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Measuring Decentralised Finance Regulatory Uncertainty

Egor Zmaznev

Supervisor: Maximilian Rohrer

MSc in Economics and Business Administration, Business Analytics

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

I develop and compare two DeFi regulatory uncertainty indexes based on the specialised media coverage frequency. By applying active learning in combination with SVM to identify uncertainty-related news articles, I show how regulatory uncertainty can be captured for emerging industries with limited data intervals. Both indexes display rising levels of DeFi regulatory uncertainty in recent years with the highest index spikes appearing during the first wave of the COVID-19 pandemic. By constructing a structural VAR model, I identified the negative effects of regulatory uncertainty shocks on total value locked in smart contracts of decentralised financial services. The negative response is consistent among the leading DeFi categories, such as lending services and decentralised exchanges. However, uncertainty shocks cause an increase of total value locked in derivatives and payment protocols.

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Acronyms

AUC-ROC — “Area Under the Curve” of “Receiver Characteristic Operator”

CBDC — central bank digital currency

dApp — decentralised application

DeFi — decentralised finance

DEX — decentralised exchange

DLT — distributed ledger technology

DTM — document-term-matrix

EBA — European Banking Authority

EMD2 — revised EU E-Money Directive

EPU — economic policy uncertainty

ESMA — European Securities and Markets Authority

FATF — Financial Action Task Force

FCA — Financial Conduct Authority

FSB — Financial Stability Board

ICO — initial coin offering

LDA — Latent Dirichlet allocation

PSD2 — revised EU Payment Services Directive

SVM — support vector machine

TVL — total value locked

VAR — vector autoregression

1. Introduction

Less than four years ago, the first decentralised financial (DeFi) application was launched. In May 2021, the total value locked in DeFi protocols reached over 87 billion dollars (*DeFi Pulse*, 2021). This drastic market rise with the growing progression and rapidly changing ecosystem of DeFi brought a set of regulatory challenges. Even up to this day, the legal status of the entire ecosystem remains unclear (Amler et al., 2021). Furthermore, the emerging nature of smart contracts — cornerstone technology for DeFi — extends the issue of regulatory complexity as possible over-regulation can strongly harm the industry at its early stage of formation (Calcaterra & Kaal, 2021). All of these aspects cause regulatory uncertainty, which traditionally has a robust effect on market development and is acknowledged to be a source of market fluctuations (Wang et al., 2019).

In this research, I analyse the relationship between regulatory uncertainty and decentralised financial services. To do so, I collect news data from 9 leading crypto-media sources to construct and compare two DeFi regulatory uncertainty indexes. The first method looks into the application of a traditional approach to capturing uncertainty with scaled news article count and the modified version explores an ML-based alternative to avoid subjective bias and maximize the value of the input data. Both indexes are based on the collected data sample, which consists of 108,071 individual news articles covering the period from June 2015 to March 2021.

The motivation to use a more sophisticated uncertainty identification strategy derives from issues associated with the specifics of emerging technologies: unlike traditional economic uncertainty, media data for emerging industries is limited to a much shorter time interval. Therefore, a possible “mislabelling” and discriminative bias possess a strong effect on the captured uncertainty measures (Tobback et al., 2018). The performance of the models is investigated with a narrative evaluation that captures key events that drive policy uncertainty for the field of decentralised finances. The validation is extended with a comparison of the constructed indexes with alternative measures of categorical policy uncertainty.

I further explore the effects of uncertainty shocks on total value locked (TVL) in smart contracts of decentralised financial protocols. Uncertainty shocks are explored across different categories of DeFi services, such as lending protocols, decentralised exchanges, payment protocols, etc.

The influence of uncertainty on economy and policymaking has been largely studied previously by Bleaney & Greenaway (1996), Bloom (2009) and Baker (2016) with an exploration of various types of uncertainty shocks. Researches showed that uncertainty shocks have proven to carry a significant negative effect on investments, provoking so-called “wait and see” market behaviour. As for cryptocurrencies, Wang et al. (2019) have shown that Bitcoin can act as a safe-haven during economic policy uncertainty shocks. Furthermore, volatility of the Bitcoin market has varying responses for the different types of uncertainty: Matkovskyy & Jalan (2019) show a negative effect of EPU and news-based uncertainty on Bitcoin volatility, yet a positive impact of the US financial and tax regulations.

The central hypothesis of this paper suggests that uncertainty from media regarding the regulation of the decentralised finances negatively affects the total value locked in smart contracts of the Ethereum-based DeFi protocols. The hypothesis is based on the overviewed regulatory complexity and the current state of regulations regarding DeFi (Amler et al., 2021; Calcaterra & Kaal, 2021; Werner et al., 2021). Additionally, previous literature suggests that crypto-assets, which are not based on smart contracts, are negatively affected by economic policy uncertainty (EPU) and news-based uncertainty (Auer & Claessens, 2020; Matkovskyy & Jalan, 2019).

This paper contributes to the literature in three major ways. The primary contribution of this research is applying a more advanced technique to better capture media uncertainty for an emerging industry with limited data interval. The secondary contribution is the identification of the effects of uncertainty shocks on DeFi services and their underlying categories. Lastly, the study identifies the key events and processes that affect the emerging global regulatory framework concerning DeFi.

The current study explores topics that are closely tied with the economic and regulatory sides of decentralised finances. Therefore, the paper can be useful for defining a clearer legislative framework for smart contracts and crypto-assets. Additionally, the study will be valuable for the researchers interested in smart contracts and the development of the crypto industry as it identifies underlying events affecting the formulation of the regulatory framework for decentralised finances.

2. Theoretical background

2.1 Decentralised Finance and regulation

In essence, this paper primarily focuses on uncertainty measures and decentralised financial applications. In a broad sense, decentralised financial systems include decentralised currencies, payment services, decentralised fundraising and decentralised contracting (Chen & Bellavitis, 2020). Previous researches have looked into ways of constructing cryptocurrency regulatory indexes as well as analysed the effects of economic policy uncertainty on the Bitcoin market, its returns and volatility (Demir et al., 2018; Gozgor et al., 2019; Wang et al., 2019). This study primarily focuses on decentralised contracting. While it shares a set of common principles with cryptocurrencies, its features further extend the concept of non-custodial financial architecture. Werner (2021) points out four essential properties that define financial service as DeFi:

- *Non-custodial*, meaning that agents hold full control over their funds without any intervention of a third party.
- *Permissionless*, in other words, no third party can censor or block an agent from using a service.
- *Openly auditable*, meaning that anyone should be able to audit and check the state of protocols.
- *Arbitrarily composed*, or in other words, service is constructed from the interacting elements.

These features require a DeFi protocol to have an underlying distributed ledger with the ability to develop smart contracts (Calcaterra & Kaal, 2021; Werner et al., 2021). The use of blockchain ensures that a service provides its users with the first three features: non-custodial, permissionless and openly audible service. Smart contracts add an element of composability (Werner et al., 2021). Due to composability, the use of smart contracts for financial services is extremely versatile: Werner et al. (2021) categorises DeFi protocols into seven categories based on the type of operation — asset management, loanable funds markets, non-custodial stablecoins, portfolio management, derivatives, layer-two DeFi (commonly referred to as scaling solutions) and privacy mixers. The concept of stablecoins is especially important to the field of decentralised finance as it is commonly employed by crypto service providers as a primary medium of exchange. Stablecoins are aimed to stabilise a token’s price in relation to the target currency by using on-chain collateral, which stores the token's primary value. Sometimes stablecoins can be outside of the scope of DeFi if they rely on a trusted third-party to operate, which makes it custodial (Perez et al., 2021; Werner et al., 2021). In this research, I only analyse the effect of the uncertainty shocks on DeFi protocols that are based on the Ethereum blockchain as the leading platform for decentralised financial services (Calcaterra & Kaal, 2021).

As smart contracts play a central part in the realisation of DeFi protocols, one of the key measurements to track a service’s adoption and scaling is the parameter of total value locked. This measure tracks the amount of cryptocurrency or crypto tokens locked in the corresponding smart contracts (Ibid.). Within the year 2020, the total value locked in DeFi services has increased by over 40 times, resulting in over 15 billion USD. Apart from the positive effects that this rise brought to the developing industry of decentralised services, DeFi has shown its vulnerability from both the technical perspective, which is in most cases connected with smart contracts rather than distributed ledger technology (DLT), as well as with economic manipulations (Werner et al., 2021). Total value lost only due to the technical breaches in the decentralised finance is 132.6 million USD as of March 2021. Additionally, decentralised financial platforms, such as DEXes (decentralised exchanges), are subject to the risk of wash trading, insider trading and frontrunning that resulted in losses of around 3 billion USD only in 2018 (Werner et al., 2021). Therefore, the issue of DeFi regulations has been one of the central topics since the early days of this emerging industry, and yet the legal status of the whole ecosystem is still not clearly defined (Amler et al., 2021; Calcaterra & Kaal, 2021; Chen & Bellavitis, 2020).

The lack of understanding of the operations and possibilities to control truly decentralised projects makes regulatory bodies uncertain regarding their further actions (Salami, 2020). Previously introduced regulations in regard to cryptocurrencies and ICOs do not always apply to DeFi protocols. It is mainly connected with the underlying technology of smart contracts, which falls into a grey regulatory area. So far, introduced regulations bring limitations to new market entrants and further technological advancements, rather than enhance the developing ecosystem (Amler et al., 2021). The global factor of DeFi services implies additional complications: the

Financial Action Task Force (FATF) specifically focuses on the challenge of global coordination to regulate DeFi with a variety of competing jurisdictions (Salami, 2020). Varying jurisdictions and differences in regulatory advancement are especially problematic as regulators have to find a balance to limit possible criminal activities while making regulations executable for early-adopting companies (Ibid).

2.1.1 Current state of regulations

With the development and maturing of technology, the deriving uncertainty decreases as emerging industry stabilizes over time. From a regulatory perspective, there are traditionally three key approaches to stabilize industry and regulate the risks associated with new technology: technology- , management- and performance-based regulations (Bonnín Roca et al., 2017). Due to the non-custodial nature of DeFi, its regulatory uncertainty primarily comes from the underlying technologies: blockchain and smart contracts. The concept of blockchain has already dragged a lot of attention in the regulatory field with the rise of many initiatives, especially during the period of "initial coin offering boom", raising the question of categorisation of digital assets and whether crypto-assets should be considered securities (Cumming et al., 2019).

Primary recommendations, definitions and regulations in regard to smart contracts-based decentralised financial services were coming to sight in 2019, which was mainly caused by the rise of ICOs. In 2019, European securities and markets authorities (ESMA) published comprehensive recommendations concerning initial coin offerings (ICO) and crypto-assets: the report provided central definitions and regulatory comments for such concepts as DLT, smart contracts, ICOs, digital wallets and trading platforms (ESMA, 2019). Apart from that, ESMA specified the risks that should be addressed by regulatory bodies, mentioning the importance of considering not only "issuance and distribution of crypto-assets but [...] the whole lifecycle of crypto-assets" (Ibid.). Specifically, ESMA emphasised the need for legal certainty to minimize the risks in regard to investor protection and assist the development of a "sustainable ecosystem" (Ibid.). EBA also issued a report specifically on the crypto-assets and application of the EU law in its regard, especially reviewing the applicability of EMD2 and PSD2 to crypto-assets in general and particularly focusing on digital wallet providers and trading platforms (EBA, 2019). In the same year, the Financial Conduct Authority (FCA) released its guidance on crypto-assets clarifying the scope of activities falling under the UK regulations: document aimed to increase consumer protection, decrease harms of market integrity and reduce legal uncertainty to assist companies in creating legitimate business activity models related to crypto-activities (FCA, 2019). The guidance provided more clarity to the term of stablecoins, however, FCA specified that stablecoins may not be considered as securities, and "design and the rights associated with a specific stablecoin" defines whether it can be treated as e-money. In the European area, the set of guidelines and advices, especially the ones proposed by ESMA and EBA, led to the draft compilation of "Markets in Crypto-assets", presented in 2020 by the European Commission (Amler et al., 2021). Presented regulatory proposals for crypto assets will supposedly be enforced by 2023 and covers an extensive range of digital assets, including stablecoins that may be classified as digital assets. However, DeFi tokens and smart contracts are not covered specifically, and while they can be referred to as "issueless" it keeps the regulatory side of DeFi at a high level of uncertainty (Ibid).

2.1.2 Stablecoins: new source of regulatory uncertainty

Past years brought even more attention specifically to the stablecoins and their use by both private entities and governments. One of the key events was the announcement of the Libra stablecoin (currently rebranded to Diem) by Facebook in 2019. It caused a mass response from governments globally due to the perceived threat to national monetary sovereignty (Taskinsoy, 2019). On the other hand, the concept of central bank digital currency (CBDC) and its implementation with the application of DLT and smart contracts has been a subject of discussions across all major economic areas.

Lack of regulatory clarity makes the majority of stablecoins operate in a grey area directly affecting connected services, such as DEXs (decentralised exchanges) (Arner et al., 2020). A large scope of possible financial architectures, including custodial, non-custodial and hybrid systems, brings additional complexities to the development of regulatory frameworks for stablecoins.

All of the aforementioned complexities, risks and legal gaps, combined with the booming tempo of DeFi scaling and development, make regulatory uncertainty have an even stronger effect on the future of the ecosystem.

2.2 Economic policy uncertainty

Economic uncertainty can be defined as unexpected changes that affect the expected outcomes and influence the economic ecosystem (Al-Thaqeb & Algharabali, 2019). Studies on the effects of uncertainty experienced a surge of interest in the second half of the previous century: back then studies were primarily looking into psychological effects and decision making under uncertainty (Menger, 1979). Then, uncertainty took a step from a theoretical economic perspective to empiric evidence, investigating the financial perspective and its effect on the investments. In particular, Bernanke (1983) looked into uncertainty and uncertainty shocks stating that such provide an impulse to the cyclical swings and investment pause may occur at higher uncertainty levels, so the agents can get more information for their decision-making. Additionally, he concluded that uncertainty shocks cause investment shrinkage as well as downsize in employment (Ibid).

With the rise of application of textual data mining and analysis, studies of economic uncertainty experienced a new rise in early 2000. Primarily, it is connected with more possibilities to measure and grasp uncertainty in a more precise manner, avoiding *ex-post* bias that has previously been an issue for stock volatility-based measures. Moreover, previously used uncertainty measures, such as S&P 500 based volatility index (VIX), are only limited to the market uncertainty indicator. With application of text mining techniques, researchers proposed new ways to measure economic uncertainty by applying sentiment analysis, constructing matching patterns and word dictionaries, as well as applying topic modelling. (Al-Thaqeb & Algharabali, 2019)

While early papers looked at specific aspects affected by uncertainty, — such as news aspect, political aspect or sentiment — combined work of Baker, Bloom and Davis (2016) proposed a novel approach to develop a news-based index combining three key components: economic (E), policy-related (P) and uncertainty component(U). The method is based on the scaled article count containing words related to the three components of the economic policy uncertainty index (EPU) with a further application of normalization and standardization. By applying a vector autoregressive model to the EPU index with Cholesky decomposition of the set of macroeconomic parameters, negative effects of uncertainty shock on industrial production, investments and employment were identified by Baker, Bloom and Davis (2016).

2.2.1 EPU and crypto-assets

The interconnection between the EPU index and cryptocurrencies has also been a subject of attention in recent studies. Bouri et al. (2017, 2019), Demir et al. (2018) and Papadamou et al. (2020) have shown that major cryptocurrencies, including Bitcoin, Bitcoin Cash, Litecoin and Ethereum, can act as safe havens to the uncertainty shocks. Papadamou (2020) emphasises the strong linkage between cryptocurrencies and EPU during the bull markets, as well as accents the stronger influence of Chinese EPU in comparison to other states. Bauri et al. (2019) provides argumentation for cryptocurrencies to be a subject of herding behaviour, which is directly connected with uncertainty: herding effects often occur with the rise in uncertainty levels. Antonakakis et al., (2019) also provided evidence for rising crypto-market connectedness during high uncertainty. Studies on EPU effects on the cryptocurrency market commonly apply the general index, proposed by Baker et al., (2016), yet the majority of papers do not look into specific cryptocurrency regulatory frameworks. Unlike previous studies, the current research is looking into ways to construct a DeFi-specific regulatory uncertainty index.

While decentralised finance has drawn a lot of attention in the previous years, it is still in its early stage of development, and in the early stage of research, therefore, this paper explores DeFi regulatory uncertainty for the first time. The active development and booming rise in adoption and popularity of DeFi protocols bring several complications to the analysis and research process for measuring uncertainty and its effects. First of all, the available data, suitable for the uncertainty measurements, is limited to the previous three to four years as far as the first DeFi protocol was launched only in December 2017. Moreover, the industry of decentralised finance very closely intersects with traditional cryptocurrencies and is represented by several categories of decentralised financial services. This brings extra complications to the textual analysis specifics of the basic EPU index construction (Harwick & Caton, 2020). Particularly, the categorical component of the EPU index is a subject of possible discriminatory bias and mislabelling due to the close intersection of cryptocurrencies and DeFi protocols. The global nature of the DeFi services also creates additional complexity, as it primarily affects the regulatory side (P-component) of the uncertainty index.

2.2.2 Capturing uncertainty for emerging industries

Limited data, normalisation sensitivity and lack of regulatory clarity are the key complexities that affect the regulatory uncertainty analysis for developing industries (Antons et al., 2020). The traditional EPU construction approach can be strongly affected by the aforementioned complications. Firstly, by applying a baseline method proposed by Baker et al. (2016), the index is constructed based on the count of articles that include words “uncertainty” or “uncertain”, “economy” or “economic” and policy-related words, such as “central bank” and “regulation”. Such an approach assumes that an article is related to EPU if it contains a set of predefined words, which leads to type I and type II errors (Larsen, 2017; Tobback et al., 2018). In other words, this method tends to overlook relevant articles and can wrongly account for unrelated articles. Secondly, with limited data, every error will strongly affect the normalisation procedure. This will result in an index falsely capturing events related to regulatory uncertainty. It also does not account for any weights of the terms, which further extends the algorithm’s tendency towards false article classification. Lastly, for such emerging industries as decentralised finance, the regulatory aspect carries a global nature. It causes the predefined dictionary for the policy aspect (P) to be specifically large and raises the issue of discriminative predisposition. To put it simply, if some words that might be relevant are not included in the pre-selected dictionary for the regulatory aspect, the method will simply ignore it (Ibid.).

Previously, Larsen (2017) and Azqueta-Gavaldón (2017) looked into the application of text mining techniques and the use of unsupervised machine learning algorithms, such as Latent Dirichlet allocation (LDA). It has shown to be easy in execution and provides good results for country-level data, however, for an emerging industry with higher topic variability, less structured textual data and a low number of topics that can be labelled as related to EPU, LDA may lead to poor results with low interpretability.

Another approach to avoid dealing with predefined keywords is the use of supervised machine learning algorithms for text classification. In this regard, Tobback (2018) proposed a method based on the combination of the SVM model and an uncertainty-based sampling method for the active learner approach. It is specifically focused to decrease type I and II errors for articles mislabelling, which is seen as the key issue for the DeFi uncertainty index to give misleading results. Specifically, for the cases with higher frequency data and limited time span, the mislabelling after the process of scaling and normalisation can result in “false” spikes that would not explain the rise of uncertainty in regard to economic policy. The SVM model combined with the active learner also addresses the issue of a skewed distribution of articles and a low number of relevant articles across the dataset.

Therefore, Baker’s EPU method serves as a “naive” baseline approach and is tested against a modified version. The modified version is based on the use of SVM algorithm in combination with a pool-based uncertainty sampling active learning technique to classify whether articles are related to EPU or not. Active learner allows us to identify the articles the algorithm is least certain about. In the current case, these articles are the ones that are the closest to the decision boundary (Appendix 2). The complete methodology for both naive and modified versions is described in chapter 3.

As far as I am primarily interested in the regulations related to the decentralised finances, the additional “categorical” terms are added to the baseline method, yet due to a large number of DeFi categories and industry’s global factor, dictionaries for categorical and policy terms are comparably large (Appendix 1). Further, the identified “categorical” terms and economic component (E) are used to limit the number of articles for active learner model training. The key underlying assumption of the modified approach is that the articles should contain words related to decentralised finance and address the economic component to be accounted as relevant for the DeFi EPU (Tobback et al., 2018).

3. Methodology

3.1 Collected data

3.1.1 News data

To analyze news-based uncertainty regarding the regulation of decentralised finances, the news data was collected from specialised media sources that focus primarily on cryptocurrencies and blockchain. The final data consists of 108,071 articles from 9 leading crypto-media sources, shown in Figure 1. Each source was selected based on the number of monthly visitors according to SEMRush keywords analytics. I have collected all the available English articles falling into the period between June 2015 to March 2021.

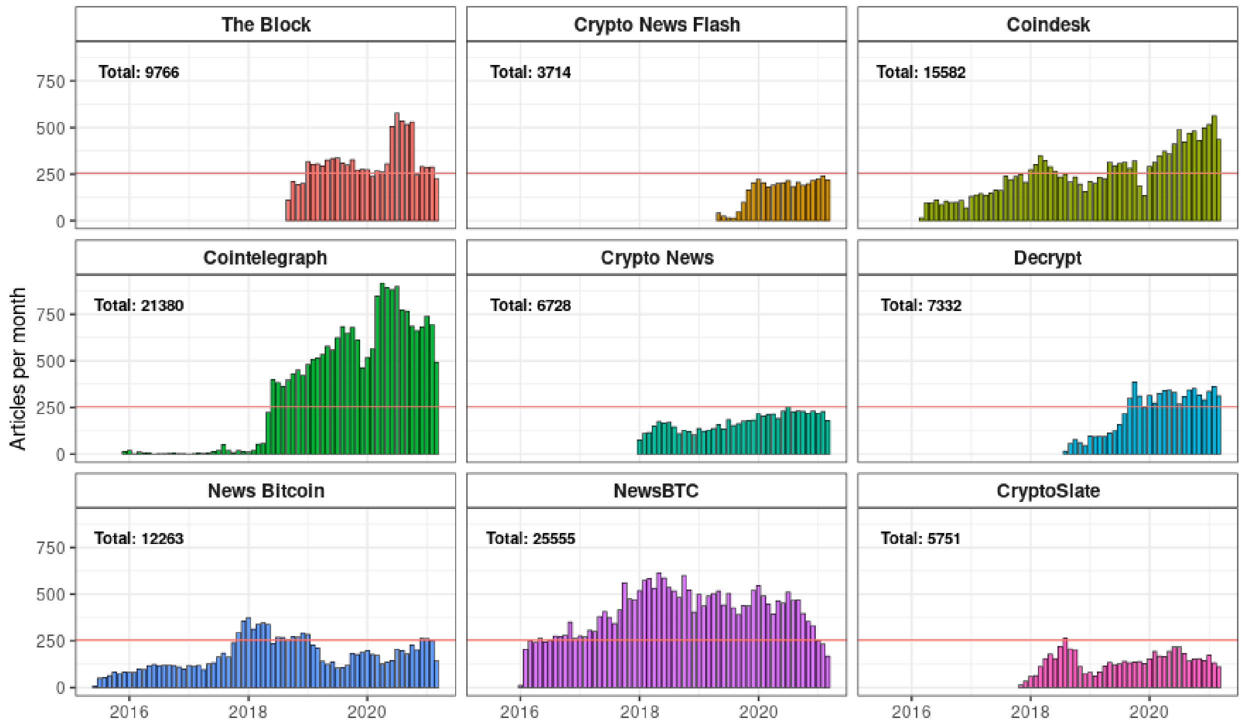

Figure 1. Number of monthly articles per media.

All the articles were collected using a custom Python scraper for every news source. Data further went through the stage of cleaning and preprocessing to remove all the unrelated articles, such as sponsored posts, ads and press releases as well as unrelated text chunks, for instance, footers and headers. Then, for the modified model input, stopwords, punctuations, web-links, highly frequent words and all the numbers were removed, which goes in line with the literature on textual data processing (Larsen, 2017). Stemming was also considered, however, based on the model testing, results interpretability was strongly affected.

Figure 1 shows the overall number of monthly articles published by the news source after data cleaning. The red line displays the average number of articles per month across all of the sources. Cointelegraph, NewsBTC and Coindesk are showing the largest number of monthly articles. Coindesk, NewsBTC and News Bitcoin covers the longest interval of publications with a comparably more stable rate of publications, while other sources tend to rise in the number of publications in the recent two years, making the graphs appear negatively skewed. Similarly to previous papers, the number of monthly articles, start date and monthly consistency strongly varies across the news sources, therefore, standardisation and normalisation were applied in both naive and modified indexes following the approach of Baker (2016).

3.1.2 DeFi protocols

Apart from the news articles, I have collected historical data on total value locked (TVL) across all the Ethereum-based DeFi protocols: it consists of timestamps, TVL in USD and Ether. The total value locked parameter displays how much value is held by smart contracts of DeFi protocols in Ether and ERC-20 tokens. Apart from the cumulative TVL, I have collected metrics by DeFi category from DeFi Pulse to further study the effect of uncertainty impulse on different types of decentralised protocols.

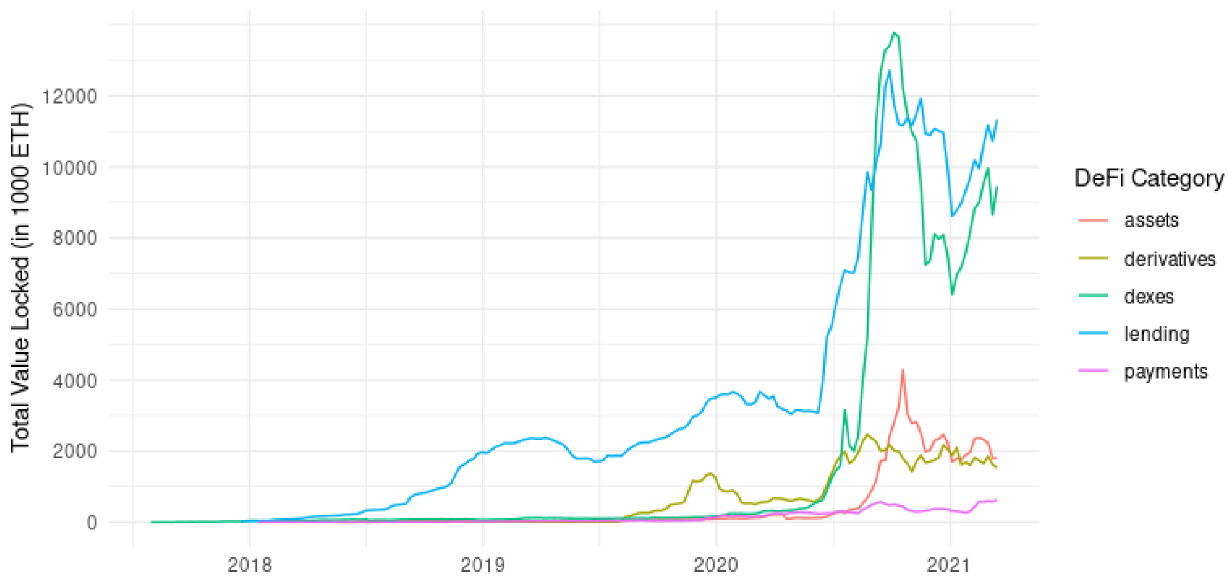

Figure 2. Total value locked by decentralised finance category from 2017 to 2021 (*DeFi Pulse*, 2021)

Collected historical DeFi data consists of the following categories:

- **Lending** — decentralised credit multi-collateral platforms. Maker, Aave and Compound are among the leading services for this category with a cumulative TVL of over $28 billion (for mid-April 2021). Additionally, the MakerDAO protocol is supposed to be the first decentralised financial service that remains active to this day. It was initially launched in December 2017. Dai stablecoin is used as a primary medium of exchange for the Maker platform, and largely adopted across other DeFi protocols. Dai value is pegged to the US dollar. (Schär, 2020)

- **DEXes** — decentralised exchanges and automated liquidity protocols for token swaps. Among the leading services are Uniswap, Curve Finance and SushiSwap with a total cumulative TVL of over $16 billion (for mid-April 2021). Unlike the traditional pair trades on the centralised platforms, the protocol does not enable the use of order book but employs market maker mechanisms, which "provides instant feedback on rates and slippage". (Adams et al., 2021)
- **Derivatives** category includes decentralised oracles, derivatives and options trading as well as prediction markets. Synthetic is the leading service in this category with over $2.14 billion of TVL (for mid-April 2021). This protocol, similarly to others in this category, provides functionality for the issuance of "synthetic" assets (which are analogous to derivative trading in traditional finance), which track and provide returns for another asset without the need to actually hold the assets. (Liu et al., 2020)
- **Payments** protocols are aimed to solve scalability issues of the Ethereum platform, improve the speed and anonymity of transactions. This is the smallest category, represented by just 5 Ethereum-based protocols and has the lowest TVL in comparison to other categories. Yet the leading payments DeFi protocol, Polygon, still has more than $1.8 billion in total value locked (for mid-April 2021). (Stepanova & Eriņš, 2021)
- **Assets** category consists of yield generating protocols that are rebalancing and optimising crypto assets to maximize yield returns. Often such protocols largely employ decentralised voting mechanics to navigate ecosystem decisions. (Stepanova & Eriņš, 2021)

Overall, data is based on historical records across 93 decentralised financial protocols with a total value locked of over $57 billion.

3.2 Quantifying uncertainty

3.2.1 Naive approach

I followed the approach proposed by Baker et al. (2016) in constructing the baseline naive model. Originally, it is based on the monthly count of articles related to economic policy uncertainty. In my case, I increased the frequency to a weekly count due to a limited data interval available for crypto-assets. Baker (2016) has previously pointed out that the EPU with the higher frequency is strongly correlated with the monthly count and provides “a useful high-frequency alternative”. Similarly, Lucey et al., (2021) formulates a cryptocurrency uncertainty index with the weekly frequency as well as further transforms the data to the weekly format for the SVAR analysis. I additionally limit the uncertainty index to the period starting from the end of 2017, as far as December 2017 was the launch of the first smart-contract based decentralised financial service.

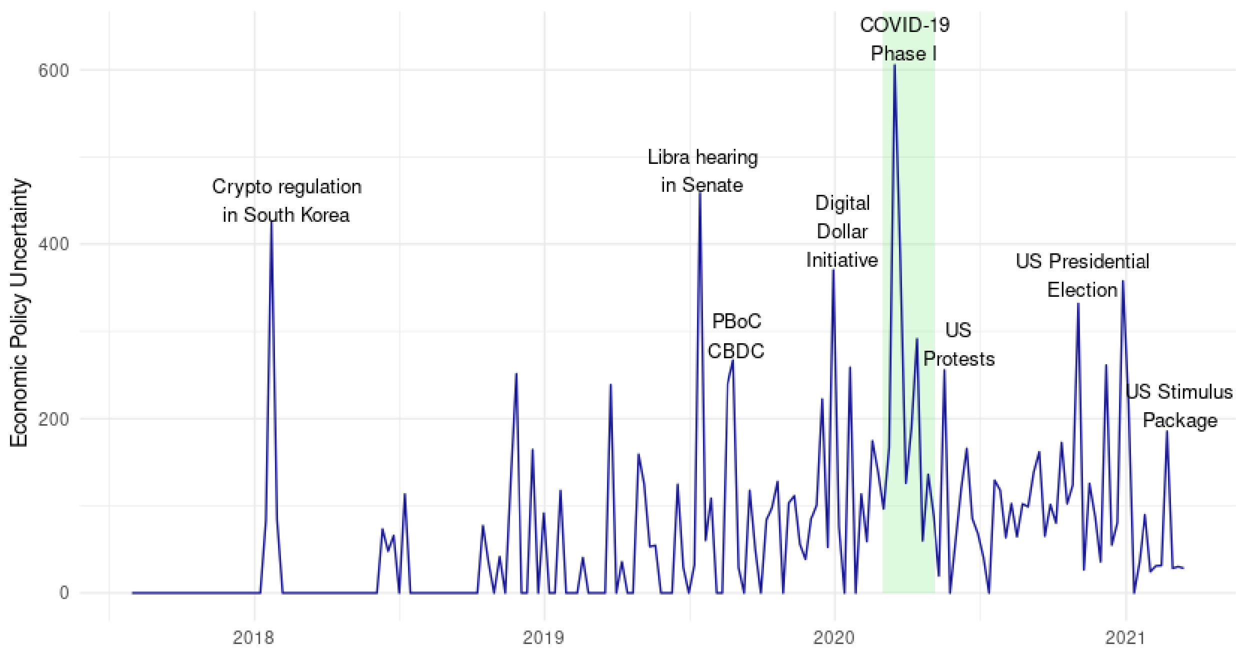

Figure 3. Economic Policy Uncertainty Index for DeFi based on the weekly article count

An article is counted as related to EPU if it contains words from the pre-defined groups, which are divided into economic, policy and uncertainty parameters and the categorical group of words. I add the words relevant to DeFi as a part of the categorical group. They are formed from the direct keywords that are directly related to DeFi, such as “decentralized finance”, as well as keywords that are related to the decentralised services and protocols, such as “DEX” or “stablecoin” (full list of terms is available in Appendix 1). DeFi categorical terms follow protocol categorization formulated by Werner (2021).

As far as raw count doesn’t deal with the varying number of articles across the media sources and time, it has to be scaled to the unit of standard deviation, and further standardised and normalised. Such data transformation follows the original technique proposed by Baker (2016).

The naive EPU index (*Figure 3*) is based on the article's raw count, which does not involve any terms weighting, and can also lead to a bias arising from the limitation of the pre-selected dictionary. It is specifically an issue in this case with the limited data interval, lack of clear understanding of the influencing regulatory bodies as well as a generic pre-defined set of terms that may lead to the article being completely ignored. These issues have been a subject of discussion and motivation for the researchers to look for modified and more complex methods to avoid the specification of the keywords.

3.2.2 Modified model: active learning approach

For the modified version of the index, I subset the articles that contain the word "economy" and categorical words related to decentralised finance, which goes along with the methodology of Tobback (2018). Then the data is transformed to the Document-Term-Matrix (DTM) format with a defined list of controls, which removes punctuation, numbers, stopwords and highly frequent words. While Larsen, (2017) additionally applied stemming, in the case with the crypto media data it negatively affected results interpretability and model's accuracy, therefore was not used in the final setting.

Resulting DTM is used as an input for the linear SVM classifier. Training is done in several iterations with the application of active learning, which queries users to label more data. The initial iteration contained 400 randomly selected articles from the defined subset and was assessed with another random 100 articles that formed a test set. Then, the pool-based active learning querying with uncertainty sampling is applied to select another 100 articles that algorithms find to be least certain about. The process is repeated based on the evaluation performance and ROC-AUC metric (*Figure 4*).

Active learning is commonly applied in cases, when labelling, such as relevance to DeFi regulatory uncertainty, is difficult to obtain and time-consuming (Settles, 2009). The active learning approach is based on querying — labelling of the unknown instances by the oracle, for example, human annotator. Yet the approach is not based on the querying of the complete dataset, opposedly, it aims to achieve high accuracy with the lowest number of labelled instances as possible (Settles, 2009). In the current paper, uncertainty sampling querying is applied, where observations with posterior probability closest to 0.5 are marked as least confident. For the SVM model with linear kernel, these are the articles that the algorithm defines as closest to the decision boundary. Pool-based sampling assumes that there is a small labelled pool of observations and a remaining pool of the unlabelled data, in our case these are the remaining articles that contain categorical (DeFi) and economic (E) components, which is based on the methodology suggested by Tobback et al. (2018). Starting labelled pool consists of 400 randomly picked observations.

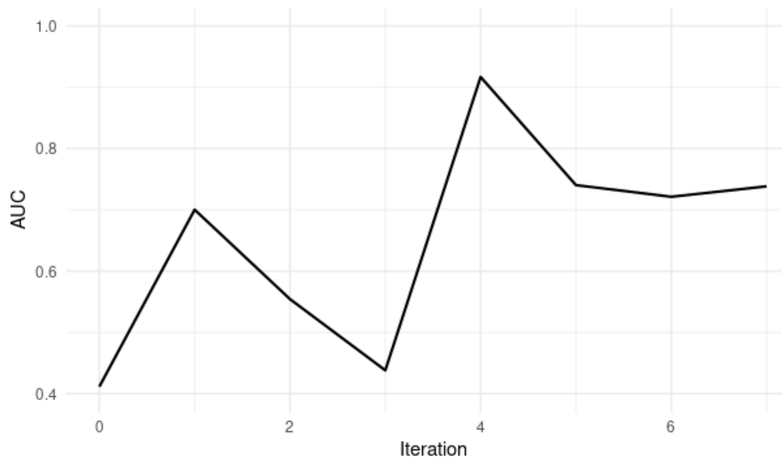

Figure 4. Evolution of AUC throughout the AL process.

Active learning iterations are repeated until the AUC shows no further improvement. The evolution of AUC with every iteration is displayed in *Figure 4*. As we can see, the initial model started with the lowest AUC of 0.41 meaning that the classifier is not able to distinguish uncertainty related and unrelated news articles. The very first iteration strongly improved the results, bringing AUC to 0.7. However, the following iteration brought the metric down to 0.45, which then was followed by its peaking point of 0.92. To ensure that model does not provide further improvements, additional 3 iterations have been made. The final SVM model used for labelling was based on the fourth iteration and contained 800 articles for training based on the AUC results.

This approach does not rely on pre-defined words, allowing to avoid bias and discriminative features of the pre-selected set of keywords. *Table 1* shows the top 20 terms with the highest variable importance. Expectedly, words related to the regulatory side are largely present with such terms as "central", "bank", "regulatory" and "regulation" being among the top ones. Notably, apart from the general term related to DeFi, "stablecoins" are among the terms with the highest importance.

Table 1. Top 20 terms by variable importance according to the trained SVM model.

Word	Importance	Word	Importance
central	100	million	70.59
defi	93.05	past	68.29
price	92.97	billion	66.06
bank	90.82	payments	65.96
ethereum	90.15	banks	65.17
regulatory	88.56	high	63.06
stablecoins	84.13	legal	62.49
regulation	80.08	token	59.40
currency	74.02	cbdc	58.00
libra	71.71	payment	56.43

Terms "libra" and "cbdc" provide proof for cases of the private and public issued token being among the leading topics of the regulatory discussions. A portion of terms seems to be also focused on the financial side deriving from such words as "million", "billion" and "payments(s)". It may be connected with the rapidly growing capitalisation and use of decentralised services, which drags more attention from the regulatory perspective. Lastly, we can observe "ethereum" among the top terms, which is also expected as a majority of the decentralised financial services are based on the Ethereum platform, while alternative dApp platforms, such as Cardano, are only starting to get traction (Werner et al., 2021).

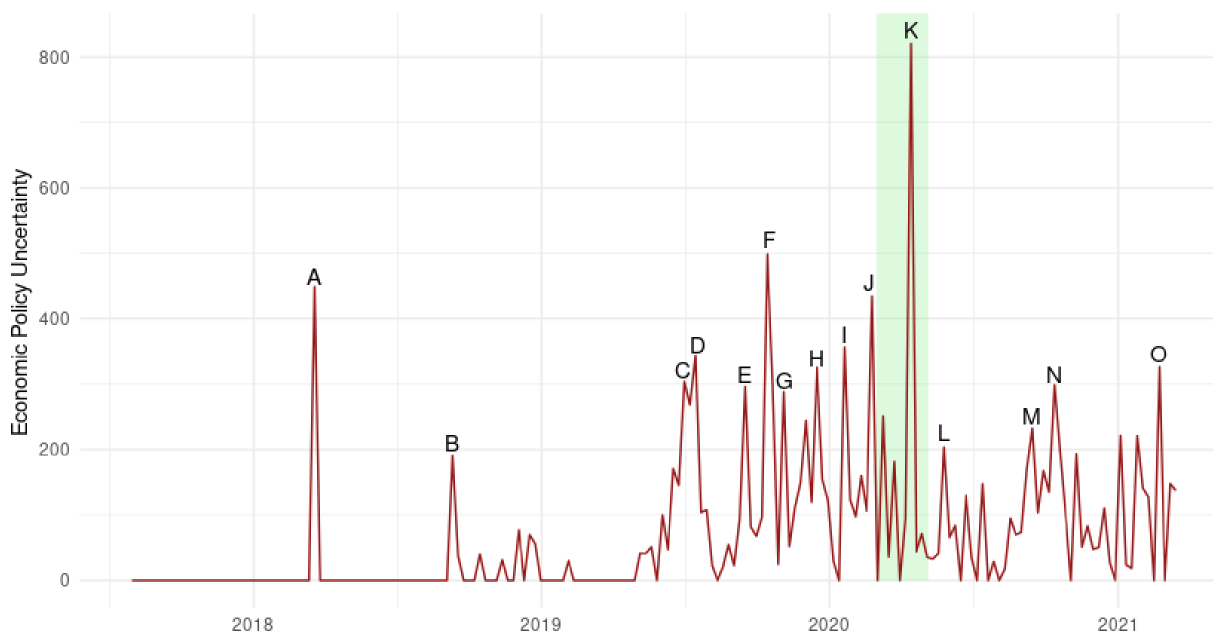

Figure 5. Economic Policy Uncertainty Index for DeFi based on the active learner SVM model

Table 2. Identified events causing DeFi uncertainty for the modified index.

Letter	Event
A	G20 Summit calls for the recommendations on how to regulate cryptocurrencies globally
B	Vice President of EC addressing crypto-assets and needing to decide how to regulate them. ECB's president discusses potential CBDC. Russian government is planning to announce crypto legislation, which is strongly discussed at EEF.
C	US House of Representatives Committee on Financial Services calling Facebook to cease any development on Libra. G20 leaders issue a declaration on crypto-assets.
D	Facebook's Libra hearing at Congress. IMF calls for regulatory actions regarding Facebook's Libra. G7 task force meeting on privately-issued stablecoins.
E	Libra representatives meeting with the Committee on payments and Market Infrastructure to discuss stablecoins regulations. Germany's finance minister suggests rejecting privately-owned stablecoins.
F	G20 calls for the IMF to examine macroeconomic implications of global stablecoins. FATF announces money laundering and financial risks posed by stablecoins. The Federal Reserve's board of governors mentions risks to consumers from private stablecoins. FSB delivers assessments on global stablecoins.
G	Meeting of the EU finance ministers on applications of the existing regulatory framework to stablecoins and "lack of clarity" in regard to Libra token regulations.
H	ECB discusses implementation of CBDC and launch of digital euro. US Congressman presents draft bill "Crypto-Currency Act of 2020" to bring clarity on how to regulate different types of crypto assets.
I	BIS survey on CBDCs. WEF creates the CBDC regulatory framework for policy-makers. FCA takes over anti-laundering authority in the UK for the crypto business.
J	G20 calls for implementation of FATF standards on virtual assets and addresses the risks of stablecoins. Financial secretary of Hong Kong announcing strengthening of AML crypto policies. Ukraine discusses CBDC implementation.
K	European Parliament issues study on legislative blindspots in regard to crypto assets and calls for the international level crypto regulations. FSB comprehensive study on stablecoins and warning to national regulators for stablecoins regulatory frameworks. Facebook publishes updated whitepaper for Libra. House of Financial Service Committee representative raises concerns on revised roadmap of Libra. China reveals testing environment for CBDC.
L	Digital Dollar Project proposes a framework for the US CBDC launch. IMF representative discusses CBDC issues.
M	Two reports on the comprehensive crypto-assets legal framework from European Commission "to clarify key issues for the crypto industry" and "enable the uptake of DLT"
N	G20 FSB publishes a report with recommendations to regulate and supervise stablecoins; new regulatory framework implementation for stablecoins by 2022. Russia announces plans for CBDC.
O	SEC Commissioner calls for the "regulatory clarity and freedom to experiment" for DeFi. India pushes for a crypto-assets regulations bill. UK government-commissioned review emphasises the need for the national crypto regulations.

4. Validation

4.1 Narrative validation

The resulting naive index (*Figure 3*) grasps some of the general events that cause market uncertainty as well as some DeFi-specific events. The start of the COVID-19 pandemic has the largest spike for the naive index, which is expected as it causes mass market and regulatory uncertainty. US Presidential elections, the proposed stimulus package and US protests are among other clear spikes for the year 2020 connected with general political and regulatory events. For the crypto-assets specific events, the Libra hearing is the second most distinct spike, followed by Digital Dollar Initiative and rumours regarding over-regulation in South Korea. While naive EPU grasps major events causing economic uncertainty, it may seem too generic concerning the crypto-assets uncertainty and DeFi uncertainty in particular. The key reasons behind this are discriminatory issues of the predefined keywords and specifics of the collected news dataset. These issues are specifically robust for the case of crypto-assets and decentralised finance: the policy component (P) cannot be defined clearly due to the global nature of cryptocurrencies and decentralised protocols, uncertainty component (U) in the naive method is highly dependent on the article author's choice of using the word "uncertainty", which has been also a subject of discussion initially raised by Baker (2016). The categorical component is also partially affected by the discriminatory bias because such keywords as "decentralised finance" had been commonly used to refer to cryptocurrencies prior to the launch of DeFi protocols in 2017. This way, articles regarding cryptocurrencies and crypto-services may have been accounted as DeFi-related, while the article's subject could be irrelevant and not follow DeFi properties defined by Werner (2021). Furthermore, the collected articles do not always follow the pattern "one story — one article", and for instance, can give an overview of the events within a certain period. This results in Type 1 and 2 errors causing visible spikes for the naive index. For example, considerable spikes for the first weeks of years 2020 and 2021 are affected by the yearly DeFi reviews and discussions, as these years were especially eventful for the field of decentralised finances.

The DeFi EPU index resulting from the modified model is displayed in *Figure 5* and the events causing the spikes are described in *Table 2*. Similarly to the naive model, the largest spike also lies within the period associated with the start of the COVID-19 pandemic. However, in this case the selected articles derive from a different set of events, in particular with the European Parliament call for crypto regulations and publishing of the related studies on crypto-assets and stablecoins (*Table 2: K*). Opposedly to the naive method, the spikes in the modified model are caused by the events that are directly linked to DeFi-related uncertainty in the emerging regulatory framework. Moreover, in comparison to the naive approach, the AL-based index captures a larger number of events that cause regulatory uncertainty in DeFi. As expected, CBDC discussions and private stablecoins (Libra, in particular) are among the major processes that cause regulatory uncertainty. For the P (policy) parameter, "G20" and "G7" as well as related boards and committees, such as the Financial Stability Board and the Financial Action Task Force, seem to appear frequently in the overviewed set of events. This result is logical as it grasps the issue of the global regulatory approach towards DeFi. Based on the weights assigned by the SVM model, the words "banks", "legislation", "draft" and "letter" are among the most discriminatory variables. Keywords "european" and "bermuda" are also assigned with the strongest discriminatory weights: the European region also appears frequently in the list of events in *Table 2*, while "Bermuda" is mentioned in the articles related to taxation of crypto-assets. Additionally, based on the narrative analysis the EU, USA, Russia and China are considered to have the strongest influence on the DeFi regulatory uncertainty from the regional perspective. For the categorical component, stablecoins stand out in comparison to other types of crypto-assets (see *Tables 1&2*). This is also in line with the overviewed background as stablecoins were previously recognised as DeFi operating in the grey regulatory area (Calcaterra & Kaal, 2021; Werner et al., 2021).

Unlike the naive index, the modified version captures more of the related events in general. It is especially true for the period between 2019 Q3 to 2020 Q3 when a large number of new DeFi protocols started to appear that expanded the scope of DeFi functions. Figure 2 shows the emergence of a variety of categories in DeFi apart from the lending services. While the second half of 2020 shows a much more drastic rise in terms of TVL for DeFi, from the regulatory perspective events of 2019 carried larger importance as the emerging industry was intensively going through the period of the initial regulatory formation. *Table 2* defines stablecoins — the basis for the majority of DeFi protocols — as a primary matter of discussions, which resulted in highly frequent uncertainty spikes series culminating at spike *K,* followed by comparably lower levels of uncertainty.

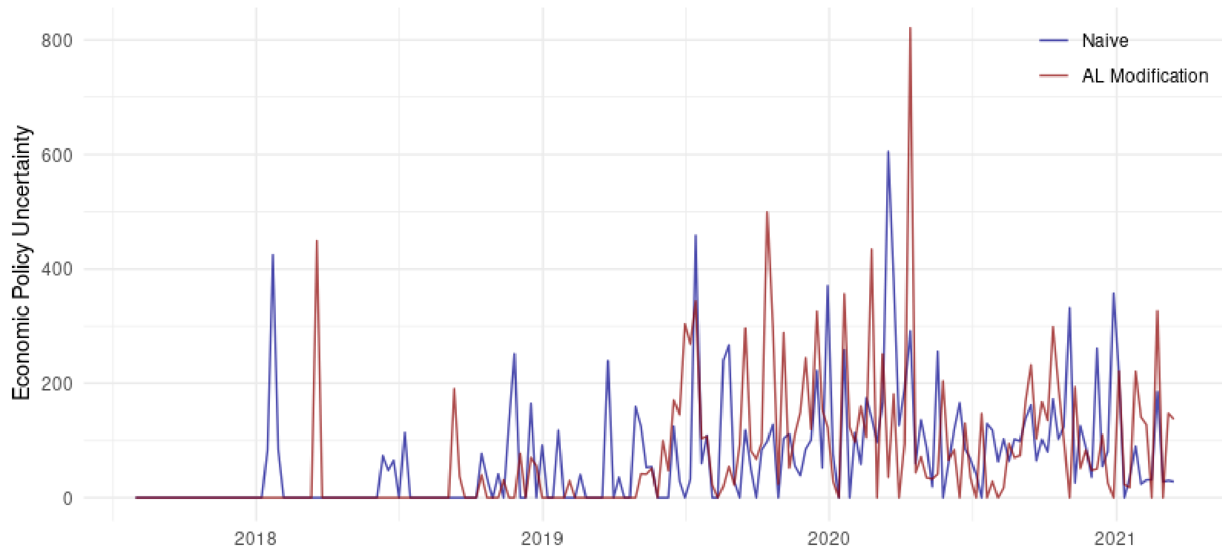

Figure 6. Comparison of constructed DeFi regulatory indexes for 2017-2021

The naive and modified indices have a moderate positive correlation of 0.347 based on the weekly frequency, while daily frequency results in the lower correlation statistic of 0.083. Visibly the large spikes appear with a certain lag between naive and modified methods: this is clearly seen for the initial spike, COVID-19 period and intervals associated with the US protests and presidential elections. Therefore, with the data aggregation to monthly frequency, correlation rises to 0.61, while the higher frequencies will lead to drastic drops in correlation. Unlike the naive version, the modified index is not as affected by the summary articles and seasonal reviews that are not related to the DeFi uncertainty: this is especially visible with the spikes for the first week of 2020 and 2021, where the naive method "jumps" without news basis. Spikes in the AL modifications are also more distinct and rise higher due to the effect of normalisation for the data with a lower number of type 1 and type 2 errors. Key identified events for the modified index are also consistent with the cryptocurrency uncertainty index, developed by Lucey et al. (2021), where Libra announcements, COVID-19 and central bank DC were identified among the biggest historical events affecting crypto-market regulatory uncertainty.

4.2 Comparison with categorical uncertainty measures

I compared both naive and modified indexes to categorical EPU measures formulated by Baker et al (2016). In addition to economic, policy and uncertainty components, a categorical class of relevant keywords is applied for the scaled news count to construct categorical EPU measures. *Figure 7* shows the correlation statistics between the DeFi uncertainty indexes and 12 categorical measures of uncertainty with monthly frequency. Only correlation statistics with a p-value below 0.01 are considered, all of the insignificant values are marked as blank.

All indexes are positively correlated meaning that they are capturing similar events. The naive DeFi index has a comparably stronger correlation with the categorical indexes based on the scaled news count, which can be explained with a similar methodology for uncertainty measurements. Specifically, the naive index has the strongest correlation with the monetary policy category.

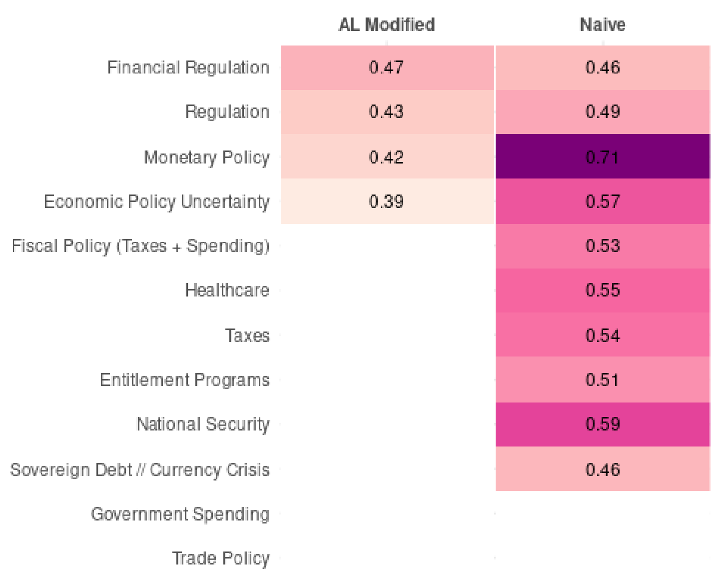

Figure 7. Correlation with categorical EPU measures (Baker et al., 2016)

Modified DeFi index is significantly correlated with a smaller number of the EPU categories in general. For the ones to satisfy the significance level, the correlation is moderate and falls into a narrow range between 0.39 to 0.47. Correlating categorical measures are related to financial, monetary and general regulatory uncertainty and least correlated with the original EPU index. The naive index is more inclined towards general economic uncertainty and specifically monetary policy, while the modified index correlated the strongest with the category of financial regulation. Based on these results, we can conclude that the naive index better grasps general events related to crypto-assets overall, while the modified index has a specific focus on DeFi. These results are also strongly supported by the related literature: in the field of DeFi, the matter of financial policies, its applicability to DeFi, need for the financial regulation and uncertainty of the applications of traditional approaches of financial regulations are among the primary subjects of concern for decentralised applications, and DeFi in particular (Zetzsche et al., 2020). Similarly to DeFi, financial policy applicability was previously a subject of discussion for ICOs (Chohan, 2019). Money laundering, financial frauds, smart contracts manipulations have also been matters of concern for FATF, FCA and FSB, falling closer to the category of financial policy. On the other hand, crypto-assets, not limited to the ones based on smart contracts, have been proven to be strongly influenced by the monetary policy and the effect of the central bank measures have been proven to influence cryptocurrency market volatility (Corbet et al., 2014; Cumming et al., 2019; Peters et al., 2015).

5. Evaluation of the effect of uncertainty

Previous researches have extensively looked into the effects of uncertainty on the cryptocurrency market. In particular, the response of cryptocurrency volatility and returns to uncertainty shocks have shown that Bitcoin volatility is negatively affected by the US economic policy uncertainty, yet positively responds to monetary, financial and tax regulatory uncertainty (Matkovskyy & Jalan, 2019). In terms of DeFi, effects of uncertainty have not been studied before, yet I expect that unlike the crypto-assets, decentralised financial protocols are affected negatively by the DeFi-specific regulatory uncertainty. As protocols operate in grey regulatory areas and regulatory bodies lack clarity on approaching the global nature of DeFi, possible overregulation can strongly influence the use of decentralised financial services (Salami, 2020).

To study the effects of uncertainty, I construct a structural VAR model with Cholesky decomposition, following the methodology proposed by Bloom (2009). Based on this model, I investigate the responses of DeFi total value locked to uncertainty shocks with a weekly frequency. Total value locked is specifically picked as a comprehensive metric for decentralised financial protocols as it directly reflects the financial side of the services as well as its usage. For the measure of uncertainty, I picked the index resulting from the modified AL-based approach as it identifies DeFi-specific events and captures a larger number of relevant news.

Uncertainty measure is ordered on top in the VAR model, while lags were defined based on the Akaike Information Criterion. In the impulse analysis, I specifically look into the response of TVL in USD and Ether, which allows me to better understand the impulse effects accounting for the cryptocurrency price fluctuations. Cholesky decomposition is applied to recover orthogonal shocks with the ordering as follows: DeFi Uncertainty Index, log(Verified Contracts), log(Average Gas Price), log(TVL Ether) and log (TVL USD). In other words, the model is formulated as:

$$A_0 y_t = \sum_i A_i y_{t-i} + B_t$$

$$where\ y_t = \begin{bmatrix} DeFi\ Uncertainty \\ log(Contracts\ Verified) \\ log(Gas\ Price) \\ log(TVL_{Ether}) \\ log(TVL_{USD}) \end{bmatrix}_t \ and\ \varepsilon_t \sim N(0,1)$$

The impulse is computed for 12 steps ahead with the weekly frequency. A_0 is a lower triangular matrix, while B is diagonal. Apart from the overall TVL response, I have also studied the uncertainty shocks effect on the underlying categories of DeFi.

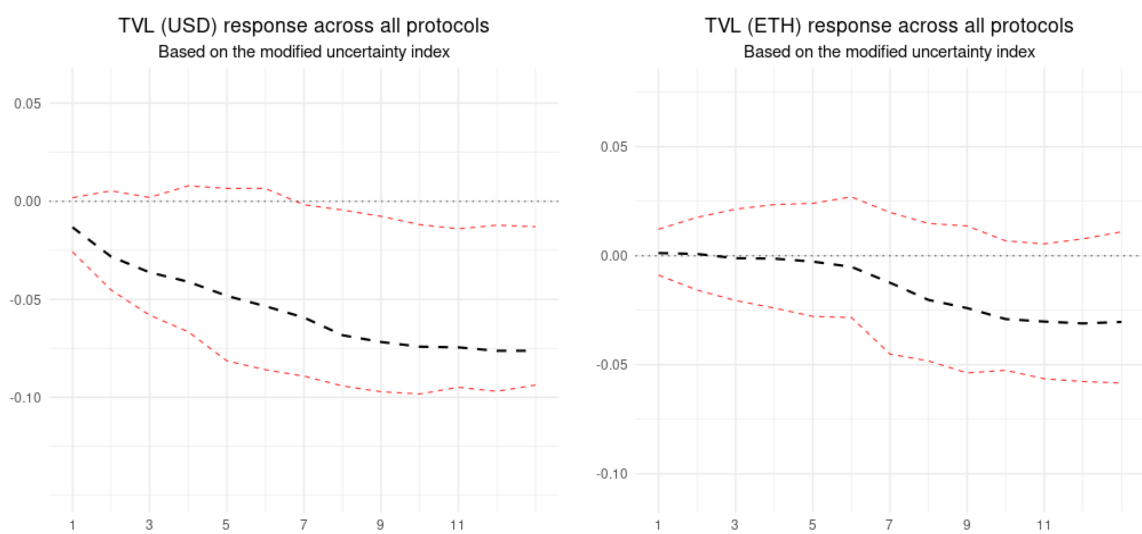

Figure 8. Response of total value locked in smart contracts of decentralised finance to uncertainty shock based on the weekly modified DeFi regulatory uncertainty index

Figure 8 shows the resulting response of TVL in the US dollars and Ether to uncertainty impulse. Both graphs prove the initial hypothesis of the negative effect of uncertainty on the DeFi market metrics, yet we can see that the results vary in terms of effect strength. Uncertainty effects are weaker for the volatility-adjusted TVL in Ether: this is true for the DeFi market overall, as well as for every category of protocols in particular. While the resulting response may also seem weak with the response varying between -0.02 and -0.075, such reaction is drastically larger than the volatility response in the Bitcoin market, where the resulting response varied between -0.002 and -0.008 (Matkovskyy & Jalan, 2019). Unlike the volatility measures, total value locked metrics provide insights on protocol usage through its financial aspects. The response does not provide any signs of a rebound within the period of 3 months, moreover, the negative effect increases around the 6th week.

Table 3. Uncertainty impulse response of total value locked by DeFi categories based on the weekly modified decentralised finance uncertainty index

	Response to weekly uncertainty impulse	
Category	**TVL (USD)**	**TVL (ETH)**
All categories	Decrease	Decrease
DEXes	Decrease	Decrease
Lending & Borrowing	Decrease	Neutral
Payments	Decrease	Increase
Assets	Decrease	Decrease
Derivatives	Increase	Increase

Responses to uncertainty shock are consistent for total value locked in the US dollar for the majority of categories (*Table 3*). DEXes and lending protocols, which currently dominate the DeFi market, also respond negatively: the effect is stronger for DEXes, while lending services response is weaker and tends to zero for USD-based TVL (Appendix: *Figure 11 & Figure 12*). For TVL in Ether, lending services show almost no response with a merely slight increase and later return to 0 rate. These two categories are the basis for the overall response for the DeFi market as lending and DEX protocols form 84% of the market's TVL (*Figure 2*).

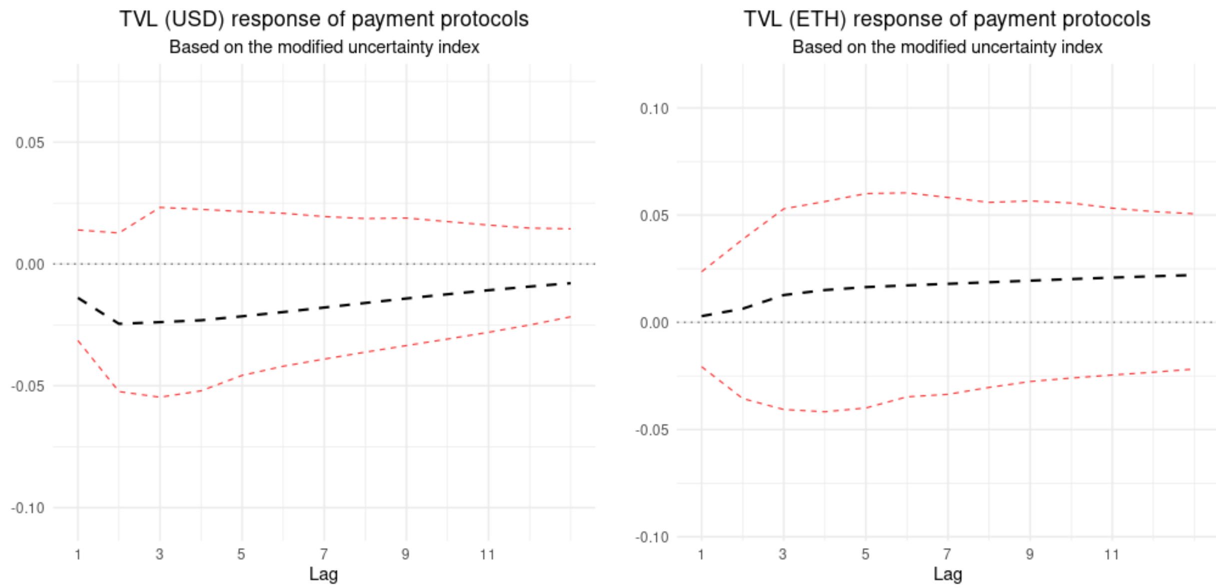

Figure 9. Response of total value locked in smart contracts of DeFi payment protocols to uncertainty shock

Payment protocols have differing responses: for the USD value locked response is negative, while Ether TVL shows positive affect. In both cases, the response has a rising tendency, however, for the US Dollar case confidence interval narrows down with every step, while the Ether-based response does not follow this pattern (*Figure 9*). Extending on the aforementioned idea, DeFi regulatory uncertainty seems to affect ETH/USD price as in both cases responses seem to follow the same tendencies and lagged patterns. While the response has an increasing effect with every lag opposing to the other categories, it is not reflected anyhow by the overall response of TVL in DeFi due to the payments being the smallest category across other protocols with the TVL in Ether below 1 000 000 tokens (for the mid-April 2021). The rising response trend of the payment protocols may be associated with the movement of assets to alternative protocols after an uncertainty impulse takes place.

The DeFi assets category, which includes yield-generating services providing token lending optimization, has a negative effect from uncertainty overall, however, its confidence bands largely increase in the first weeks after the impulse (Appendix: *Figure 13*). Over time, bands narrow down and response to uncertainty almost vanishes by tending to 0. Due to the protocols' mechanics, this category is strongly dependent on the leading type of lending DeFi services, such as Maker, Compound and Aave, which provide market-adjusting interest rates for tokens.

Therefore, a negative response is expected and falls in line with the aforementioned "Lending & Borrowing" category.

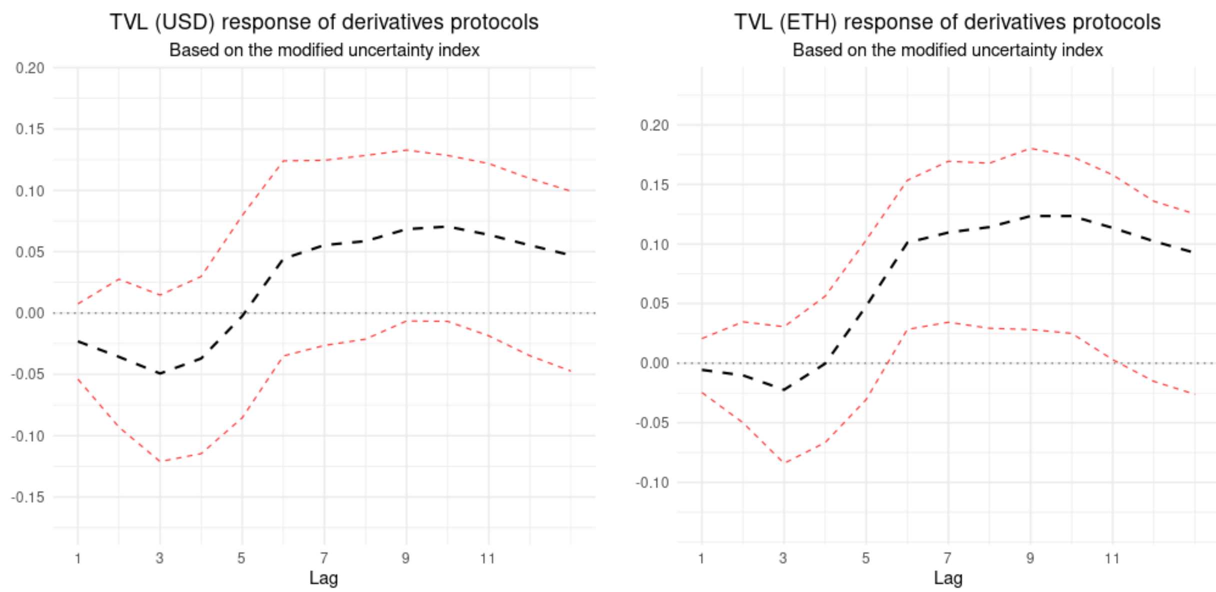

Figure 10. Response of total value locked in smart contracts of DeFi derivatives protocols to uncertainty shock

Lastly, the derivative category unlike any other shows the positive rise of TVL for both USD- and Ether-based responses (*Figure 10*). At first, it carries a negative impact, yet at week three the response knocks back and results in the strongest effect across the other categories, almost reaching the level of 0.15. Notably, not only is the response different to the other categories but also a stronger effect for the Ether-based TVL is observed. Even though the effect is visibly stronger, it is not reflected by the total market response (*Figure 8*) as far as derivatives are among the least adopted protocol categories (*Figure 2*), having similar TVL to assets category. Differing effect for derivatives is also expected, because unlike other services, smart contracts from this category are tied to the value of the external assets. Moreover, the leading derivative protocol, Synthetic, maintains over 66.9% of the category's TVL and primarily focuses on the "real-world assets value", such as gold, oil and fiat currencies.

6. Conclusion

This paper introduces and compares text-based approaches to construct DeFi regulatory indexes using news frequency count. A more precise DeFi uncertainty index is based on a more sophisticated methodology using active learner in combination with the SVM model for text classification. This approach also suggests a solution to commonly addressed issues of emerging industries, particularly limited data availability. The modified index is tested against the categorical EPU index: the advanced method has shown to better capture industry-specific uncertainty. Unlike the naive model, the modified version does not have false seasonal spikes of uncertainty and identifies more industry-related events. When compared to categorical EPU indexes, DeFi regulatory uncertainty shows the strongest correlation with financial regulatory uncertainty (*Figure 7*). This goes in line with both narrative validation and the overviewed background: the lack of global regulation of DeFi often raises concerns about its use for money laundering and financial manipulations (Werner et al., 2021).

The active learner model is restricted to the pool of articles containing categorical and economic components, which can be considered as a key limitation of the methodology. Similarly to Tobback et al. (2018), this is based on the assumption that the relevant articles should contain words related to the field of DeFi and the economic aspect of uncertainty. However, restricting the pool to a subset of articles is necessary, otherwise, the articles labelling process would take way more time, making this approach irrationally inefficient in use. Furthermore, all articles without any filtering would lead to a heavily skewed distribution of classes, especially in cases with emerging technologies.

Constructed indexes show that in recent years, regulatory uncertainty in DeFi grows tremendously. In particular, during the first wave of COVID-19 DeFi uncertainty reached its peak, achieving levels four times higher than average. One of the explanations for growing uncertainty might be a lack of understanding of how regulation should be approached regarding DeFi (Amler et al., 2021; Calcaterra & Kaal, 2021; Werner et al., 2021). The disruptive nature of blockchain is further extended by smart contracts in decentralised applications, creating even more complications for the regulatory bodies. Implementation of Libra stablecoin from Facebook serves as a great example of large concerns and uncertainty from regulators (*Table 2*). From the first announcement to the latest updates on stablecoin development, it provoked uncertainty impulses associated with a number of responses from such regulatory authorities as FATF, FSB, FCA and national regulatory bodies.

Based on the impulse-response analysis, the total value locked in DeFi protocols is negatively affected by regulatory uncertainty (*Figure 8*). The effect is comparably stronger for TVL in USD, which is supposedly connected with volatility growth caused by uncertainty. This goes in line with studies on the effects of EPU on Bitcoin markets (Matkovskyy & Jalan, 2019). However, the response is not consistent across all of the DeFi services. While leading types of protocols, such as lending services and DEXes, have a negative impact from uncertainty shock, derivative and payment protocols have the opposite effect. The reason behind the response of derivative protocols can be its strong linkage to the value of external assets. For payment protocols, the growing trend in response to uncertainty shock is supposedly connected with the movement of investments to alternative protocols as well as the issue of rising gas prices in the Ethereum network.

Index constructed for DeFi in this paper is done for the first time. My findings suggest that the DeFi uncertainty measure can be useful for future research on smart contracts, decentralised applications and the regulatory side of crypto-assets. Furthermore, this paper proposes that the applied methodology can be useful for the analysis of regulatory uncertainty in emerging industries.

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Appendix

1. Categorical EPU for DeFi

The original EPU method was proposed by Baker et al., (2016) to measure policy-related uncertainty. The method is based on index construction based on three components: economic (E), policy (P) and uncertainty (U). If an article contains keywords from each of the components, it is considered as related to uncertainty. Then the number of articles are summed over chosen frequency, in most studies on traditional economics monthly frequency is picked. The monthly count of articles is further scaled and normalised due to varying numbers of news from media sources.

On top of the EPU index, categorical measures of uncertainty are constructed. In addition to three base components, an additional "categorical" component is added, which contains a set of relevant keywords. Based on this method a large variety of uncertainty indexes have been constructed, such as the financial policy uncertainty index (Baker et al., 2016) or cryptocurrency uncertainty index (Lucey et al., 2021). For the purposes of this paper, the "category" component consists of keywords relevant to decentralised finances and underlying types of DeFi protocols. Keywords are based on DeFi systematization of knowledge (SoK), compiled by (Werner et al., 2021).

Table 4. Term set for constructing naive DeFi regulatory index.

Note: term variations, such as plural forms, are included as well.

Component	Terms
Category	"defi", "decentralised finance", " "decentralized borrowing" decentralized lending", "stablecoin", "decentralised exchange", "yield farm", "DEX", "decentralized oracle"
Economy	"economy", "economic"
Policy	"regulation", "Congress", "Supreme Court", "government", "European Commission", "legislation", "jurisdiction", "compliance", "central bank", "Financial Stability Board", "Financial Action Task Force", "Financial Conduct Authority", "ESMA", "ECB", "FCA", "EBA", "FATF", "FSB", "SEC"
Uncertainty	"uncertainty", "uncertain"

2. Active learner

The active learning method is based on data querying: out of a pool of available data, an algorithm picks an observation it needs the most to better perform prediction. Picked observation is passed on to the annotator, which can be automatic or manual. Usually, the process is repeated several times until the evaluation parameters, in case of this study it is AUC statistic, are not showing further improvement.

Active learning is commonly applied in cases when data is unlabelled. By applying active learning, algorithm training can be performed with a smaller training set. The current paper uses uncertainty sampling as a querying strategy: the active learner is picking instances it is least certain about how to label. In other words, available labelled observations are used as a training set to construct an initial model (based on the SVM model in this paper) and classifies the unlabelled observations. For uncertainty sampling, entropy-based strategy or parameter of least confidence are commonly used, but for the cases with binary classification, both approaches are equivalent to each other. (Settles, 2009)

3. Effects of uncertainty impulse on DeFi categories

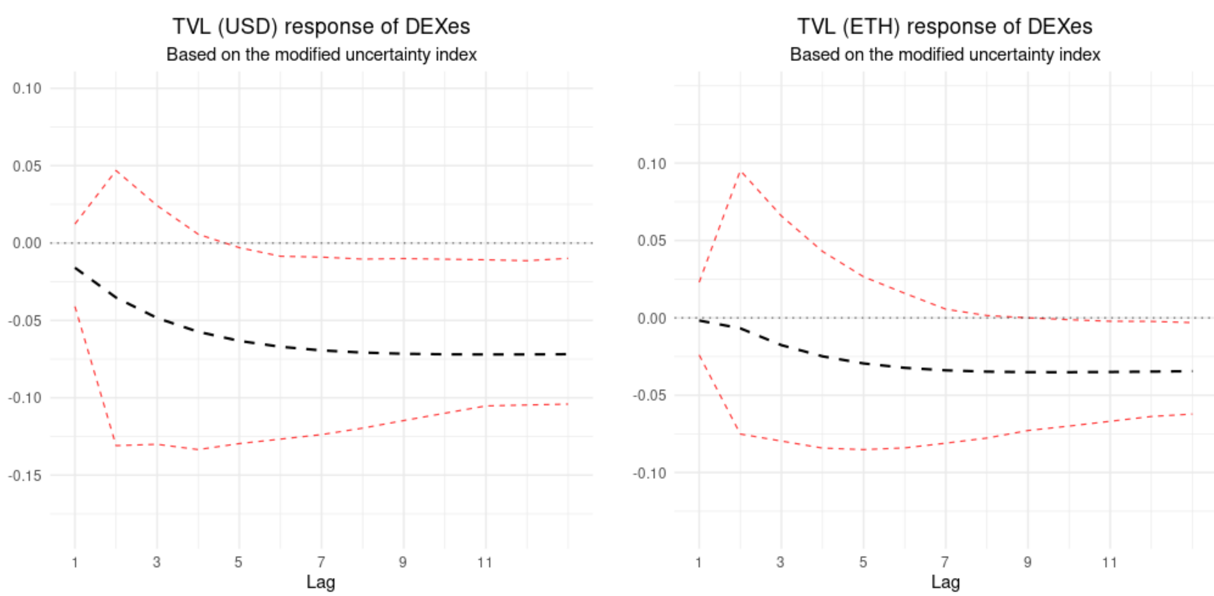

Figure 11. Response of total value locked in smart contracts of DEXes to uncertainty shock

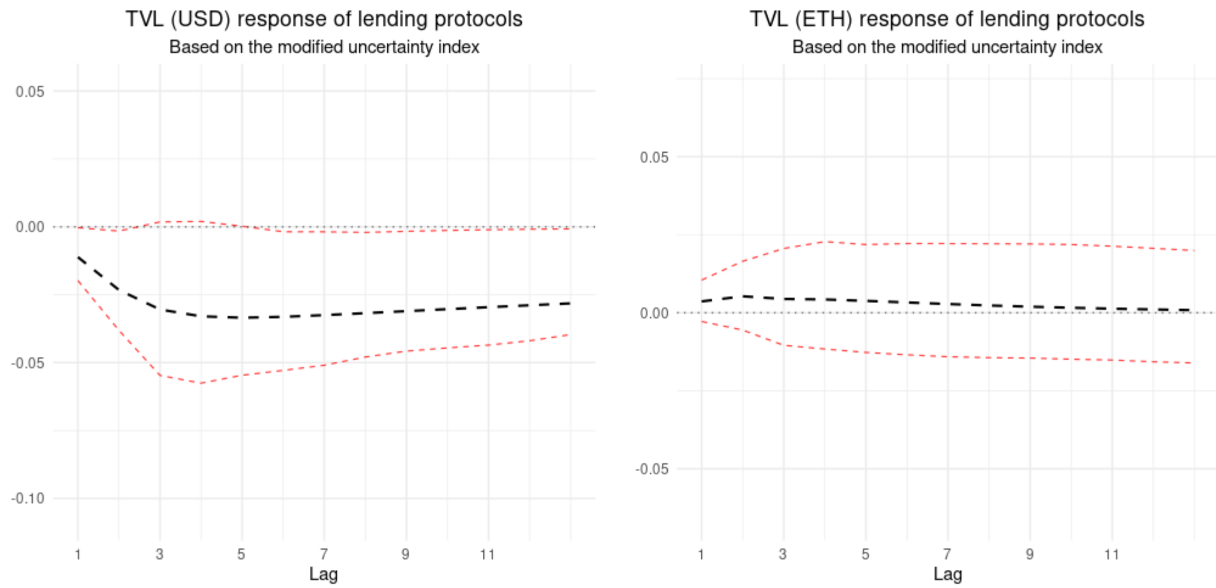

Figure 12. Response of total value locked in smart contracts of DeFi lending & borrowing protocols to uncertainty shock

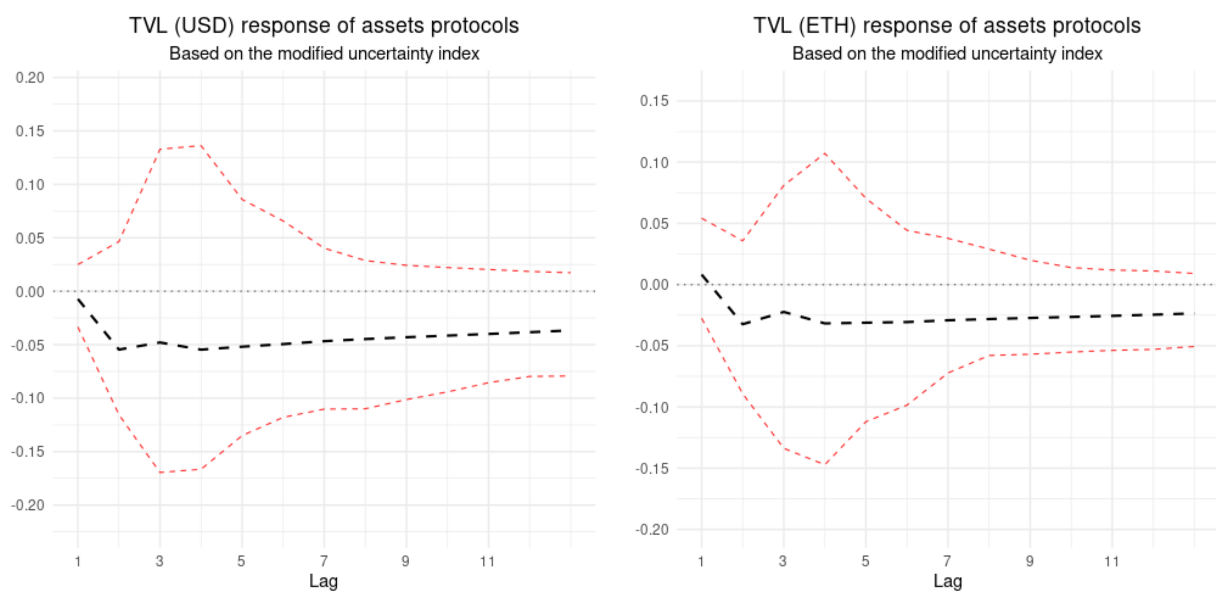

Figure 13. Response of total value locked in smart contracts of DeFi assets and portfolio management protocols to uncertainty shock