The same regression analysis was done using the self-reported geographical locations of sellers, rather than the locations inferred by currency analysis. Similar results were found, with cannabis price in Canada significantly lower than the average and US as the country with the highest price. A small selection of locations are presented in Table 3.3, see Appendix A.2 for the full table.

Table 3.3: Cannabis price per gram of different selected locations, from feedback. The numbers are averages for the entirety of our data period.

Location	Average Price
Australia	10.18
Canada	7.29
Germany	10.06
Netherlands	7.60
New Zealand	8.63
Norway	15.09
United Kingdom	7.46
United States	9.62

Table 3.4: Cannabis price differences between locations by their underlying currency

Underlying currency	Avg. price per gram in USD	Price difference
Other	8.78	-
AUD	9.03	0.25
CAD	7.68	-1.10
EUR	9.08	0.30
GBP	10.43	1.64
USD	10.92	2.14

3.6.4 Australia

The legalization of cannabis in ACT came to effect as of 31 January 2020, as described in section 2.2.3. The population of ACT is 428 060 as of 2019, making up a mere 1.7 % of Australia's total population. Noting this, one might reasonably assume that a legalization event in ACT would *not* make a dramatic impact on Australian cannabis prices at large. However, we hypothesize that if a particular area in the country became a safe hub for growing and possessing moderate amounts of cannabis, that area could serve as a "safe haven" for enterprising cannabis retailers who seek to serve the entirety of Australia's domestic market. Assuming this hypothesis is true, *and* assuming that new enterprises will be quick to capitalize on the new legal situation in ACT, the legalization event might still be observable in our data.

From end of November until mid January, Empire Market was not operating as normal. The website was slow, and the time used for a single scrape increased significantly. This resulted in decrease in usage and transaction volume as seen in Figure 3.5. Taking note of this, and observing that the cannabis sales volume and the general sales volume are moving in tandem, it seems reasonable to assume cannabis sales were *not* significantly impacted

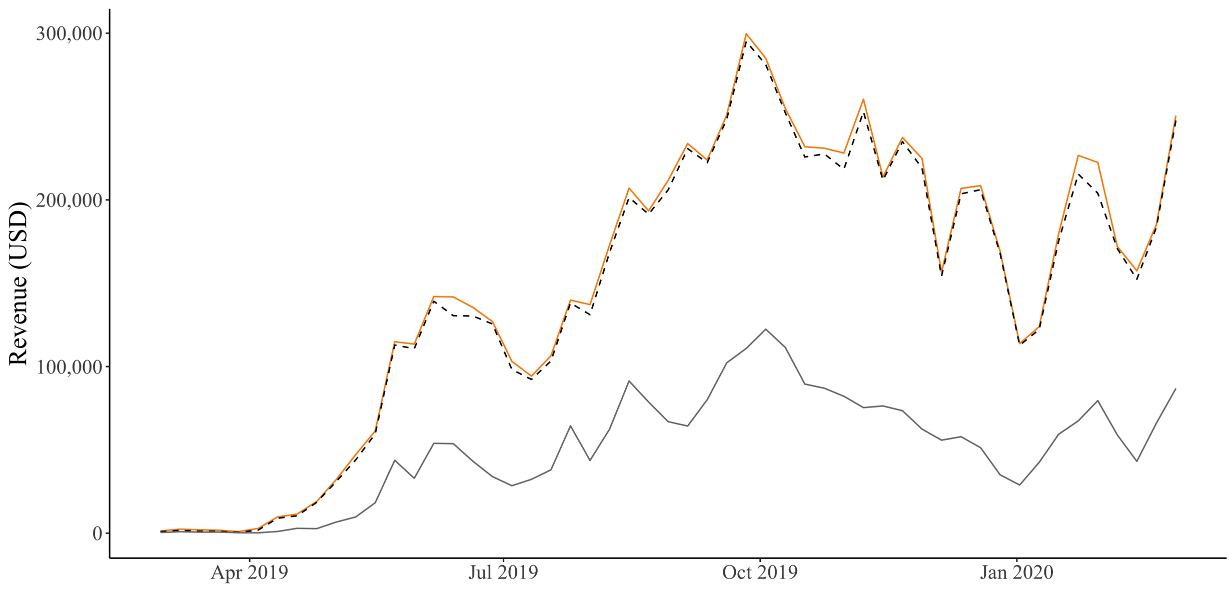


Figure 3.5: Sales volume of cannabis, drugs and all listings in Australia, denoted by solid black, dotted black and solid orange lines respectively.

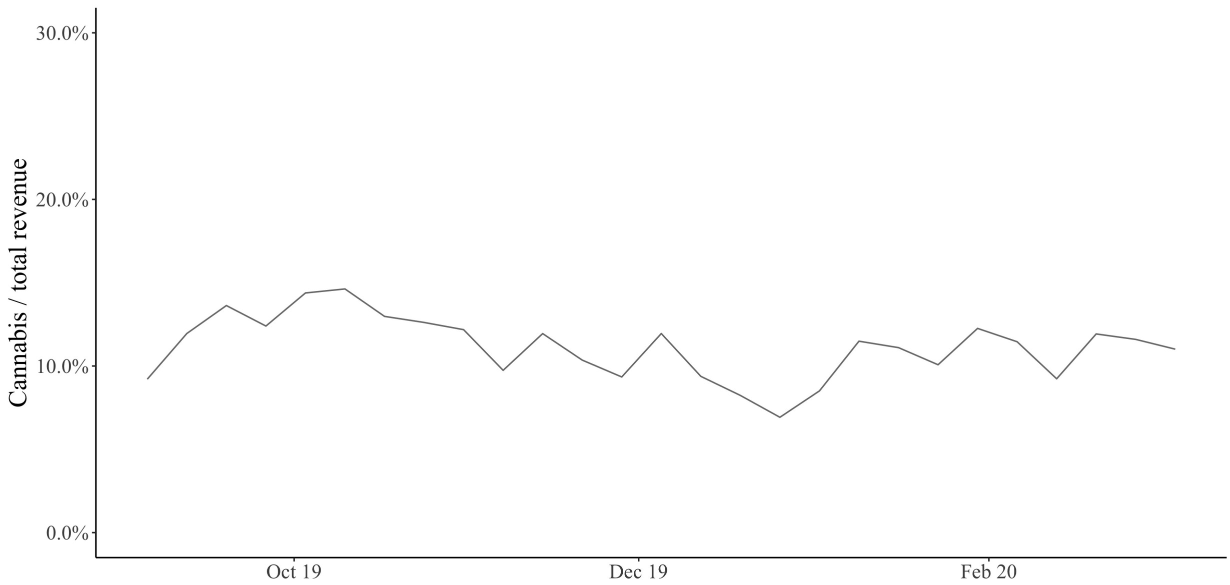


Figure 3.6: Sales volume of cannabis as a percentage of total sales volume across all goods in Australia.

by the legalization event of 31 January 2020. To deal with the changing volume, analysing cannabis revenue in relation to total volume will arguably remove some of the noise. Due to the great intraweek variances in transaction volume, as described in Hjelstuen & Longva (2020, p. 39), this analysis is based on weekly aggregations of volumes.

A piecewise linear model will, by using a dummy variable, identify if the relation between Y and X is depending upon whether X is smaller or larger than the threshold value X^*:

$$Y_t = \beta_0 + \beta_1 X_t + \beta_2 D_t + \beta_1 D_t X_t + \epsilon \Big\} \qquad D_t = \begin{cases} 0 & \text{if } X < X^*; \\ 1 & \text{if } X \geq X^*; \end{cases} \tag{3.2}$$

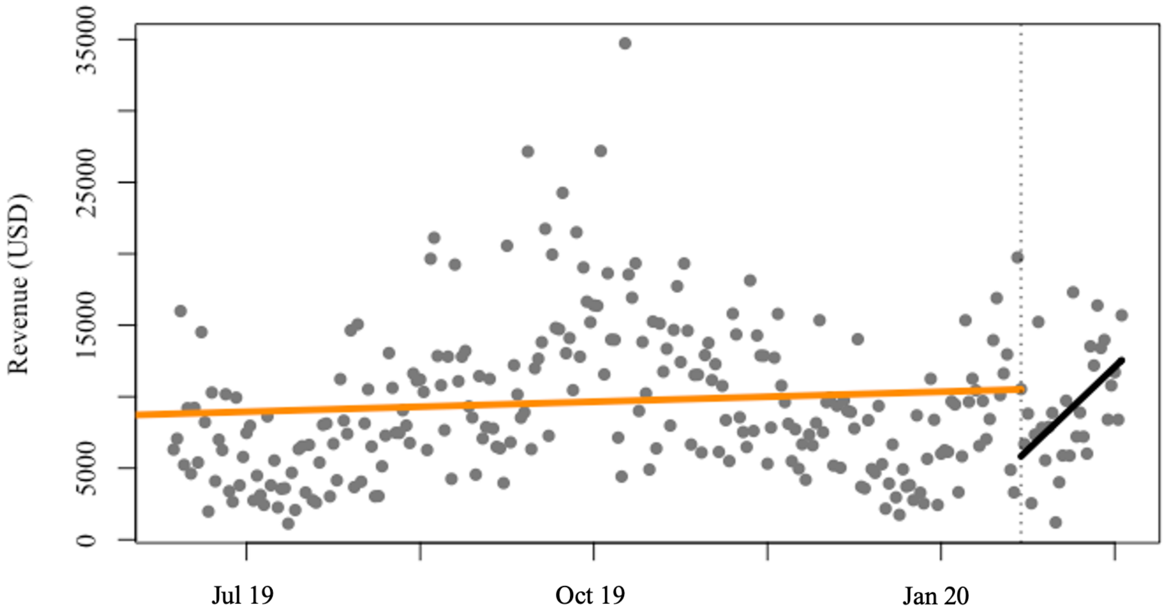
The model presents the trend of cannabis revenue in relation to time and the significance of the dummy variable, with the date of legalization as the threshold value. The piecewise linear model on Empire Market the last 9 months in Figure 3.7a with regression lines before and after 31 January 2020 shows a non-significant change (dummy variable p-value of 0.86). Similar, cannabis as fraction of total revenue on Empire Market, the model can reject any hypothesis of a significant change (dummy variable p-value of 0.66).

3.6.5 Canada

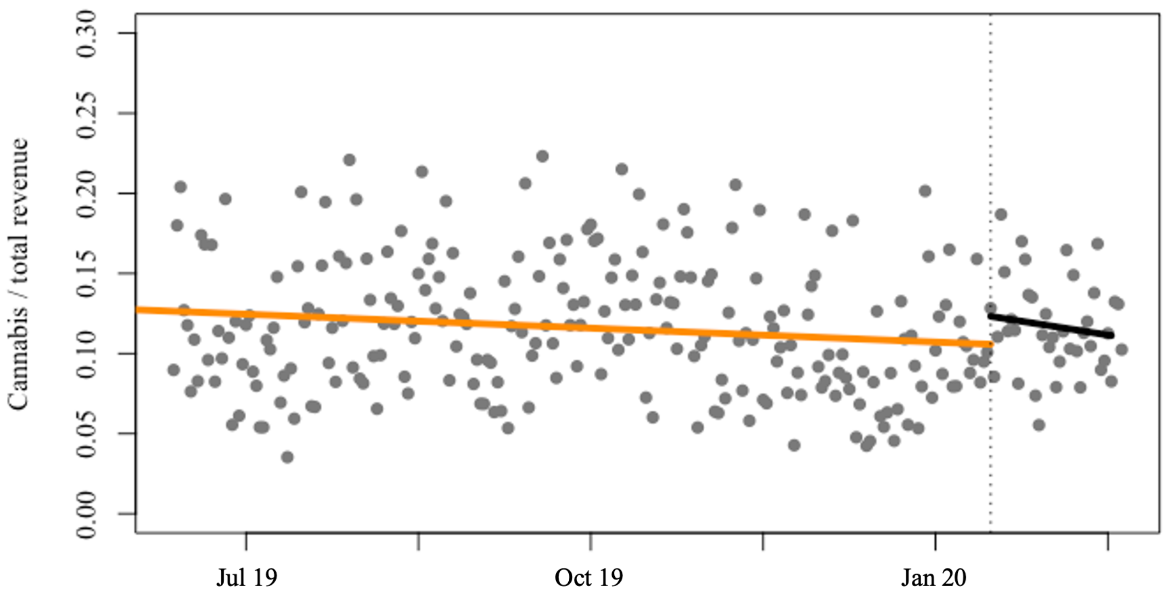
Getting hold of 2018 data from Dream Market, the major dark web marketplace at the time, opened the possibility of studying the effect of the *Cannabis Act* in Canada, which became effective 17 October 2018. The Cannabis Act affected more people and legalized cannabis with fewer caveats than the Australian legalization event, and it applied to the entire country simultaneously. Accordingly, one might expect that eventual consequences of the Cannabis Act would be more explicitly observable in our data than the ACT law.

We can observe a pronounced drop in Dark web cannabis price for the Canadian market after legalization, falling from a high of 11.97 CAD per gram in Q3 2018 to a low of 5.13 CAD in Q1 2020 (see Table 3.5). This constitutes a 57 % decrease.

Piecewise, linear regression lines on data from Dream Market and Empire Market are shown in Figure 3.8, representing the volume of cannabis sales as a percentage of total sales volume. Regression lines are plotted before and after 17 October 2018, showing a non-significant change (dummy variable p-value of 0.37). As can be seen in the figure, there was a great spike in cannabis sales during the weeks immediately following the legalization. For the subsequent 6 months, we do not have data. No significant change in trend is found by this type of analysis.



(a) Cannabis sales



(b) Cannabis sales relative to total

Figure 3.7: Piecewise linear models of cannabis sales before and after legalization

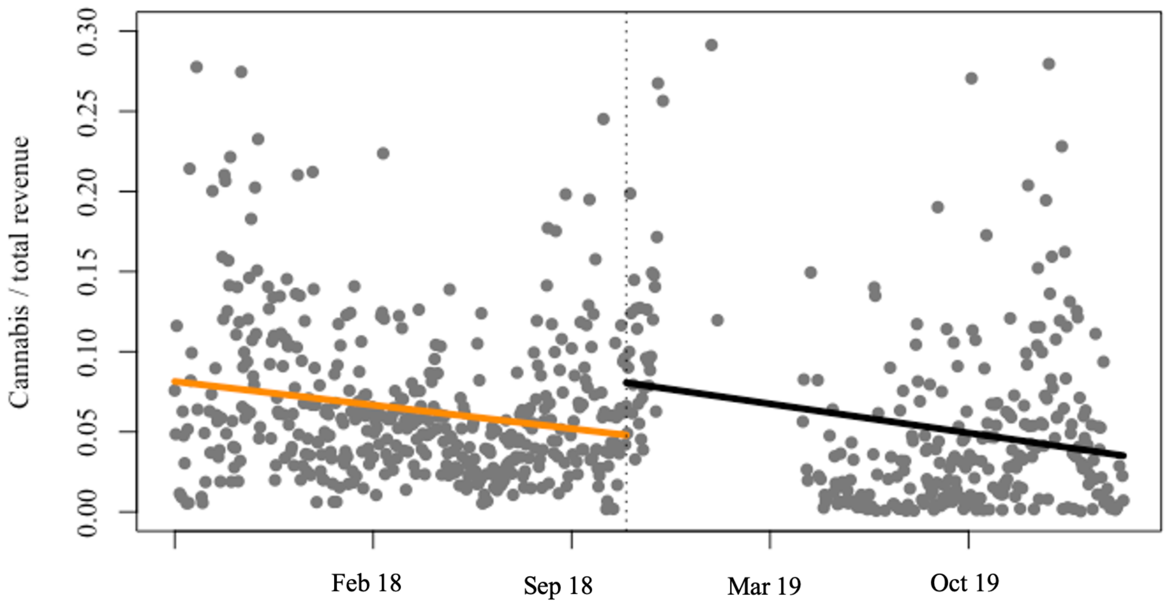


Figure 3.8: Piecewise linear model of cannabis sale before and after legalization

Difference in difference is a statistical analysis technique well suited to quantify the effect of a disruptive market event. Difference in difference is analyzing the outcomes of two groups for two time periods. One of the groups is affected by an event (the legalization of cannabis) in the second period, but not in the first period. The second group is not affected by the event during either period. The *global* change in the second group is subtracted from the first group to remove biases as a result of global trends and permanent differences between the groups. The model follows:

$$Y = \beta_0 + \delta_0 D_2 + \beta_1 D_1 + \delta_1 D_2 D_1 + \epsilon \tag{3.3}$$

D_2 is a dummy variable for the second time period. The dummy variable D_1 captures possible differences between the groups prior to the event. δ_1, the coefficient of interest, multiplies the interaction term, $D_2 * D_1$, which is the same as a dummy variable equal to 1 for those observations in the first group in the second period. We compare our first group, the Canadian market, with the 'control group', which is the global market. The Figure 3.9 shows the daily ratio of cannabis sale to total sale for both Canada and the rest of the world. The difference in difference analysis indicates an increase in cannabis sold as the difference in ratio development increased by 0.007. In other words, the proportion of cannabis sale increased by 26.0% in Canada in the period from legalization until April 2020.

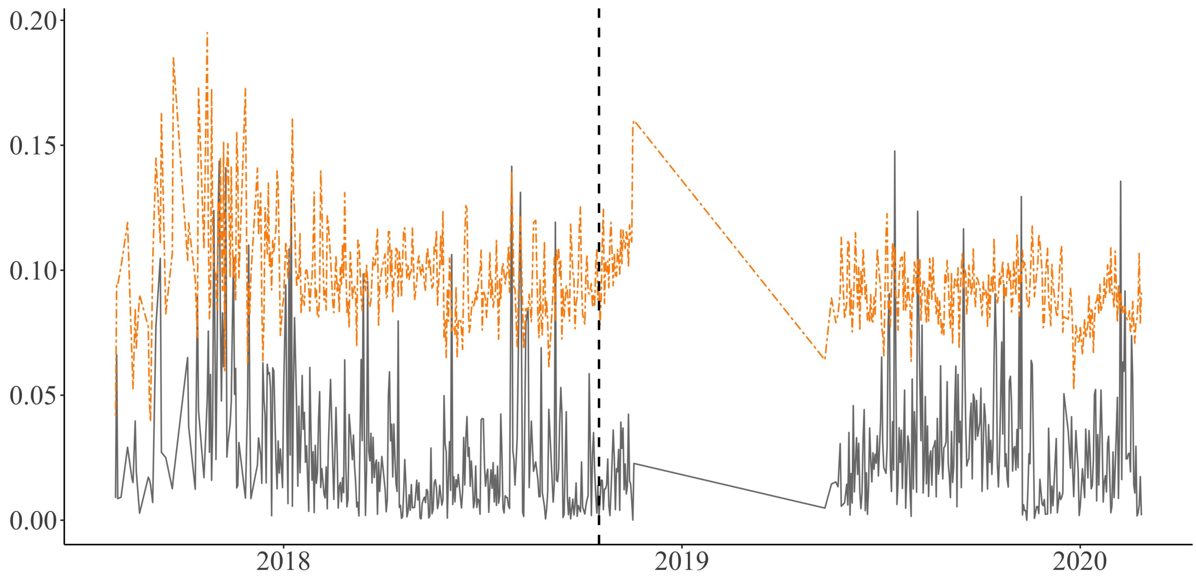


Figure 3.9: Cannabis volume relative to total volume in Canada and rest of the world, before and after legalization. We lack data between November 2018 and April 2019.

3.6.6 Canada price survey

Data from Statistics Canada indicates an increase in general use of Cannabis after legalization, although no increase is seen among the youths, similar to the results seen in Colorado (Rocky Mountain High Intensity Drug Trafficking Area program, 2019).

The price of legal and illegal cannabis were 10.30 CAD and 5.73 CAD at the end of 2019 according to Statistics Canada, 2020. Table 3.5 shows quarterly averages of Canadian cannabis prices through the legalization period. Statistics Canada calculate prices based on self-submitted quotes using its *StatsCannabis* crowdsourcing survey. The agency has used caution when interpreting the data, removing outliers. To be able to compete and keep market share, illegal vendors are decreasing their prices of cannabis. The price difference between legal and illegal cannabis grew from 35% to 45% through the year after legalization. Significantly lower prices combined with a greater product variety make the illegal vendors able to compete with the licensed retail stores.

We hypothesize that the price per gram of Canadian Dark web cannabis has dropped in response to the competition by legal stores. However, even *after* legalization, illegal vendors still account for the majority of cannabis sales in Canada. One reason is definitely supply problems legal cannabis has faced. The many new producers have struggled with government labelling requirements, processing challenges and shipping difficulties, leading to supply shortages. According to McClintock, 2019, the problems lasted for several months, and they are yet not able to produce the same quality products as offered on the illegal market. The legal sources did not provide non-smoking alternatives like edibles (totaling

18.5% of cannabis sold in Canada on Empire Market) until over a year after legalization. Despite these hardships, Price (2020) considers that the situation is improving as of 2020. A gradual progress in product quality and variety should, if anything, stimulate to further decrease in price of illegal cannabis.

Table 3.5: Price of cannabis in Canada (in CAD)

	Legal (Statistics Canada)	Illegal (Statistics Canada)	Illegal (observed feedback)	Illegal (observed listings)
1Q 2018		6.79	7.76	11.53
2Q 2018		6.81	8.65	12.02
3Q 2018		7.29	11.97	13.92
4Q 2018*	9.82	6.51	9.22	9.95
1Q 2019	10.21	6.23		
2Q 2019	10.65	5.93	6.67	
3Q 2019	10.12	5.59	6.22	
4Q 2019	10.30	5.73	5.59	8.49
1Q 2020	NA	NA	5.13	5.12

* Post legalization

Chapter 4

Concluding Remarks

Cannabis constitutes an enduringly large share of listings and recorded purchases on the Dark web. Sellers offer cannabis in various quantities, with a median value of 14 grams. Sellers of cannabis enjoy an overall higher level of customer satisfaction than sellers in general, which might or might not indicate a greater degree of professionalism in the cannabis niche. From our analysis of the underlying currencies used to price cannabis products, it appears that cannabis is relatively more popular in Europe than other articles on the Dark web.

The Drugs of Dependence Amendment Bill 2018 did not significantly affect the market of Australian Dark web cannabis. However, the Cannabis Act in Canada appears to have caused a significant drop in price and increase in volume. Taking into account that the Canadian law impacted the whole of Canada, whereas the Australian law had impact only in the Australian Capitol Territory, this result was not surprising. Despite the legalization event, illegal retailers still account for the majority of cannabis sales in Canada. Offering lower prices, better quality and greater variety, they are, for the time being, able to compete with legal sources. However, we ascertain that their total profit is lower than during the period before legalization, because the added competition has set a new, less favourable price equilibrium for the supplier side of the market.

Soska & Christin (2015) and Décary-Hétu & Giommoni (2017), have evaluated the effects of law enforcement crackdowns on Dark web marketplaces. Their research suggests that such efforts by law enforcement have little to no lasting effect on the Dark web ecosystem as a whole. Our findings suggest that the Canadian Cannabis Act, unlike crackdowns by law enforcement, *did* make a lasting impact on the Cannabis niche of the ecosystem. Taking note of this and considering the negative societal effects of Cannabis prohibition, it seems both prudent and pertinent to review current laws and measures to combat illegal cannabis retail.

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Appendix A

A.1 Open Marketplaces

Table A.1: Illicit online marketplaces as of 2019

Market	Operational	Launch date	Closure reason
Agartha	Yes	March 2019	
Apollon	Yes	March 2018	
Cryptonia	No[1]	April 2019	Scam
Empire	Yes	March 2018	
Samsara	Yes	July 2019	
Silk Road 3.1	No	May 2017	Scam
Nightmare	No	January 2019	Scam
Dream	No	November 2013	Hacked
Tochka	Yes	January 2015	
Berlusconi	No	July 2017	Raided
The Majestic Garden	Yes	NA	
Cannazon	Yes	March 2018	

[1] Closed 19 November 2019. Plan to open in beginning of 2020

A.2 Price per gram tables

Table A.3: Cannabis price per gram of different locations from listings

Location	Price per gram	Price difference	Significance level
World	9.50	-	***
Afghanistan	7.36	-2.14	**
Africa	6.06	-3.44	***
Albania	5.30	-4.20	***
Algeria	5.97	-3.53	
American Samoa	7.60	-1.90	**
Andorra	7.98	-1.52	***
Angola	9.24	-0.26	
Anguilla	6.21	-3.29	***
Antarctica	6.11	-3.39	***
Argentina	5.41	-4.09	
Armenia	9.19	-0.31	
Aruba	6.12	-3.38	***
Asia	6.17	-3.33	***
Australia	9.98	0.48	*
Austria	9.39	-0.11	***
Azerbaijan	9.08	-0.42	**
Bahrain	7.76	-1.74	
Bangladesh	6.14	-3.36	***
Belarus	7.09	-2.41	***
Belgium	8.94	-0.56	***
Bolivia	6.14	-3.36	***
Bosnia	5.13	-4.37	***
Brazil	7.04	-2.46	***
Bulgaria	6.26	-3.24	***
Cambodia	15.00	5.50	*
Canada	6.72	-2.78	***
China	6.06	-3.44	***
Croatia	6.17	-3.33	***
Cyprus	1.58	-7.92	***
Czechia	4.17	-5.33	***
Denmark	8.26	-1.24	***
Egypt	6.14	-3.36	***
Eritrea	6.17	-3.33	

Estonia	4.10	-5.40	***
Europe	9.27	-0.23	***
Faroe Islands	7.13	-2.37	**
Finland	14.07	4.57	***
France	9.22	-0.28	***
Gambia	7.16	-2.34	
Georgia	3.50	-6.00	***
Germany	10.04	0.54	***
Gibraltar	2.09	-7.41	***
Greece	1.76	-7.74	***
Greenland	9.81	0.31	
Guernsey	0.22	-9.28	***
Hungary	0.38	-9.12	***
Iceland	6.37	-3.13	***
India	8.19	-1.31	***
Indonesia	4.19	-5.31	**
Ireland	11.12	1.62	***
Italy	6.91	-2.59	***
Isle of Jersey	0.22	-9.28	***
Kyrgyzstan	9.81	0.31	
Latvia	1.58	-7.92	***
Liechtenstein	7.31	-2.19	***
Lithuania	7.13	-2.37	**
Luxembourg	10.03	0.53	
Macedonia	3.44	-6.06	***
Malta	7.13	-2.37	**
Moldova	7.13	-2.37	**
Monaco	1.39	-8.11	***
Montenegro	3.50	-6.00	***
Netherlands	9.39	-0.11	
New Zealand	6.97	-2.53	***
Norfolk Islands	22.82	13.32	***
North Macedonia	6.17	-3.33	
Norway	7.08	-2.42	***
Oman	0.22	-9.28	***
Poland	7.73	-1.77	***
Portugal	7.22	-2.28	***
Puerto Rico	7.47	-2.03	***
Romania	3.21	-6.29	***

Russia	12.83	3.33	***
San Marino	2.09	-7.41	***
Serbia	3.50	-6.00	***
Slovakia	1.68	-7.82	***
Slovenia	1.56	-7.94	***
South Africa	6.32	-3.18	***
South America	5.69	-3.81	***
Spain	7.58	-1.92	***
Swaziland	7.62	-1.88	
Sweden	7.71	-1.79	***
Switzerland	8.61	-0.89	***
Tajikistan	9.81	0.31	
Thailand	6.14	-3.36	***
Tunisia	13.31	3.81	**
Turkey	4.50	-5.00	***
Turkmenistan	9.81	0.31	
Ukraine	3.68	-5.82	***
United Arab Emirates	9.71	0.21	
United Kingdom	9.76	0.26	
United States	10.79	1.29	***
United States Minor Outlying Islands	6.94	-2.56	***
Uzbekistan	9.81	0.31	

Table A.2: Cannabis price per gram of different locations from feedback

Location	Average Price	Price Difference	Significance level
World	8.87		***
Afghanistan	6.56	-2.31	
Australia	10.18	1.31	***
Austria	11.05	2.18	***
Bangladesh	8.69	-0.18	
Belgium	10.50	1.63	***
Brazil	10.90	2.03	
Bulgaria	4.99	-3.88	
Canada	7.29	-1.58	
China	5.98	-2.89	
Czechia	7.87	-1.00	
Denmark	0.92	-7.95	***
Estonia	0.05	-8.82	
Europe	7.16	-1.71	
Finland	15.47	6.60	***
France	8.97	0.10	***
Germany	10.06	1.19	***
Greece	4.61	-4.26	*
India	16.46	7.59	***
Ireland	14.40	5.53	***
Italy	8.41	-0.46	*
Morocco	8.28	-0.59	
Mozambique	6.63	-2.24	
Nepal	5.77	-3.10	
Netherlands	7.60	-1.27	*
New Zealand	8.63	-0.24	
North America	12.23	3.36	***
Norway	15.09	6.22	*
Poland	7.93	-0.94	**
Portugal	10.47	1.60	***
Slovenia	10.47	1.60	***
South Africa	6.00	-2.87	
South America	4.25	-4.62	
Spain	6.84	-2.03	
Switzerland	10.36	1.49	***
Tuvalu	0.53	-8.34	**
Uganda	9.30	0.43	
United Arab Emirates	6.74	-2.13	
United Kingdom	7.46	-1.41	**
United States	9.62	0.75	***