Money and Exchange Rates from a Computational Perspective

University of Reading

Andrew Clark

December 13th, 2021

Abstract

Money changes incrementally with technological growth. In this set of three papers, we examine money and exchange rates using practitioner technologies through an assessment exercise, a counterfactual exercise, and simulation modeling of a new application of monetary policy.

A Pound-Centric Look at the Pound vs. Krona Exchange Rate Movement from 1844 to 1965
A longitudinal (1844-1965) assessment of the British pound sterling and Swedish krona exchange rate was constructed utilizing The London Times article news sentiment, gold price, gross domestic product, and other relevant metrics to create a dynamic system state-based model to predict the British pound sterling and Swedish krona yearly exchange rate. The model slightly outperforms a naive random walk forecasting model.

Why Private Cryptocurrencies Cannot Serve as International Reserves but Central Bank Digital Currencies Can
This chapter begins with a recap of Bitcoin and its primary motivation and mechanisms, followed by an overview of the top 10 cryptocurrencies by market capitalization. The focus is on cryptocurrency price dynamics and volatility relative to those of fiat money and gold, assets that have traditionally served the functions of money and as international reserves. Counterfactual analysis was performed using the Bank of England's foreign currency reserves to determine the hypothetical performance in terms of the relative volatility of two alternative reserve portfolios, including Bitcoin and Ethereum. Revisiting the functions of money and international reserves, it is outlined why private cryptocurrencies do not meet the requirements for both money and international reserve assets, whereas central bank digital currencies do meet these requirements. The chapter concludes with a discussion of areas

where blockchain-based and financial innovations could be beneficial in international trade, payments, banking, and finance.

Complex System Modeling of Community Currencies

A complex dynamic system subpopulation model for the construction and validation of a novel form of local complementary currency is proposed, with the case study of Grassroots Economics Foundation's Community Inclusion Currency recently implemented in Kenya. The implementation is framed in an economic context and bridges the gap with related literature in computer science. Community currencies can act as a local liquidity-provision institutional device in poor or isolated economic regions to increase their internal exchange and economic value-added, serving as a market-based mechanism to alleviate poverty.

Executive Summary

Money changes incrementally with technological growth. Throughout history, we have seen money evolve along with society, from stones as currency to a fiat economy verging on digital money; technological change and monetary evolution go hand in hand. In this set of three papers, we examine money and exchange rates using practitioner technologies through an assessment exercise, a counterfactual exercise, and simulation modeling of a new application of monetary policy.

A Pound-Centric Look at the Pound vs. Krona Exchange Rate Movement from 1844 to 1965
To predict the exchange rate between the British pound sterling and the Swedish krona, a model was constructed using advanced computer science techniques to analyze newspaper articles along with relevant economic data. The model created performs better than a standard economic model during WWI and WWII, times of uncertainty and economic upheaval.

Why Private Cryptocurrencies Cannot Serve as International Reserves but Central Bank Digital Currencies Can
An overview of the first cryptocurrency, Bitcoin, is provided, along with an analysis of the top 10 largest cryptocurrencies. By analyzing the price changes of the cryptocurrencies compared to traditional money and gold, we highlight the instability of these new forms of money. A counterfactual simulation was performed to show holding these currencies would have affected the Bank of England's financial situation during the past 10 years. Discussions are outlined on how private cryptocurrencies do not meet the needs of money or international reserves, and how the recent cryptocurrency bubble compares to historical financial bubbles. The chapter concludes with a discussion of areas where blockchain-based technologies could be beneficial

in international trade, payments, banking, and finance.

Complex System Modeling of Community Currencies
A discussion of alternative forms of currency is given, along with recent developments on using vouchers to alleviate poverty and promote economic growth. Using *Grassroots Economics* Foundation's Community Inclusion Currency recently implemented in Kenya as a case study, a unique complex simulation model is defined and run to demonstrate how the community inclusion currency system works; and provide a platform for performing experiments in a Digital Twin environment before testing policy changes in the live system.

Dedication

For my wife, Lauren

Acknowledgements

I want to thank my advisors, Dr. Mihailov and Dr. Reade, along with my mentor, Dr. Zargham, for all of their teaching, assistance, and support.

Glossary of Computer Science Terminology

Definition 1 ***Algorithm***: *An algorithm is a set of well-defined, step-by-step instructions to solve a specific problem and generate an output using a set of input data.*

Definition 2 ***Feature***: *Single attribute or variable used as an input into a model, such as GDP, inflation, and exchange rate.*

Definition 3 ***Model***: *An optimized algorithm that takes input features and returns an output. For example, a trained model given all the features of a house (age, location, number of rooms, and square footage) and predicts its market value in USD.*

Definition 4 ***Artificial Intelligence (AI)***: *A general term for a group of technologies that mimic human decision-making.*

Definition 5 ***Machine Learning (ML)***: *Machine Learning is a field of computer science and mathematics that uses complex algorithms to process large amounts of data and learn patterns in the data.*

Definition 6 ***Generalization***: *A model's ability to adapt to new or previously unseen data.*

Definition 7 ***Interpretability***: *Interpretability is the ability to understand how a model arrives at a decision given a set of inputs.*

Definition 8 ***Supervised Machine Learning***: *A type of machine learning where a model trained with inputs and labeled outputs. After the model has learned from the patterns in the training data, it is used to predict the value or label of previously unseen data.*

Definition 9 ***Unsupervised Machine Learning****: A type of algorithm that learns patterns from unlabeled structured or unstructured data.*

Definition 10 ***Deep Learning****: A type of algorithm known as an Artificial Neural Network. Deep Learning used to process large amounts of data through several layers of "neurons" in a manner inspired by how neurons in the human brain work.*

Definition 11 ***Natural Language Processing (NLP)****: A form of AI that enables machines to process text and extract or process information*

Definition 12 ***Computer Vision (CV)****: A field of computer science that works on enabling computers to see, identify and process images in the same way that human vision does.*

Definition 13 ***Digital Twin****: A virtual representation of a physical object, such as an airplane, or of an ecosystem, such as an economy. A recent joint NASA and U.S. Air Force paper defines a digital twin as: "... an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin" [Glaessgen and Stargel, 2012], [Gelernter, 1991], and [Fuller et al., 2020].*

Definition 14 ***Hyperparameters****: Parameters of an algorithm that are not learned during model training, but are specified beforehand.*

Definition 15 ***Big Data****: Large sets of data that are either structured, such as in a database, or unstructured, such as log files.*

Definition 16 ***Application Programming Interface (API)****: A programmatic interface between multiple software or hardware systems.*

Definition 17 ***Optical Character Recognition (OCR)****: Software that converts images, usually scanned, that contain text into text.*

Definition 18 ***Open Source****: Software released under a license that allows users to use, modify, and enhance its source code [Laurent, 2004].*

Definition 19 ***System Identification****: A methodology to build mathematical models of dynamic systems using measurements of input and output signals [Söderström and Stoica, 1989].*

Contents

Chapter 1

Introduction

Economics is by definition an interdisciplinary field that from its founding has had influences from key individuals from various backgrounds and skillsets. Economics has one foot in the past and one foot in the future, being tasked with providing meaning to historical events and taking those insights to help guide and predict the future. This "dual mandate" puts economists in the thankless position of often being wrong in their predictions, having to find ways to understand why they are wrong and improve their predictions to satisfy mankind's constant yearning to know the future.

During the Age of Enlightenment and the development of probability theory, with Adam Smith's founding of political economy, economists were able to begin using mathematics to add structure and reasoning to their economic theories. Initially refined in the actuarial sciences, economists began applying probability along with their mathematical equations to formally define and provide a means of validating their theories. With the founding of econometrics in the 1930s by future Nobel winners Frisch and Tinbergen (), the application of mathematical models for understanding and predicting economic phenomena was established. With the continued evolution of probability and statistical theory, in addition to the introduction of computers, the use of more advanced modeling became possible. With the rapid increase in computing potential provided by Moore's Law, and Huang's Law and distributed cloud computing, complex simulations and models that never dreamt to be possible are now in reach, allowing economists to test out and refine theories in virtual, Digital Twin.

This dissertation focuses upon the application of practitioner technology to extant problems in monetary economics as a driving theme. Chapter 2 falls under an 'assessment' exercise and assesses forecasting exchange rates by using machine learning in a complex dynamic system way. Chapter 3 includes a 'counterfactual' exercise on cryptocurrencies and their capability to operate in a reserve asset context. Chapter 4 provides a new application area in monetary theory, focusing on community currencies and how cryptocurrency technology can be leveraged to create value-added community currencies, illustrated using complex system modeling simulation techniques. Additionally, tying this thesis together is its focus on expanding our knowledge of money and monetary interactions, and our ability to simulate and predict our surroundings using modern open-source programming and simulation technologies.

In Chapter 2, the exchange rate between the British pound sterling and the Swedish krona is examined and forecasted for 1844 to 1965. A Natural Language Processing (NLP) model was used to perform sentiment analysis over news articles from The London Times that mention either the pound sterling or the krona during the period studied. Once the sentiment index was created, a multistep complex system machine learning model was applied using other inputs such as GDP to generate one-year exchange rate predictions. During WWII, the proposed model outperforms a naive random walk and performs without statistical difference from the random walk during the majority of the period studied. Sources from Central Banks, specifically the Bank of England and the Sveriges Riksbank, were used to help with the analysis. Key contributions to the literature include the use of NLP for historical newspaper analysis; the use of a machine learning model for economic forecasting; and a multistep dynamic system paradigm for economic forecasting.

Chapter 3 is an analysis of private cryptocurrencies and poses the argument that, due to their instability, community-driven cryptocurrencies such as Ethereum and Bitcoin have no place in Central Bank's reserves. It is argued that Central Bank Digital Currencies (CBDC) can and do work as a reserve asset class; however, a question is raised as to why they are needed. Additionally, a counterfactual analysis of the Bank of England's reserves from 2011 to 2019 is conducted to determine how to reserve assets would have performed if community-driven cryptocurrencies had been included. The chapter concludes with a discussion of areas where blockchain-based technologies could be beneficial in international trade, payments, banking, and finance. This chapter was an early contributor to economic research on how blockchain cryptocurrencies function, what the leading currencies are, and how they can be applied effectively in key economic areas. Its key contributions, besides bridging token economics and computer science with monetary economics, are a point-in-time analysis of the top 10 private cryptocurrencies by market capitalization; and discussions of stable coins, and security token offerings.

Chapter 4 presents a complex dynamic system subpopulation model for the construction and validation of Grassroots Economics Foundation's Community Inclusion Currency. The modern application of community currencies is introduced, and the proposed topological model is framed in economic and computer science contexts. The chapter subsequently describes the model's simulation, results, and prescribes the next steps in applying it to operational decision-making. The use of a subpopulation model applying research on the meso-layer of economic modeling is relatively novel, and the proposed model is a key contributor to the literature. Additional contributions are n etymological bridge between 'monetary economic theory', cryptoeconomics, and computer science.

The common thread connecting these three chapters is the application of practitioner technology to problems in monetary economics. Chapter 2 is an 'assessment' of historical economic analysis. Chapter 3 includes a 'counterfactual' exercise of central bank reserve assets, as well as an analysis of private cryptocurrencies and central bank cryptocurrencies. Chapter 4 provides a new application area of subpopulation dynamic system modeling to community currencies.

Chapter 2

A Pound-Centric look at the Pound vs Krona Exchange Rate Movement from 1844 to 1965

2.1 Introduction

Traditional forecasting models often have difficulty outperforming random walk models [Meese and Rogoff, 1983][1]. Two recent trends in economics utilized in this paper to explore alternatives for increasing the accuracy of forecasting models: machine learning, and dynamic system modeling.

With the rise of big data and machine learning, interest in the application of machine learning to economics is increasing, with many central banks and research organizations exploring the applicability of machine learning to some of their economic workflows. Machine learning is an extension of statistical modeling; however, its goals are often different from statistical modeling. Separating the signal from noise can sometimes be difficult, with the consensus being that machine learning can augment existing methods and increase capabilities for handling Big Data [Chakraborty and Joseph, 2017] and [Athey and Imbens, 2019].

Complexity science and dynamic system modeling has risen in prominence in the field of economics in the aftermath of the 2007-2008 financial crisis, with some universities creating research groups on complexity and network

[1]This chapter is adapted from a discussion paper of the author's Clark [2020b]

science[2].

The purpose of this chapter is to:

1. Illustrate the application of machine learning for sentiment analysis of historical newspaper articles.

2. Create a machine learning model for forecasting yearly exchange rates that is generalizable but also optimized for the period and the British pound sterling and Swedish krona.

3. Illustrate the application of dynamic systems modeling as a paradigm for embedding machine learning or econometric models.

2.2 Literature Review

In the past few years, machine learning and sentiment analysis have become an economic research area, with a variety of papers appearing from numerous sources. Gentzkow et al. [2019] provide an excellent introduction to the use of text as an input to economic research and describe various techniques and applications of natural language processing. Gentzkow et al. [2019] describe the high dimensionality of text data, and the need for using advanced computational techniques to process it. Gentzkow et al. [2019] describe many applications, citing the early work by Cowles [1933], one of the first papers on analyzing news text for prediction of stock prices, for the use of sentiment analysis for forecasting. Nowcasting, using alternative data sources to estimate current macroeconomic variables, as defined by Bańbura et al. [2013] is another area where text data and natural language processing processing has been successfully used in economics.

A noteworthy paper from the Bank of England by Chakraborty and Joseph [2017] has described machine learning and how it applies to the economics profession in an easy to interpret way. In their introduction, Chakraborty and Joseph [2017] critique machine learning that it is primarily focused on prediction, while economics and econometrics are focused on causal inference. Chakraborty and Joseph [2017] noted that due to the "black box" nature of many machine learning algorithms, policy problems could be

[2] Examples include the Institute for New Economic Thinking (INET) at the Oxford Martin School and University of Amsterdam Center for Non-Linear Dynamics in Economics and Finance (CeNDEF).

divided into prediction and causal inference parts, allowing the use of machine learning for the predictive aspect and econometrics for causal inference.

Bholat et al. [2015] provide an overview of the potential uses of text mining, or natural language processing, for central banks. Primarily focused on unsupervised machine learning techniques, Bholat et al. [2015]'s handbook provides a brief introduction to the uses of supervised learning in text mining as well. Bholat et al. [2015] state that text mining allows a central bank to analyze a wide range of data sources that cannot be quantitatively analyzed with other techniques. A tangible example is the investor sentiment of markets in the central bank's jurisdiction. Text analysis also allows the central bank to evaluate if its messaging is being accurately understood by the public.

A paper by Shapiro et al. [2017] uses text analysis of economic and financial newspaper articles to measure economic sentiment. Sixteen US newspapers from 1980 to April 2015 were used to create a "corpus" of economic news articles. Shapiro et al. [2017] compared their "lexical" computational approach of sentiment analysis against common survey-based techniques, which was shown to provide an increase in accuracy. Additionally, Shapiro et al. [2017] evaluate how macroeconomic variables respond to sentiment impulse shocks, and found that positive sentiment shocks increase economic output, consumption, interest rates, and reduce inflation.

2.2.1 Complex System Theory

To model the British pound sterling and the Swedish krona exchange rate movement over the period studied, a novel dynamic complex systems model was created, utilizing a recently open-sourced computer automated design tool called cadCAD created by BlockScience [2018]. cadCAD (complex adaptive systems computer-aided design) is a Python-based, unified modeling framework for dynamic systems and differential equation simulations. It is capable of modeling systems at all levels of abstraction from Agent-Based Modeling (ABM) to System Dynamics (SD) with integration to existing data science workflows and paradigms.

Complex systems combine many elements that interact with each other in unique and complex ways. Complex system behavior are difficult to model due to properties that include nonlinearity, adaption, feedback loops, emergence, and spontaneous order, as defined by Voshmgir and Zargham [2019]. Complex system theory is interdisciplinary, with influence from economics, engineering, physics, and biology, to name a few. Within economics, with the establishment of research groups, as outlined in section 2.1, interest is growing in complex system theory, and its potential to add a more holistic approach to economic modeling. As the paper by Focardi [2015] outlines, Artificial Economics and state-based modeling is gaining popularity and is an open research area, which this paper contributes to.

2.3 Problem Framing

The focus on the British pound sterling and the Swedish krona is a result of data availability; and the desire to apply new technologies such as natural language processing to previously unexplored historical data. Natural language processing processes have been used extensively in economic contexts to contemporary datasets for investor and consumer sentiment, as discussed in section 2.2 however, its application to historical data hasn't been explored extensively. Through the use of scanning and optical character recognition (OCR) software, historical archives are now accessible for natural language processing analysis. From an economic and exchange rate data perspective, The Bank of England and the Sveriges Riksbank are two central banks that have kept impeccable records since their founding and provide the required data for analysis. The Bank of England is used as the 'bank of reference' because of the English language for text data. Scanned historical documents pose difficulty for OCR, adding language translation on top makes the data preparation task even more difficult. Additionally, the mid 19th to the mid 20th centuries provide a fascinating geopolitical backdrop where the world's central banks moved away from the gold standard, two World Wars changed the face of Europe, and the world's economies began using floating exchange rates. Reporting the news during this volatile period, The London Times preserved archives that can be used to look into the psyche of the English people. Chosen initially because of data availability, time provides an opportunity, however, limited due to data constraints, to see how major events affected both newspaper sentiment and exchange rates. The aforementioned facts provide a rich historical dataset for forecasting yearly exchange rates between these nation-states. In the following section, we will go through the data acquisition and preprocessing steps undertaken before beginning model construction.

2.4 Data Aggregation, Preparation, and Cleansing

2.4.1 News Articles

To obtain historical news articles mentioning the Pound or Krona, the Gale Times Digital Archive was used. The Gale Times digital archive contains OCR software to turn images into the text to allow news articles to be downloaded as text files. Advanced search criteria are available in the Gale archive, and the following search criteria were used:

1. Title = krona or pound or sterling
2. Publication Date > 1843 < 1966
3. Publication Section= "Business News" OR "News"
4. Document Type= "Article" OR "Editorial"

As no bulk download option or application program interface (API) was available on the database, 670 articles that met the before-mentioned criteria were manually downloaded. The news articles were imported into a Jupyter [2014] notebook and cleaned by removing a Gale-imposed disclaimer on OCR [3]. Additional text pre-processing was conducted, such as removing line returns, converting all characters to lower case, and removing stop words. This preprocessed data was downloaded as a Comma-Separated Values (CSV) for use in our sentiment analysis model described below.

2.4.2 Economic Data

Yearly exchange rate data were obtained from the Sveriges Riksbank's detailed historical archives of the bank [Lobell, 2010, Bohlin, 2010]. The UK Gold data was obtained from MeasuringWorth Officer and Williamson [2019], the Swedish GDP obtained from Edvinsson [2014] and the UK GDP was obtained from Bank of England [2019]. All of the data was preprocessed by renaming columns, changing datatype formats, subset to include only the

[3] Jupyter notebooks are interactive scientific computing environments that allow the researcher to combine mathematical notation, narrative, and code in one consolidated location.

relevant time range, 1844-1965, and merged into a format usable in the simulations.

2.4.3 News Articles

Although we will use an actual natural language processing algorithm for the sentiment modeling, we are using a word list for analysis of the news articles. The Loughran and McDonald [2010] sentiment word list were used to construct a word count sentiment index of all the articles downloaded. Although the word list was constructed off of modern English, as a rough comparison tool, it has the potential to provide insight. The index was created by aggregating all news articles for a given year, counting the individual words for the number of occurrences, and comparing the overlap with the Loughran-McDonald Sentiment Word Positive, Negative, and Uncertainty word lists. The index was calculated by positive, negative, and uncertainty divided by total words, respectively. The following algorithm was used to determine the sign given to the data:

$$\text{if negativePercentage} > \text{positivePercentage and negativePercentage} > 0.51:$$

$$\text{sign} = \text{NEGATIVE}$$

$$\text{elif positivePercentage} > \text{negativePercentage and positivePercentage} > 0.51:$$

$$\text{sign} = \text{POSITIVE}$$

$$\text{else:}$$

$$\text{sign} = \text{NEUTRAL}$$

For purposes of our modeling, we will use a more sophisticated sentiment modeling solution, although insight is provided by examining a traditional word counting approach. From Figure 2.1, we can see that the majority of articles had a neutral sentiment, with a significant amount of negativity from 1920 to 1960, with a low point of 1940-1945 with extremely low values. Due to the historical context and England's precarious situation, extreme negative values makes sense.

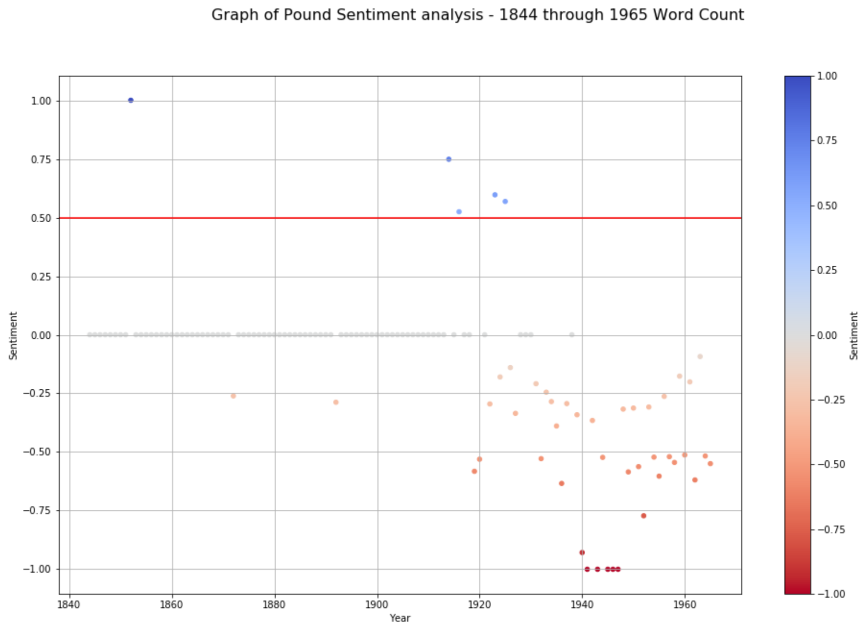

Figure 2.1: Loughran-McDonald Sentiment Word Lists analysis. -1 means very negative sentiment and 1 means very positive sentiment.

2.5 Modeling

2.5.1 Sentiment Analysis

Sentiment analysis is a very nuanced field of study that requires vast amounts of training data, an in-depth knowledge of the target domain, as well as insight into the linguistic meanings of words during the period of study.

To examine historical documents that first must go through optical character recognition (OCR) to turn images into text-only exacerbates the problem, see Section 2.4. To the author's knowledge, no extensive sentiment classification datasets have been created for English Financial Newspapers between 1844 and 1965. As such, a few shortcut optimizations were made to complete this study. After extensive research, the Flair library by Zalando Research was chosen due to its pre-trained word embeddings, model structure, and the fact that it was built in PyTorch, a leading Python-based deep learning library [Akbik et al., 2018]. Flair uses cutting-edge natural language processing techniques, with the specific English sentiment model trained from the standard sentiment analysis IMDB dataset [Maas et al., 2011]. The Flair recurrent neural network (RNN) based model provides cutting-edge performance, with the noted downside of not being specific to the time or specific textual writing. However, based on the accuracy obtained on IMDB data, which is a standard natural language processing dataset used throughout the literature, we are confident that the added benefit of using the deep neural network outweighs the lack of specificity given by the Loughran-McDonald word count.

2.5.2 Complex Dynamic System model

cadCAD

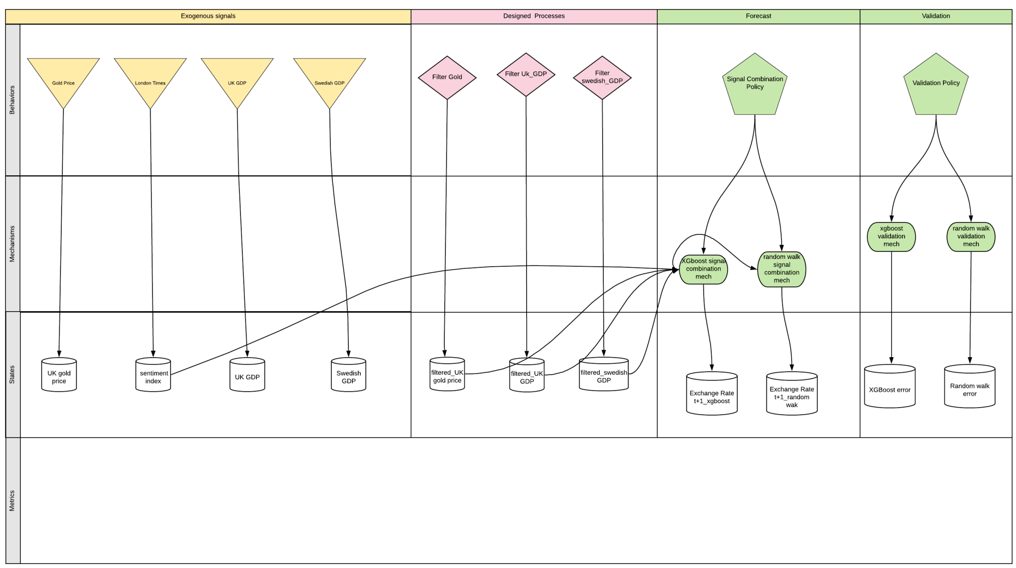

Figure 2.2: Differential specification of the proposed model

As discussed in the 2.2.1 subsection, a complex system approach provides a more comprehensive view of the state of the system, which can translate into an increase in prediction capacity.

In cadCAD simulation methodology, there are four layers to a simulation: Behavior States, Policies, Mechanisms, and Metrics. Using system modeling syntax, it is possible to describe the interaction and information flows between the four layers [Zargham, 2019]. **States** are systems variables that represent quantities at the given point. They can either be values that show the change between periods or 'sink' variables to show the amount of a value at any given point. **Policies** determine the inputs into the system and can come from exogenous signals, or the algorithmic policy. **Mechanisms** are functions that take the policy results and update States to reflect input changes. **Metrics** are Key Performance Indicators (KPIs), that are computed from state variables to assess the system.

The way to think of cadCAD modeling is analogous to machine learning pipelines, which normally consist of multiple steps when training and running a deployed model [scikit-learn developers, 2020]. There is preprocessing, which includes segregating features between continuous and categorical, transforming or imputing data, and then instantiating, training, and running a machine learning model with specified hyperparameters. cadCAD modeling can be thought of in the same way as states, roughly translating into features, are fed into pipelines that have built-in logic to direct traffic between different mechanisms, such as scaling and imputation. Accuracy scores, Area Under the Curve (AUC), etc. are analogous to the metrics that can be conFigured on a cadCAD model, specifying how well a given model is doing in meeting its objectives. The parameter sweeping capability of cadCAD can be thought of as a grid search, or a way to find the optimal hyperparameters for a system by running through alternative scenarios. A/B style testing that cadCAD enables is used in the same way machine learning models are A/B tested, except out of the box, in providing a side-by-side comparison of multiple different models to compare and contract performance. Utilizing the field of system identification, dynamic systems models can be used to "online learn" by providing a feedback loop to generative system mechanisms.

The flexibility of cadCAD also enables the embedding of machine learning models into behavior policies or mechanisms for complex systems with a machine learning prediction component.

Kalman Filter

Our cadCAD system takes in the exogenous process variables to the constructed dynamic system and appends them as four separate state variables. Kalman filters are used to mute the volatility changes between years for the UK Gold price, UK GDP, and Swedish GDP values [Kalman, 1960].

Kalman's filters are constructed for each internal state variable to transform the actual value into a filtered value that is more accurate for predictions over time due to the reduced noise.

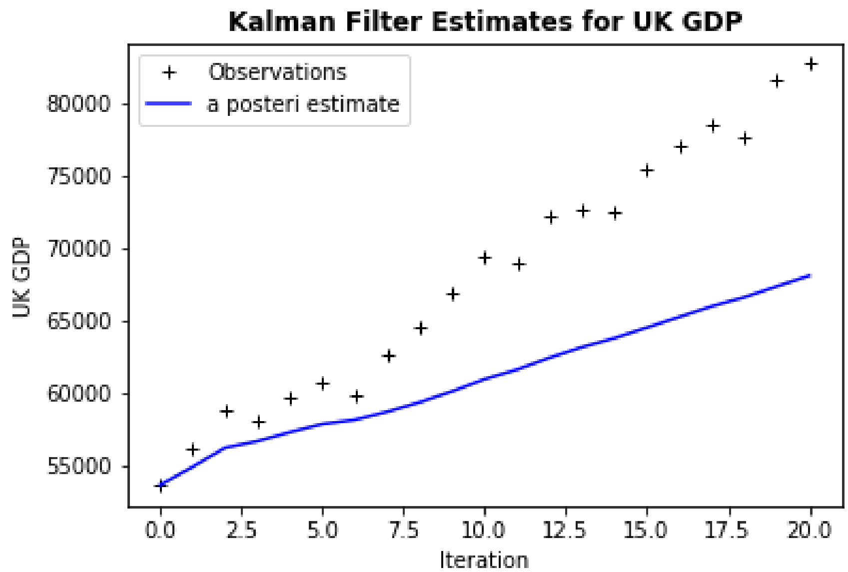

Figure 2.3: 22 years training of UK GDP Kalman Filter. A slow response to changes in the value results in better forecasting performance

The Kalman filters are trained for 22 years, 1844 to 1864, before the model begins to allow 100 years of model forecasting, see Figure 2.3. The parameters of the Kalman filters are passed into a prediction function for use in subsequent samplings. As Kalman filters are one-step predictors that take in the last observed value and the system parameters to estimate the system state, at each time step, the Kalman filters are retrained. As extremely lightweight algorithms, Kalman filters have been used from Economic Forecasting to Apollo program navigation and works well in our use case for variable processing [Schneider, 1988].

2.5.3 XGBoost

As the predictor inside the system simulation, an XGBoost machine learning model, created by Chen and Guestrin [2016], is utilized. XGBoost is a gradient boosting ensemble learning algorithm with the additional attributes of tree penalization, leaf node shrinking, Newton boosting, and randomization [Synced, 2017]. Gradient boosting algorithms are an ensemble of decision trees that can be optimized over different loss functions when trained on data. Gradient boosting can be applied to both classification, a discrete number of outcomes, such as Pass or Fail, or to regression outcomes, e.x. continuous numerical outputs, as utilized in this chapter. Gradient boosting can be broken down into the concepts of decision trees, ensemble learning, and boosting, which are described in the succeeding paragraphs.

Decision trees are interpretable models that are built from information about an attribute and represented in “branches” to make conclusions about the item’s target value, encoded in “leaves”. Decision trees can be used for classification models, discrete outcomes, such as true/false, or regression models, continuous outputs such as all real numbers between 0 and 100. With regression trees, the final prediction for a given instance is calculated by summing the score from the leaves of the tree. To calculate the optimal weight or score of each leaf, the data is split recursively based on the Exact Greedy algorithm until splitting no longer adds value to the predictions [Chen and Guestrin, 2016].

Boosting is the process by which an ensemble of models is constructed, as in XGBoost. Boosting takes the incorrect results made by decision trees and weighs them to correct the prediction for subsequent models. These individual models are then combined to create an ’ensemble’ of models.

XGBoost derivation

In this section, the XGBoost mathematics will be walked through, as enumerated in Chen and Guestrin [2016]. To a train a dataset, with n rows and m columns $D = (x_i, y_i)(|D| = n, x_i \in R^m, y_i \in R$ with XGBoost, K additive functions are used to predict the output.

$$\hat{y_i} = \Phi(x_i) = \sum_{k=1}^{K} f_k(x_i), f_k \in \mathcal{F} \tag{2.1}$$

where $\mathcal{F} = \{f(x) = w_q(x)\}(q : R^m \rightarrow T, w \in R^T$ is the space of regression trees. q represents each tree’s struct that maps to the corresponding leaf index. T is the number of leaves in the regression (or decision) tree[4]. Each

[4]For the remainder of our derivation, we will refer only to regression trees, as the

f_k corresponds to a unique, independent tree with the structure q and leaf weights of w. To learn the set of functions used in a model, the following regularized objective function is minimized:

$$\begin{gathered}\mathcal{L}(\Phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \\ \text{where } \Omega(f) = \gamma T + \frac{1}{2}\lambda\|w\|^2\end{gathered} \tag{2.2}$$

l is a differentiable convex loss function that measures the difference between the target y_i and the prediction $\hat{y}_i$. Ω penalizes for the complexity of the model by smoothing the final learned weights to help mitigate overfitting. The regression tree ensemble equation above includes parameters and functions that cannot be optimized in the Euclidean space with traditional methods. As such, the model is trained in an additive manner. To minimize the following objective function, where $\hat{y}^(t)$ is the prediction of the i-th instance of the t-th iteration, adding f_t is required.

A greedy algorithm is an algorithm that follows the problem-solving heuristic of making the locally optimal choice at each stage

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t)$$

In the above equation the f_t that most improves the model described in equation 2.5.3 is added. By using the second-order Taylor approximation, the objective function can be written to allow for Euclidean space optimization techniques.

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} [l(y_i, \hat{y}_i^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t)$$

where $g_i = \partial_{\hat{y}_{(t-1)}} l(y_i, \hat{y}^{(t-1)})$ and $h_i = \partial^2_{\hat{y}_{(t-1)}} l(y_i, \hat{y}^{(t-1)})$ are first and second order gradient statistics on the objective function. By removing the constants, at step t, the objective can be simplified to:

$$\tilde{\mathcal{L}}^{(t)} = \sum_{i=1}^{n} [g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \Omega(f_t) \tag{2.3}$$

XGBoost model used in this chapter has a regression outcome.

By defining $I_j = \{i|q(x_i) = j\}$ as the instance set of leaf j, we can rewrite equation 2.5.3 into the following equation 2.5.3 by expanding Ω:

$$\bar{\mathcal{L}}^{(t)} = \sum_{j=1}^{T}[(\sum_{i\in I_j} g_i)w_i + \frac{1}{2}(\sum_{i\in I_j} h_i + \lambda)w_j^2] + \gamma T \tag{2.4}$$

Assuming a fixed structure $q(x)$, the optimal weight w_j^* of leaf j can be computed by:

$$w_j^* = -\frac{\sum_{i\in I_j} g_i}{\sum_{i\in I_j} h_i + \lambda} \tag{2.5}$$

Next, we can calculate the optimal value which corresponds to the optimal weight, w_j^* by:

$$\bar{\mathcal{L}}^{(t)}(q) = -\frac{1}{2}\sum_{j=1}^{T}\frac{(\sum_{i\in I_j} g_i)^2}{\sum_{i\in I_j} h_i + \lambda} + \gamma T \tag{2.6}$$

Equation 2.5.3 is used as a scoring function to evaluate the quality of a tree structure q, and works for a wider array of objective functions. Due to computational considerations, it is infeasible if not impossible to iterative all potential tree structures, q[5]. In order to evaluate across all potential tree structures, a greedy, local optimal, algorithm starts at a single leaf and iteratively adds branches to the tree. To evaluate potential splits, assuming that I_L and I_R are instance sets of left and right nodes after a split, with $L = I_L I_R$, the loss reduction of a split is shown in the following equation:

$$\mathcal{L}_{\text{split}} = \frac{1}{2}[\frac{(\sum_{i\in I_L} g_i)^2}{\sum_{i\in I_L} h_i + \lambda} + \frac{(\sum_{i\in I_R} g_i)^2}{\sum_{i\in I_R} h_i + \lambda} - \frac{(\sum_{i\in I} g_i)^2}{\sum_{i\in I} h_i + \lambda}] - \gamma \tag{2.7}$$

[5]This chapter's model exacerbates the computational difficulties since it is retrained at every time step.

Chen and Guestrin [2016]'s approach for the tree learning best-split problem defining in 2.5.3 is deemed the exact greedy algorithm. The exact greedy algorithm is computationally taxing but is optimized by first sorting the data by feature values before it iterates through the sorted data to calculate the gradient statistic values for the score in equation 2.5.3. See algorithm 1 for the exact greedy algorithm.

Algorithm 1 Chen and Guestrin [2016] Exact Greedy Algorithm for Split finding

Input: I, instance set of current node
Input: d, feature dimension

```
gain ← 0
G ← Σ_{i∈I} g_i, H ← Σ_{i∈I} h_i
for k = 1to m do
    G_L ← 0, H_L ← 0
    for j in sorted(I, by x_jh do
        G_L ← G_L + g_j, H_L ← H_L + h_j
        G_R ← G − G_L, H_R ← H − H_L
        score ← max(score, G_L^2/(H_L+λ) + G_R^2/(H_R+λ) − G^2/(H+λ))
    end for
end for
```

Output: Split with max score

The XGBoost model used in this chapter's simulation model is constructed within a mechanism of the cadCAD model with the inputs of Kalman filtered gold, UK GDP, Swedish GDP, and our NLP aggregated yearly sentiment index. For each time step of the simulation, the XGBoost model is retrained with the latest Kalman Filter values and the aggregated yearly sentiment to make a one-step prediction. The one-step predicted value is appended to the prediction state variable that records all values. This iteration continues from years 1856 to 1964, creating a more accurate model over time and allowing us to see the accuracy of the forecast over time.

2.5.4 Comparative Model: Random Walk

To validate how well the proposed model is performing, a naive random walk model based on the following equation was constructed:

$$y_t = y_{t-1} + e_t$$

Where t this equal to time, y is a variable, and e_t is the error term.

Meese and Rogoff [1983] have shown that naive random walk models almost always outperform econometric models, especially in short-term horizons. Work by Fama [1970, 1965], Mandelbrot [1963], among others, expound on the Efficient Market Hypothesis (EMH) of asset prices, which is a theoretical foundation for the random walk. In essence, the EMH says that in an efficient market, asset prices will take on random walk properties. As such, it is theorized that if the proposed model performs as well as a random walk, then the proposed model format is sound and warrants more exploration and application.[6]

Order of Events

The various components of the simulation, and its structure, Figure 2.2, have been described above, here we will enumerate the sub steps of a system time step.

```
partial_state_update_blocks = [
    {
        'policies': {
        },
        'states': {
            'Year': update_timestamp,
            'sentiment':sentiment_exo,
            'uk_gdp': uk_gdp_exo,
            'gold': gold_exo,
            'swedish_gdp':swedish_gdp_exo,
        }
    },
```

Figure 2.4: Example of a Partial State Update Block

[6]A vector autoregression (VAR) was initially compared but performed poorly and was excluded from further analysis. Its MSE and RMSE are included in table 2.2 for reference.

State Variables	Purpose
Year	Integer of the simulation year
uk_gdp	UK GDP
sentiment	The NN derived aggregated newspaper sentiment data
gold	Gold value per ounce in pounds
swedish_gdp	Swedish GDP in pounds
uk_gdp_filter	Kalman filtered UK GDP
gold_filter	Kalman filtered Gold value per ounce in pounds
swedish_gdp_filter	Kalman filtered Swedish GDP in pounds
exchange_rate_t+1_xgboost	Predicted krona pound exchange rate from XGBoost
exchange_rate_t+1_random_walk	Predicted krona pound exchange rate from random walk
xgboost_mse	Stepwise MSE from XGBoost
random_walk_mse	Stepwise MSE from the random walk model

Table 2.1: State variables for the system model

1. In the exogenous processes partial state update block see Figure 4.11 for an example of the code structure, the sentiment, GDP, and gold data is read into the system and the system year is incremented. See Table 4.2 for a listing of the system state variables.

2. In the designed partial state update block, the model takes the raw inputs of UK GDP, Gold, and Swedish GDP and updates their respective Kalman filters, and updates the filtered variables by appending the new results.

3. In the forecast partial state update block, the XGBoost model is trained on the filtered values and the corresponding aggregated sentiment, and optimized with squared error; and one time step is forecasted. The random walk value takes the current year's actual exchange rate value and forecasts next year's value to be the same.

4. In the final partial state update block, validation, the mean squared error is calculated for both the XGBoost forecast and the random walk.

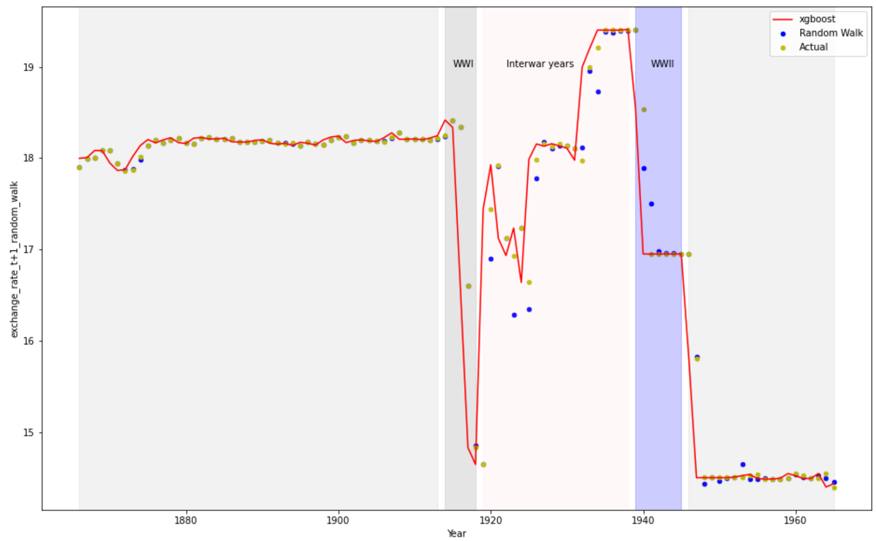

Figure 2.5: Actual vs predicted. Grey shading means models performed identically, pink the naive model outperformed and blue, our model outperformed

2.6 Validation

After our simulation was run for 100 years, we plotted the results of the XGBoost model and the random walk model, and compared them to the actual values, as seen in Figure 2.5.

If we look at the step wise validation of MSE between the random walk and the XGBoost model, we can see that at times the XGBoost outperforms the random walk model, but overall, the random walk model performs slightly better, although the difference is insignificant. To confirm this, we use the aggregated Mean Squared Error and Root Mean Squared Error over the full simulation, two standard time series evaluation criteria, and recorded in Table 2.2.

Based on Table 2.2, we can see that XGBoost is, on the whole, very slightly outperformed by the random walk model. To test if this is statistically significant, we employ the Diebold-Mariano test [Diebold and Mariano,

Metric	Model	Result
MSE	XGBoost	0.26
RMSE	XGBoost	0.51
MSE	Random Walk	0.25
RMSE	Random Walk	0.5
MSE	VAR	1.83
RMSE	VAR	1.35

Table 2.2: Validation values

1995]. The Diebold-Mariano test assumes a null hypothesis of statistical equality between two forecasts. When we run this test off Python code developed by [Tsang, 2020], we receive a test statistic of 0.67 and a p-value of 0.50, which means that the random walk model and the complex systems XGBoost model introduced in this paper are statistically equivalent, which validates our hypothesis that a complex systems model could equal or outperform a random walk.[7]

If we break the results down further, before 1914, the models performed identically, see Table 2.3. During WWI, our model's MSE values were nearly identical to those of the random walk. During the interwar years, the naive random walk model outperformed our model, whereas, during WWII, our model outperformed. And finally, after WWII, both models were nearly identical, with a rounding error difference on the RMSEs.

[7]For the VAR model, the Diebold-Mariano p-value was 0.016, assuming a 0.05 alpha value, the VAR, and random walk models were not statistically equivalent.

Metric	Model	Period	Result
MSE	XGBoost	Pre-WW1	0
RMSE	XGBoost	Pre-WW1	0.05
MSE	Random Walk	Pre-WW1	0
RMSE	Random Walk	Pre-WW1	0.05
MSE	XGBoost	WW1	1.25
RMSE	XGBoost	WW1	1.12
MSE	Random Walk	WW1	1.24
RMSE	Random Walk	WW1	1.12
MSE	XGBoost	Interwar	0.75
RMSE	XGBoost	Interwar	0.86
MSE	Random Walk	Interwar	0.61
RMSE	Random Walk	Interwar	0.78
MSE	XGBoost	WWII	0.28
RMSE	XGBoost	WWII	0.53
MSE	Random Walk	WWII	0.47
RMSE	Random Walk	WWII	0.68
MSE	XGBoost	Postwar	0.09
RMSE	XGBoost	Postwar	0.31
MSE	Random Walk	Postwar	0.09
RMSE	Random Walk	Postwar	0.3

Table 2.3: Validation values by period

2.7 Conclusion

In this chapter, historical London Times news articles were downloaded and analyzed to gather data on how sentiment affected the exchange rate between the Pound and Krona during the century between 1865 and 1965. Through the lens of complex system theory, a simulation model was created and trained with an XGBoost model to forecast one-year exchange rates. The model was retrained every year and during the period studied, outperformed a random walk during WWII, and had an equal performance during all years except the interwar years.

As the chapter has shown, although machine learning provides great promise to create accurate economic models, it is not a panacea and can have a hard time outperforming naive models, especially if frequent data is unavailable. As big data and machine learning are becoming more prominent in economics, the importance of quality data and variable parsimony cannot be overlooked. As this chapter has shown, complex modeling and machine learning can be useful tools in economic modeling, however, their complexity, interpretability, and degree of performance enhancements need to be weighed against any performance lifts.

Chapter 3

Why Private Cryptocurrencies Cannot Serve as International Reserves but Central Bank Digital Currencies Can

3.1 Cryptocurrency as the new monetary frontier

Cryptocurrencies, such as Bitcoin, Ethereum, and the numerous other digital tokens, have emerged as alternative units of account and forms of saving or speculation in the last 10 years[1]. Easily accessible via the Internet and accumulated in 'wallets', cryptocurrencies are one of the most meaningful recent financial innovations and have occurred on an amazingly grand scale.

It is surprising that, to the best of my knowledge, until recently, there was very little in the economics literature analyzing the rationale for, the mechanism behind, and the potential benefits of cryptocurrencies. Bitcoin is not the first attempt to create money outside the modern-day banking system and the government enabled trust of currency, however, how Bitcoin emerged is unique. Computer scientist[s] concealed behind the anonymity and decentralization of a money supply algorithm attempted to create a credible, private,

[1] This chapter is adapted from a joint discussion paper with the author and his advisor, [Clark and Mihailov, 2019]

democratic money by reliance on modern sophisticated computer technology and instantaneous communication links around the world. As it came from computer science, enhanced by cryptography, the new form of money, cryptocurrency, is complicated by its inception and seems to have sometimes ignored economics, or monetary theory, and the considerable knowledge it had acquired over centuries and centuries of use and study of money.

Academic economists, and more recently central bank economists, have begun to produce literature to analyze and understand this new paradigm of currency and to expose defects or weaknesses in its current and projected functioning. Due to the advanced technology used and the computer science-based terminology employed, understanding the potential benefits and costs of cryptocurrencies creates the need for interdisciplinary research. As Berentsen and Schär [2018] have put it: "To understand the Bitcoin system, it is necessary to combine elements from the three disciplines of economics, cryptography, and computer science" (p. 9).

This chapter contributes to this emerging interdisciplinary literature by approaching it from the angle of monetary theory and international economics, attempting to answer if cryptocurrencies can perform the role of international reserves for central banks. Based primarily on a counterfactual simulation of volatility compared to that of standard reserve assets, we conclude that cryptocurrencies fail to satisfy the usual requirements for reserve assets, due to their extreme volatility. However, we find that Central Bank Digital Currencies (CBDCs) do have the theoretical capability to perform as reserve assets. The chapter concludes with a discussion of useful applications of cryptocurrencies, such as simplifying cross-border transactions.

3.1.1 The History of Bitcoin

Bitcoin, the "original" cryptocurrency, was developed by 'Satoshi Nakamoto', an unknown individual or group of individuals, who is remaining anonymous until now. Nakamoto [2009] shared an initial paper titled "Bitcoin: A Peer-to-Peer Electronic Cash System" with a cryptography email list. It was conceived to provide a medium of exchange that was owned by the community participants and was not orchestrated by a central party, such as a central bank, or nation-state. It has a finite potential supply of coins, which are "mined" for by solving increasingly difficult mathematical equations.

Bitcoin is based on a distributed ledger technology (DLT), with transactions recorded into blocks, which, when linked together as a chain, are called a blockchain. To form a chain, an SHA-256 cryptographic hash[2] of each block is created, linking back to the genesis, original block (which was created by Nakamoto, with the following text embedded: "The Times 03/Jan/2009 Chancellor on brink of second bailout for banks" [Davis, 2011]).

As pointed by Berentsen and Schär [2018], p. 5, "for a virtual currency to function, it is crucial to establish at every point how many monetary units exist, as well as how many new units have been created". In addition, there must exist some "consensus mechanism that ensures that all participants agree about the ownership rights to the virtual currency units" (ibid), which is "the core innovation of the Bitcoin system and allows consensus to be reached on a larger scale and without any personal relations" (ibid). The miners play a key function in this consensus mechanism, as they collect pending Bitcoin transactions, verify their legitimacy, and assemble them into what is termed a "block candidate". Through such an activity, each miner aims to earn newly created Bitcoin units, and the aim is achieved whenever a miner can convince all other network participants to add his or her block candidate to their copies of the Bitcoin Blockchain. This Bitcoin mining is "permissionless", in the sense that anyone can become a miner: this looks simple and low-cost, as it just needs downloading the respective software and the most recent copy of the Bitcoin Blockchain. Yet, it is not that simple or low-cost, due to the highly specialized hardware needed as well as the concurrent access to cheap electricity for a miner to make profit from the mining activity, as big "mining farms" do. In effect, there are a few large miners dominating the "production" of these new generally accepted blocks. For one of these latter blocks to be generally accepted, fulfillment of a specific set of predefined criteria is required, such as the legitimacy of a transaction and the so-called "fingerprint" of the block candidate. This fingerprint is obtained by the miner through computation of the block candidate's hash value and must

[2]SHA-2 (Secure Hash Algorithm 2) is a set of cryptographic hash functions designed by the United States National Security Agency (NSA) and the National Institute of Standards and Technology (NIST) – see, e.g., Penard and van Werkhoven [2008]. The SHA-2 family consists of six hash functions with digests (hash values) that are 224, 256, 384 or 512 bits, including SHA-256, which is one of the strongest hash functions available. SHA-256 and SHA-512 are novel hash functions computed with 32-bit and 64-bit words, respectively. A cryptographic hash (also called digest) is a kind of "signature" for a text or a data file. SHA-256 generates an almost-unique 256-bit (32-byte) signature for a text. Here is an example: for a message "abc", the SHA-256 hash should be "ba7816bf8f01cfea414140de5dae2223b00361a396177a9cb410ff61f20015ad" – see, e.g., Veness [2019].

possess an extremely rare feature, namely, the hash value must be below a certain threshold value, i.e., it must begin by several zeroes. Berentsen and Schär [2018], p. 6, provide the following example of a fingerprint of a block that was added to the Bitcoin Blockchain in 2010:

$$\text{Block \#69785 (July 23rd, 2010, 12:09:36 CET)}$$

$$\underbrace{0000000000}_{\text{need to be zero}}$$

$$14243293b78a2833b45d78e97625f6484ddd1accbe0067c2b8f98b57995$$

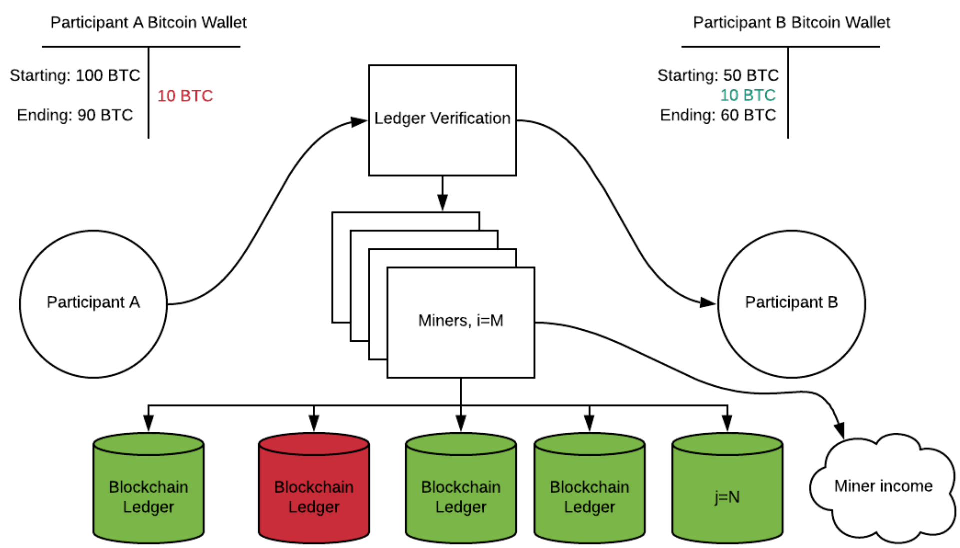

Figure 3.1: Bitcoin Blockchain transactions

Figure 3.1 outlines how a transaction is verified and executed in Bitcoin (roughly, blockchain in general). Every node of the blockchain contains the full ledger, with "miners" verifying that participant A has the amount of money they want to send to participant B. In the diagram, the ledgers in green all agree while the red ledger contains conflicting information and majority rules to rejection of the red ledger. Of the copies of the ledger, the majority rules on which is the "ground truth" and the transaction is settled, with the resulting deduction from participant A and the addition to participant B added to a new block of the chain. When enough transactions have been aggregated, the new block is “mined” and appended to the existing chain. The verification of the blockchain by various miners eliminates the possibility of participant A double-spending their money. Miners are rewarded in fractions of created bitcoin from the decentralized system for their effort. The decentralized instead of “centralized” nature of transaction execution gets rid of the middleman “market maker”, allowing money transfers, including international transfers, to be almost instantaneous and without fees.

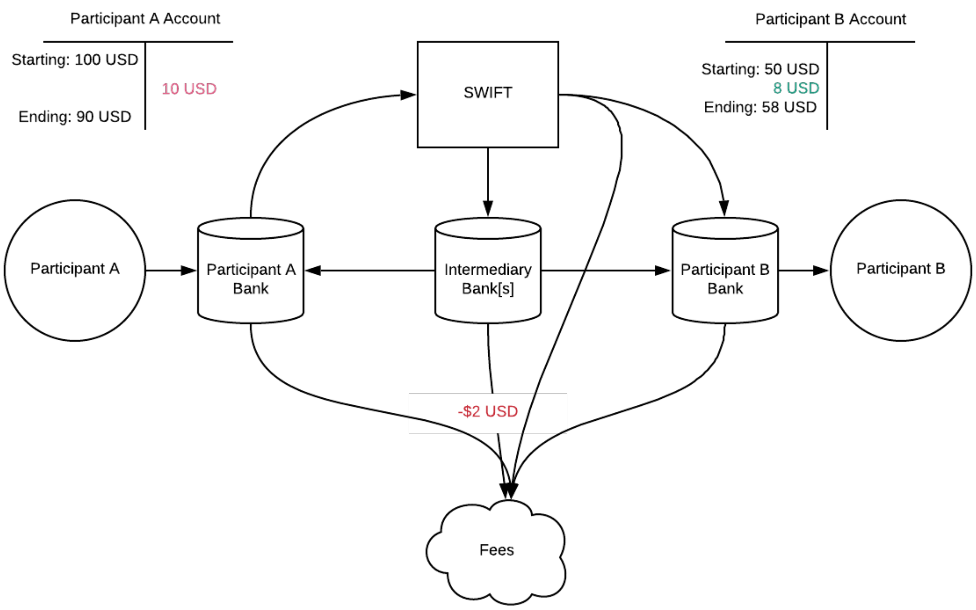

Figure 3.2: Traditional Banking Transactions

For comparison, Figure 3.2 illustrates, at a high level, how banks settle international transactions. Participant A wishes to send Participant B 8 USD but a transaction fee of 2 USD needs to be included (this fee amount is fictitious and only illustrative), so the cost to Participant A is 10 USD. In this example, Participant A and Participant B live in different countries. Participant A notifies their bank, which initiates a SWIFT[3] message to Participant B’s bank. If the two banks do

[3]SWIFT stands for the Society for Worldwide Interbank Financial Telecommunications. It is a global messaging network used by banks and financial institutions to securely transmit information and instructions related to transfers of money abroad. SWIFT was created in 1974 to circumvent the problems of low speed and security concerns typical for the earlier means of message confirmation via Telex.

not have a direct relationship, SWIFT will find an intermediary bank which has an account at both these banks. The intermediary bank debits and credits the respective accounts to facilitate the transaction and charges a fee for its services (2 USD in our example). This process usually takes between 3 and 5 business days to complete, along with SWIFT fees and administrative expenses.

To prevent double spending of Bitcoin, each transaction must point to the output of a previous transaction containing adequate funds. The validated blockchain is broadcast to all the network nodes, as the official version of the chain. This process is effective, assuming the double spender does not control 51% of the mining network. Some transactions may not be final, however, as – due to the consensus model – transaction clearing is probabilistic and not deterministic. Bitcoin's blockchain is based exclusively on the public/private cryptographic paradigm that proves that Bitcoin transactions are legitimate and makes them irreversible. Each individual has a unique public key/address, or Bitcoin account (more such accounts are possible, as in banking), similar to a real-world address with a house number with a mailbox, "wallet", and a corresponding unique private key/address used to spend/send one's bitcoins (to another Bitcoin address), similar to a real-world key that opens the mailbox, which is to be kept secret and is known only by the individual. The individual's private key is used to encrypt a transaction to create a digital signature of the transaction and thereby make it irreversible, which can be decrypted only with their public key. Its analog is a handwritten signature, except that using this asymmetric encryption, it is creatable by one specific private key, so unless the individual's private key is stolen, the signature is wholly unique and secure. Any small change, no matter how slight the signature, will create a different hashed signature value. This asymmetrical encryption, when applied to transactions, allows the network to detect impostors and fraudulent transactions. These signatures are unique, even if generated from the same private keys, which makes them impossible to copy. These digital keys are not stored on the Bitcoin network but are created and stored by software called a "wallet", which is used to own/hold and transact in Bitcoins. There are many types of wallets: web and mobile wallets, desktop wallets, hardware wallets, paper wallets (or "cold storage" – simply Bitcoin private keys printed on a piece of paper).

In this public/private cryptographic paradigm, if the end user loses his or her private key, then their Bitcoins are lost forever. According to Krause [2018], 20% of all Bitcoins have been lost.

3.1.2 Stablecoins

Stablecoins are cryptocurrencies designed to reduce volatility by being backed by a non-crypto asset or assets. Stablecoins are predominately based on fiat, but some are also based on commodities, such as gold. There are some Stablecoins backed by other cryptocurrencies, such as MakerDAO[Maker Foundation, 2014]. Stablecoins provide complications not experienced by "traditional" cryptocurrencies, however, such as the centralization by a third party and the need for external audits to verify that holdings that underlie the asset. Not all Stablecoins have to be collateralized, however. It is theoretically possible for a purely algorithmic stablecoin to exist, where if the demand for the coin increases, additional stablecoins are created to maintain the peg to the given underlying asset [Berentsen and Schär, 2019]. Conversely, if demand decreases, a secondary asset, such as a bond, is issued to sell against the stablecoin and reduce the supply. Basis was a pure algorithmic stablecoin that raised a large amount of funding and attention but was recently closed officially because of regulatory issues, with the remaining funds returned to investors Nader [2018], Jenkinson [2018], De [2019]. Berentsen and Schär [2019] believe investors realized that the economics of the Basis coin was resting on shaky foundations and requested a shutdown.

Two collateralized stablecoins that have had some successes are Tether and Dai. Tether is the largest and most well-known stablecoin. Founded in 2014, it uses an off-chain collateralization model. Tether has faced some controversy concerning Tether's claims of being 100% backed by USD. No independent audit report has been produced, which is very worrisome when Tether claims to always be fully transparent. Tether Limited [2014] also claims that "the value of our reserves is published daily and updated at least once per day". However, based on the website, there is no evidence that they are updating the statement on the website (which is not downloadable). Another problem identified by Berentsen and Schär [2019] are that off-chain bank accounts are a central point of attaching where governments can freeze the account and thus shut down the stablecoin. Profitability is also a concern for stablecoins like Tether having the temptation to engage in fractional reserve banking to make a profit when fees for deposits and withdraws aren't enough. Essentially, since Tether is off-chain and dependent on the same risks of a traditional financial institution, the value proposition and appeal of off-chain collateralized stablecoins are minimal for long-term viability.

Facebook's Libra has garnered a lot of interest; however, the system is not live yet (launch expected early 2021) [Libra Association, 2020]. Libra was established with a large consortium of major financial firms, some of which have pulled out since the initial announcement, however. Libra is designed as an off-chain collateralized stablecoin fully backed by a reserve of real assets, primarily USD and US Treasury bills. The consortium members will provide liquidity to help maintain trust in the currency. Libra appears to be better positioned than Tether, however, the same downsides of an off-chain collateralization model remain.

Dai is the most prominent example of an on-chain collateralized stablecoin.

Asset	Market cap	24-hour trading volume
Stablecoins	$24.63B	$92.07B
Cryptocurrencies	$575.56B	$215.27B
FX Markets		$6.6 trillion

Table 3.1: Stablecoins relative to the broad cryptocurrency and forex markets as of November 25, 2020 [CryptoSlate, 2020, BIS Monetary and Economic Department, 2019]

Dai is pegged to the USD and is a series of smart contracts on Ethereum. An individual uses the Maker platform to deposit an asset into a smart contract as collateral for a loan, using the system called Collateralized Debt Position Smart Contract (CDP) [Maker Foundation, 2014]. Once the CDP is created, the user can create Dai in equivalent USD value to the CDP. Dai can then be used just like any other cryptocurrency. The user can pay back the equivalent amount of Dai at any point to cancel the CDP and withdrawal their original assets. Currently, the minimum collateral requirement is 150%. Meaning, that the user must deposit $150 to get $100 worth of Dai.

Stablecoins are untested in extreme financial situations having never been through a major financial crisis, as noted by the G7 Working Group on Stablecoins [2019] the impact of global stablecoins October 2019. There are many regulatory issues that stablecoin will have to overcome before it could become a major financial instrument, such as legal certainty, sound governance, KYC/AML considerations, data privacy, cybersecurity, tax compliance, etc. The Financial Stability Board (FSB) created a comprehensive report on the key regulatory issues around stablecoins to the summit of the G20 Finance Ministers and central bank Governors in April 2020, with the final report in July 2020 [G7 Working Group on Stablecoins, 2019]. The standard response by European and the United States regulators thus far has to take a technology-neutral view and apply existing KYL and AML requirements to stablecoins, which may limit the appeal of stablecoins over financial intermediary asset classes [Lipton et al., 2020].

Regarding adoption, Stablecoins are a small component of the relatively small cryptocurrency market with 4.25% of all cryptocurrencies being Stablecoin, which shows they are not yet a major player in the already relatively small cryptocurrency market [CryptoSlate, 2020]. See Table 3.1 for a comparison.

In conclusion, based on the aforementioned research, stablecoins are very inefficient and require, at minimum, 100% collateral to ensure price stability and have not gained wide adoption. Off-chain collateral, as in the case of Tether, doesn't appear to be long-term sustainable due to their custodial requirements. On-chain collateralization, such as Dai, appears to work in practice, although it is at times inefficient in capital allocation. Purely algorithmic stablecoins do not appear realistic at this current juncture.

3.1.3 A Summary of the Top-10 Cryptocurrencies by Market Capitalization, June 6, 2020

We begin our analysis of the cryptocurrencies by first looking at the top ten cryptocurrencies by market capitalization, summarized in Figure 3.3 according to data from CryptoCompare [2020]. The cryptocurrency markets are very volatile, and these top 10 currencies change rather regularly, however, certain currencies like Bitcoin and Ethereum are constant components.

Origins and Key Features

Bitcoin is the original cryptocurrency, developed by Satoshi Nakamoto [2009]. Nakamoto also described the decentralized peer-to-peer (p2p or P2P) payment blockchain that all cryptocurrencies are based on. In a public blockchain, there is no intermediary or central governing authority.

Ethereum is a decentralized platform based on blockchain technology that runs "smart contracts", i.e., business and legal requirements defined in code, or, to quote ethereum.org: "applications that run as programmed without any possibility of downtime, censorship, fraud or third-party interference" [Ethereum, 2014]. Ether, the Ethereum cryptocurrency, is considered the "fuel" of which the decentralized network of applications runs. Started in 2014, Ethereum is sponsored by the Swiss non-profit Ethereum Foundation.

XRP is a currency created by Ripple to aid enterprises in more quickly transferring funds between currencies while providing low exchange rate fees [Ripple, 2012]. Started in 2012, Ripple is a blockchain-based distributed system.

Crypto.com Chain Crypto.com Chain [2020] is a purpose-built settlement public blockchain built for enabling transactions. Crypto.com has a CRO token that enables cross-asset intermediary currency settlement. It is fast and has high scalability, with 50,000 transactions confirmed per second.

Tether is a cryptocurrency that is designed to be a stablecoin, meaning it will always have a price pegged to USD at 1.00 [Tether Limited, 2014]. Tether has been embroiled in a series of controversies revolving around price manipulation and a lack of audited evidence substantiating their claims to have a large enough reserve to be able to maintain the stable coin.

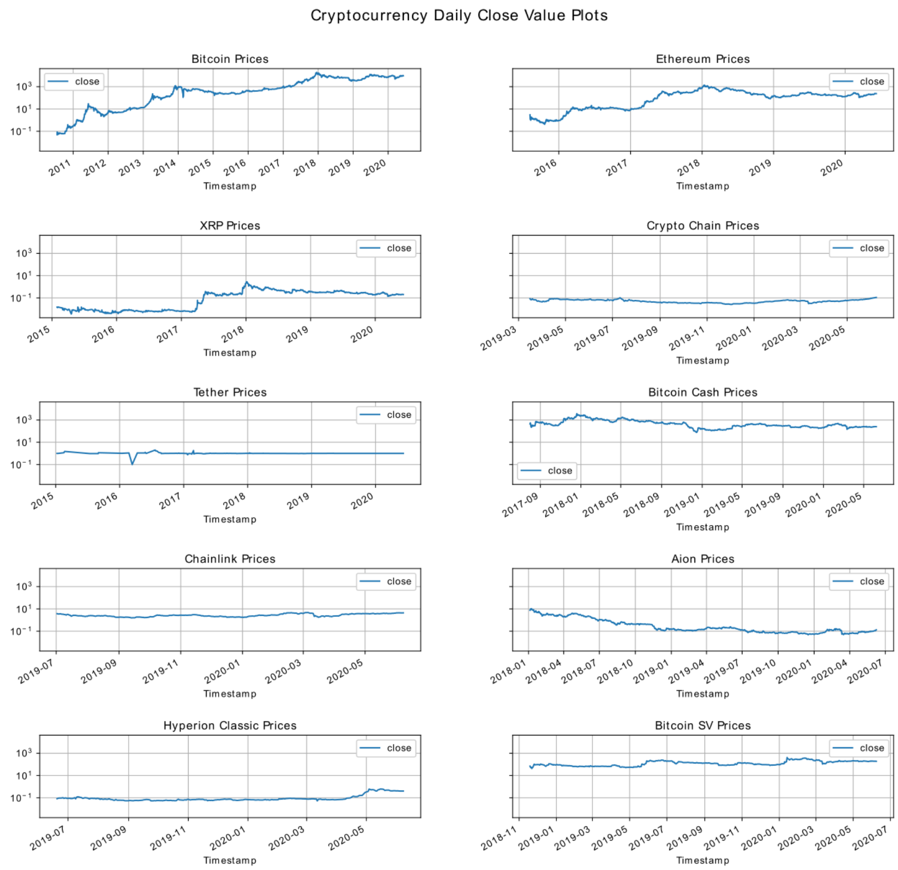

Figure 3.3: Top 10 cryptocurrencies, USD Prices are all on the same Y axis, in log scale

Bitcoin Cash is a new version of Bitcoin created in August 2017 when a group of developers broke off from the Bitcoin blockchain to increase the transaction limit for blocks [Cash, 2017].

Chainlink The Chainlink is a decentralized oracle network for complex smart contracts on any blockchain network [Ellis et al., 2017]. Chainlink's network provides the same security that smart contracts have, and can be connected to any external API.

Aion Aion is a token from The Open Application Network [The Open Foundation, 2017]. The Open Application Network is a common protocol to connect blockchains, allowing efficient and decentralized applications to be built that connect to multiple different blockchains in a hub and spoke model.

Hyperion Hyperion is the first tokenized Venture Capital Fund [Invictus, 2018]. The fund is built to give token holders exposure to returns from early-stage blockchain investing. Hyperion has low fees, suited for retail investors, and is close-ended.

Bitcoin SV Bitcoin SV doubles down on the original vision that Satoshi Nakamoto had for Bitcoin: to replace every payment system in the world [Bitcoin Association, 2018]. On November 15, 2018 Bitcoin Cash was hard forked to turn into Bitcoin SV [Rodriguez, 2019] The split was as a result of block size, with the Bitcoin SV developers advocating for an increase in the block size from 32 MB to 132.

Changes since original study Since the initial study was done in 2019 for Reading's discussion paper with advisor Dr. Mihailov, 5 of the top 10 tokens have changed. A remarkable level of volatility and change, but is not surprising given the number of projects and immaturity of the cryptocurrency arena. When you consider the trust and price stability that is required for a reserve asset, the number of changes is untenable.

Although some of the underlying technology specifications and processes are different, all of these cryptocurrencies are based on the original blockchain decentralized and distributed ecosystem proposed and created by Bitcoin. Ethereum created an original environment, which can loosely be defined as an operating system, which enabled smart contracts (business and legal requirements defined in code) and the ability to create distributed applications (commonly referred to as dApps) on the platform. Ripple was engineered to provide fast and convenient transfers between agents, while Hyperion is a tokenized investment fund. To an extent, all of the other currencies listed above are primary derivatives of these main concepts and capabilities.

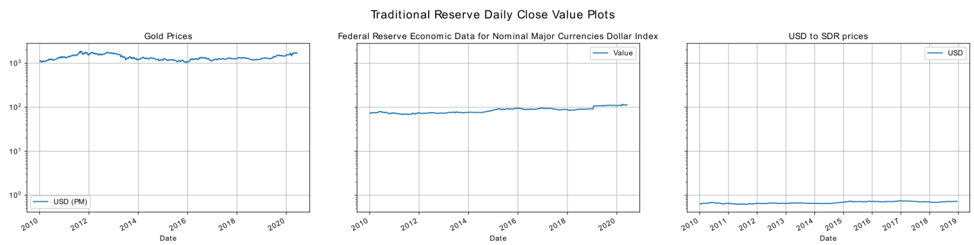

Figure 3.4: Traditional Reserve Assets, USD Prices in log scale

Price Volatility: Dynamics and Standard Deviation

We begin our quantitative study of cryptocurrencies by examining their prices from inception until June 2020, using data from CryptoCompare [2020].

As one can see from Figure 3.3, modern cryptocurrencies, beginning with Bitcoin, have been around for a little over 10 years. By observing the logged daily closed value ranges, the USD price of Bitcoin rose persistently from nearly 10^{-2} to a bit above 10^4 and then trend down, and recently has begun to trend upwards again, while that of Tether displays two episodes of short-lived spikes of the order of about 10^3 but fluctuates most of the time around 10^0, and is arguably the least volatile of the group, as would be expected as a stablecoin. The remaining cryptocurrencies displaying, in general, much more volatile price dynamics, with some similarities as well as differences in the patterns.

For comparison, plots of price volatility of traditional reserve assets over the same period are provided in Figure 3.4. The three traditional assets shown here and commonly used as money and international reserves are gold, in USD, a basket of major world currencies compiled by the Federal Reserve Economic Data (FRED) service, and the USD price of IMF's Special Drawing Rights (SDR).

As one can see from Figure 3.4, the volatility of the traditional reserve assets is orders of magnitude lower. Indeed, the three respective curves are almost flat, with the gold price most volatile of the three and highest, at, 10^3 on the log scale.

To compare in a more direct and meaningful way the volatility of the top-ten cryptocurrencies with that of our three measures of traditional reserve assets, Table 3.2 lists the standard deviations (SD) and the respective orders of magnitude (OM), while Figure 3.5 provides a corresponding visual plot in a bar chart. The most volatile cryptocurrency is by far Bitcoin SD of 3612.98 and corresponding OM of 3.56, followed by Bitcoin Cash SD of 524.50 and an OM of 2.72 and Ethereum SD of 230.62 and OM of 2.36, as can be seen in Table 3.2 The lowest volatility among the cryptocurrencies is the new stable coin CRO, as well as the stablecoin USDT, and the new entrant Hyperion, HYN. CRO has the lowest SD at 10.017,

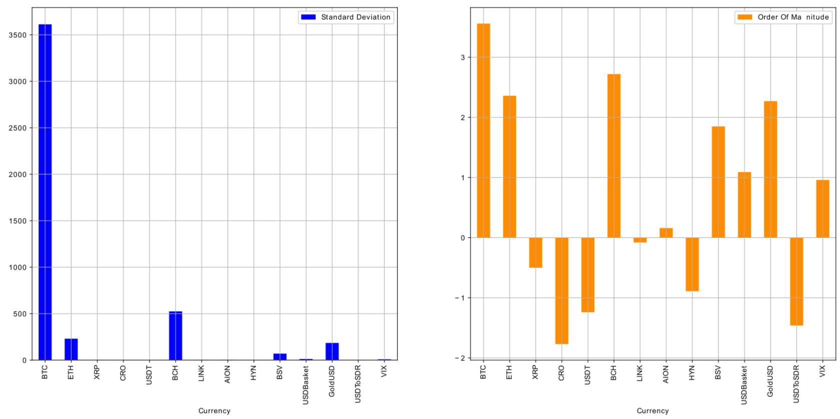

Figure 3.5: Top-10 Cryptocurrencies and Reserve Assets Order of Magnitude and Standard Deviation

Currency	Standard Deviation	Order Of Magnitude
BTC	3612.98	3.56
BCH	524.50	2.72
ETH	230.62	2.36
GoldUSD	184.89	2.27
BSV	70.09	1.85
USDBasket	12.33	1.09
VIX	9.03	0.96
AION	1.44	0.16
LINK	0.82	-0.08
XRP	0.32	-0.5
HYN	0.13	-0.89
USDT	0.06	-1.24
USDToSDR	0.03	-1.46
CRO	0.02	-1.77

Table 3.2: Sorted Standard Deviations and Orders of Magnitude

with an OM of -1.77. USDT has an ST of 0.058 and an OM of -1.24. HYN has the third-lowest, as could be expected, being very new, with an SD of 0.13 and an OM of -0.89.

These least volatile cryptocurrencies, all engineered for stability, during their short lives, plus AION, LINK, and XRP, are less volatile than the Gold in USD and FRED currency baskets, which are two of our three comparison reserve assets. This comparison uncovers a huge difference across the cryptocurrencies in terms of volatility, of OM of about 5 takes the most volatile vs the least volatile (and less so across the traditional assets, of OM of about 3), one should be careful to note that, as just stressed, we have not observed these low-volatility cryptocurrencies for a long enough period and through a full-scale financial crisis to know their true maximums of volatility. Regardless of the other facts that we emphasize later in this chapter, we could theoretically gauge the effectiveness of cryptocurrencies as a potential reserve currency, we would need to see how it performs in a global recession.

Price Volatility: Coefficient of Variation

Since the price levels of the different cryptocurrencies are quite different, we use in this subsection the coefficient of variation (CV) metric, defined as the SD divided by the sample mean ($\frac{\sigma}{\mu}$, in standard notation,), to normalize the measure of variability. Table 3.3 describes in descending order the order of magnitude of the coefficient of variation measurements. Figure 3.6 shows this data in a graphical format.

As expected, the USD-price of the fiat currency basket of reserves, the SDR reserve asset and the USD gold price, all have a very low CVs, 0.144 for the currency basket, compared to the cryptocurrencies whereas the lowest non-stable coin CV, BSV, is almost five times higher, at 0.51.

Following this introductory section, the chapter is structured as follows. The second section looks at the importance of cryptocurrencies relative to traditional major fiat money in global transactions, and then proceeds to outline a counterfactual analysis that simulates three scenarios of allocating a small fraction of the Bank of England's international reserves to cryptocurrencies, concluding why such an action seems highly improbable. Section 3.3 summarizes the standard functions of money and of international reserves, to argue that cryptocurrencies cannot fulfil the role of international reserves, but that central bank digital currencies potentially can fulfill this role. Section 3.4 provides, in turn, a scaling of the recent cryptocurrency bubble to earlier failures of private money and three prominent bubble boom-and-bust cycles in historical perspective, and the final section outlines some concluding remarks.

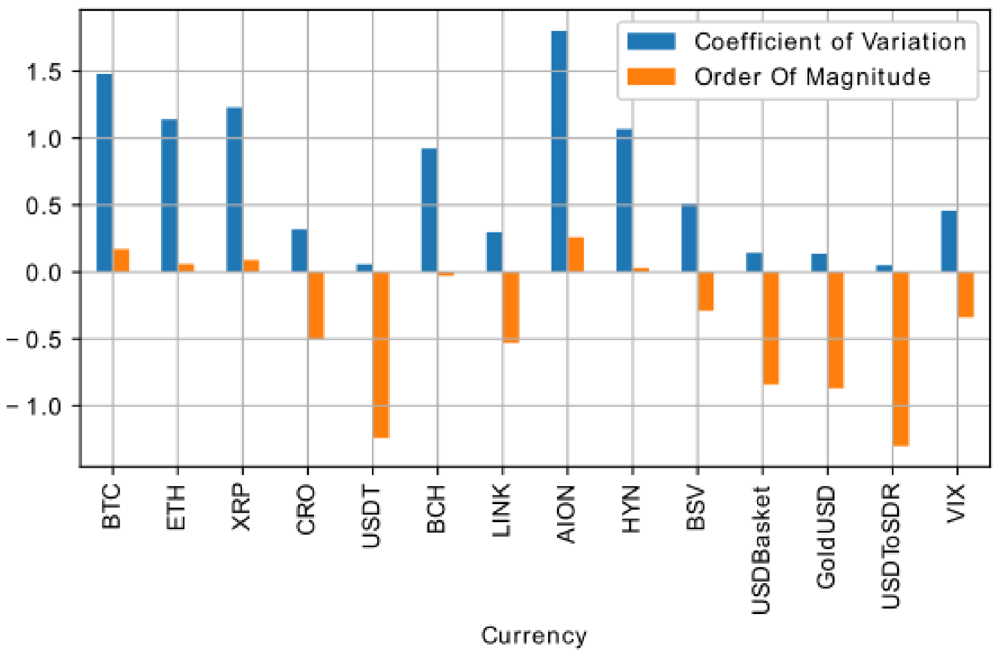

Figure 3.6: Top-10 Cryptocurrencies and Reserve Assets Order of Magnitude and Coefficient of Variation

Currency	Coefficient of Variation	Order Of Magnitude
AION	1.803373	0.26
BTC	1.480216	0.17
XRP	1.230661	0.09
ETH	1.140783	0.06
HYN	1.068829	0.03
BCH	0.923758	-0.03
BSV	0.510582	-0.29
VIX	0.45896	-0.34
CRO	0.319019	-0.5
LINK	0.297794	-0.53
USDBasket	0.143927	-0.84
GoldUSD	0.136085	-0.87
USDT	0.05799	-1.24
USDToSDR	0.050597	-1.3

Table 3.3: Sorted Coefficient of Variations and Orders of Magnitude

3.2 Relative Importance of Cryptocurrencies in Global Transactions

This section addresses two related and central questions concerning the potential role of cryptocurrencies as international reserve assets.

3.2.1 Cryptocurrency Market Capitalization Relative to US Dollar and Euro Transactions Turnover

To ascertain how far cryptocurrencies have come to potentially compete with major fiat currencies in international transactions, we here summarize the relative importance of cryptocurrencies against traditional foreign exchange (forex) markets. We do so by comparing the market capitalization of cryptocurrencies with the volumes of USD and EUR forex markets. A plot of cryptocurrency market capitalization was obtained from CoinMarketCap.com [Chez, 2013] for reference – see Figure 3.7.

At the cryptocurrency market's peak, which occurred on January 8, 2018, a the market capitalization of 814.2 billion USD was reached, with a 24-hour transaction volume of 43.6 billion USD. It has since fallen drastically, bottoming out

Figure 3.7: Total Cryptocurrency Market Capitalization, In USD

at 115.9 billion USD market capitalization on December 9, 2018, and at the time of this writing, June 7, 2020, has risen to a market capitalization of 539.8 billion USD with a 24-hour range of approximately 211.9 billion USD. For comparison, the average daily over-the-counter (OTC) foreign exchange transactions in USD were 4,438 billion and in EUR 1,591 billion, as of 2016, obtained from the Bank for International Settlements [2016] Triennial Central Bank Survey of foreign exchange and OTC derivatives markets. It can be noted that it is not a fully fair comparison, however, as cryptocurrency appear to, at times, function more like a speculative asset class than strictly as a currency market. The addition of a mixture of US and European stock, bond, commodity, and derivative markets would therefore need to be added to the reported turnover of forex transactions to have a more apples-to-apples comparison. This means that the gap in volume between cryptocurrencies and traditional currencies is significantly larger than the aforementioned figures indicate. The current volumes in the cryptocurrency market are many times smaller than the current volumes in forex markets, let alone financial markets in broader terms that would include speculative capital similarly to the cryptocurrency markets.

3.2.2 Counterfactual Analysis of Bank of England's Foreign Currency Reserves

To gain some visual insights into what could have happened if a central bank had invested a fraction of its international reserves into cryptocurrency, we proceed

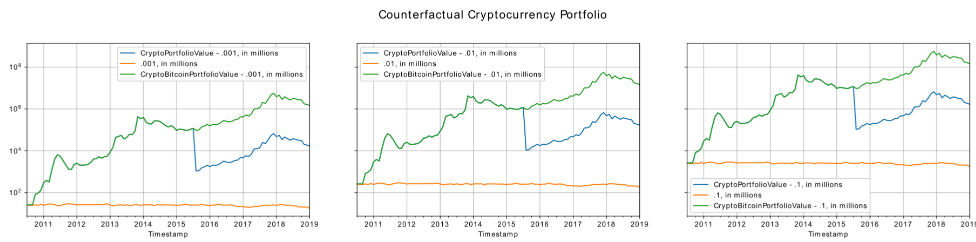

Figure 3.8: Counterfactual Simulation of Bank of England's International Reserves: 3 Scenarios, USD Value (log-scale)

next to a counterfactual analysis illustrated graphically.[4] We simulate how the Bank of England's (BoE) foreign currency reserves would have performed over the given period if they were 0.1%, 1%, or 10% allocated to the two most common crypto-currencies, Bitcoin and Ethereum. For the data we gathered from CryptoCompare, the Bitcoin pricing quotes began on 2010-07-31, while the Ethereum quotes began 5 years later, on 2015-07-31. We took the BoE end-of-month foreign reserve balances and multiplied them by 0.001, 0.01, and 0.1, respectively, to extract the quantity, in millions of USD dollars, that could have been allocated to cryptocurrencies. For purposes of this illustration, the full 0.1%, 1%, or 10% was assumed invested in Bitcoin only from 2010-07-31 to 2015-07-31, and then rebalanced in 2015-07-31 to a portfolio of 50% Bitcoin and 50% Ethereum. We assume only these two rebalancing of the compositions of BoE's international reserves occurred during the entire period of our counterfactual analysis, depicted in Figure 3.8.

Additionally, we calculated the coefficient of variation and its order of magnitude for the respective three scenarios in BoE's reserve allocations.[5] For the period studied, the "cryptocurrency-inclusive portfolio" performed better than the "traditional portfolio" of international reserves. However, this is only because we assume that the counterfactual analysis, with its first rebalancing allocating a fraction of BoE's reserves into Bitcoin, began as early as the advent of Bitcoin at a value of $0.08 USD per coin in July 2010, much before cryptocurrencies became widely known and discussed: so the meteoric rise in the counterfactual crypto-inclusive reserve portfolio is exclusively dependent on an extreme level of risk-taking and omniscient prediction we ascribed to the BoE in such a scenario. Yet, central banks are not private equity or venture capitalist firms, so this type of speculative

[4] A similar computation for the case of Barbados has recently been discussed in Moore and Stephen [2016].

[5] Source code is available in a Python Jupyter notebook, upon request.

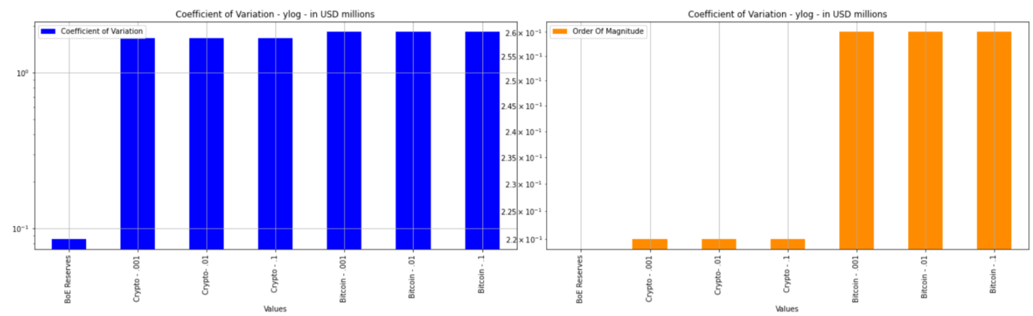

Figure 3.9: The figure shows a very low Coefficient of Variation for the BoE's reserves compared to the counterfactual crypto portfolio, which has an order of magnitude higher of variation, as would be expected with the nascent asset class.

investment is highly improbable. If, instead, we had assumed that the BoE had invested in cryptocurrencies just before the burst of their bubble in mid-December 2017, it is clear from the same figure that a loss in value of reserves would have been suffered by the Bank. More fundamentally, and beyond any choice of the particular timing of "catching up the rising wave of the crypto market", it is clear that the gyrations in price and the resulting high degree of variability in yield make cryptocurrencies a nonstarter as an additional international reserve asset. Cryptocurrencies behave as a speculative investment in high-frequency (hourly and daily) financial markets and, therefore, do not possess the desirable properties of international reserve assets, as we argue further down in more detail.

3.3 Why Private Cryptocurrencies Cannot Perform The Functions of Money and International Reserves

3.3.1 The Functions of Money

This section will serve as a brief overview of the functions of money to better inform the following discussion of why private cryptocurrencies do not adequately perform as money. Money is defined as containing the following three attributes [Publisher, 2016]:

1. It is a store of value,

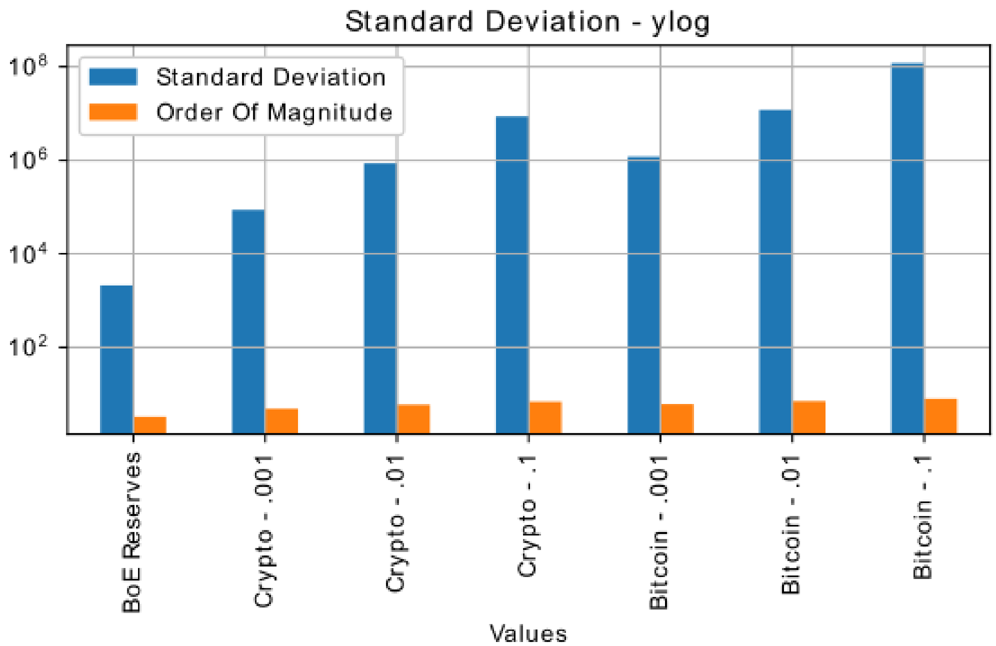

Figure 3.10: The figure shows a very low Standard Deviation for the BoE's reserves compared to the counterfactual cryptocurrency portfolio, which has an order of magnitude higher of variation, as would be expected with the nascent asset class.

2. A unit of account and

3. A medium of exchange

The previous sections 3.1.3 and 3.2.2 have showcased how poorly the unit of account and store of value attributes of money are encapsulated by private cryptocurrencies, with their volatility, in many cases, orders of magnitude above the traditional reserve assets. Additionally, few vendors or stores currently accept cryptocurrencies for point of sale settlement, although the number of companies accepting cryptocurrencies does continue to increase. However, only 'common', long-standing cryptocurrencies such as bitcoin are accepted [Haqqi, 2021]. Even if private cryptocurrencies are accepted by some vendors, their usage has a marginal impact on the monetary base, as previously shown from the peak 24-hour transaction volume of private cryptocurrencies (peak 24-hour transaction volume of private cryptocurrencies was 43.6 billion USD vs the 2016 BIS 4,438 billion USD 24-hour volume). These figures put the size of the cryptocurrency market into perspective, less than 0.01 of the daily USD volume, not the global traditional currency volume. Although garnering a lot of excitement, current private cryptocurrencies are not major players in the current monetary economic paradigm, which is largely digitized, although with traditional, government-backed currencies.

Williamson [2018] brings up an interesting point about the inefficiency of Bitcoin, and expounds on how Bitcoin fails to perform well in the aforementioned forms of money, and most likely cannot survive long-term. Being an inelastic money supply, Bitcoin is impractical as a unit of account and medium of exchange. As Bitcoin reaches its limit of potential coins to mint, its utility will decrease as with the mining slowdown, there is less of an incentive to use it. Bitcoin is the first viable private cryptocurrency, but goes against monetary economic theory and is extremely deflationary. One of the arguments on why the gold standard doesn't work and a contributing factor of why the UK and USA left the gold standard, was because gold's supply only increases at 1% or so percent per year, which isn't as fast as the economy. Bitcoin will hit its cap of 21 million coins sometime around 2140, however as we get closer to the maximum value, we are currently at around 18.5 million mined, it will be more and more expensive to mine for each coin, which may dampen its utility as a currency [Phillips, 2021]. Without miners in the ecosystem, the value will crash to close to zero when investors realize that arbitrary code on a set of servers doesn't provide any store of value long term. To prevent this, transaction fees will need to increase to incentivize miners to continue validating blocks, which will increase the cost of use, and turn Bitcoin into an expensive asset class, but not the best medium of exchange.

In a recent paper featuring a two-currency model of cryptocurrencies and fiat money in competition and coexistence, Benigno [2019] shows that the growth rate of cryptocurrency sets a lower bound on the nominal interest rate and the attainable inflation rate. In a world of multiple competing currencies issued by profit-maximizing agents, the central bank completely loses control of the nominal interest rate and the inflation rate. Benigno's paper is one of the first theoretical explorations of the implication of private cryptocurrencies for monetary policy, and it is evident from his analysis that private cryptocurrencies radically change and limit the ability for monetary control of the central bank over the policy rate and inflation, and hence over the macroeconomy as a whole.

3.4 Scaling the Promise and Failure of Cryptocurrency into a Historical Perspective

How "unique" or not is Bitcoin, and cryptocurrencies in general, relative to the history of private money and the magnitude of earlier financial bubbles? We briefly address these two questions of perspective and comparison, in turn, in the present section.

3.4.1 Failures of Major Forms of Private Money in the Past

Bitcoin may seem to many as a new, even revolutionary, form of "private money", which it is to an extent, but history should not be forgotten. Scholars of monetary theory and banking history are very well aware of the long debates on the pros and cons of private money and free banking in Western societies [Champ, 2007]. Private money is any token used as money that is not backed by a sovereign or central bank but is issued instead by a bank, a company, or even an individual[6]. "Free banking" allows for such a "private money-issuing competition" across banks, and for maintaining over time their systems of tokens for payments and credit. The general conclusion among monetary experts is that numerous attempts of establishing private money have failed historically for various reasons, three of which are listed below:

1. Financial crises. In times of (prolonged) financial turbulence, private money has a poor record of use, and often vanishes

2. Perceived backing – lack of trust in the issuer

[6]See chapter 4 for a case study in a new blockchain-based private money.

3. Lack of liquidity

Bitcoin, and cryptocurrency in general, is not an exception from the earliest forms of private money, and is likely to suffer from the same common problems.

3.4.2 The Booms and Busts of the Major Financial Bubbles in the Past

To place the relative magnitude of the recent Bitcoin and cryptocurrency bubble into perspective, it is important to also scale it to similar episodes in the recorded financial history of mankind. While this, the boom-and-bust cycle may have scary dimensions for the current generation of observers, or speculators who gained or lost fortunes from it, analogous bubbles have occurred many times, and the less distant of them to us, have been studied in economics and financial literature. Among the most notorious examples of irrational exuberance episodes have been the "tulip mania" in Holland (circa 1625-1637), the related Mississippi and South Sea bubbles in 1719-20, the Ponzi financial pyramids in Chicago and the US of the 1930s, the similar Ponzi schemes invented by anonymous financial criminals in many Eastern European transition economies in the early 1990s, the housing crash in the US, the UK, and many other advanced economies in 2007-08 and the related parallel events of the global financial crisis.

Using data from Garber [1990], an approximated visual comparison of the magnitudes and dynamics of the recent Bitcoin crash relative to the three earliest recorded – and among the most prominent in the economics literature, see Figure 3.11[Clark and Mihailov, 2019]. As many of us might have suspected, the Bitcoin bubble appears to have been unprecedented in its amplitude and sharpness of the boom-bust cycle: a price increase from close to 0 through a peak just below 18,000 USD per coin and plunging back to below 4,000 USD, literally within a year. Only tulip mania comes close to it in terms of peak magnitude, seems worst in terms of crash abruptness, but the increase preceding the peak appears to have been much more gradual and longer-term (several years, not months). The Mississippi bubble is roughly two times less impressive than the Bitcoin boom-and-bust cycle in terms of its peak magnitude, and the South Sea bubble is so "dwarfed" by what happened with Bitcoin that it does not look like a bubble given the historical relative scale in our Figure 3.11. If international reserves were invested, even if at a minuscule share of 1% or 5%, in Bitcoins at some point in the second half of 2017, it could have a significant effect on trust in central banks and negatively impacted their reserve positions.

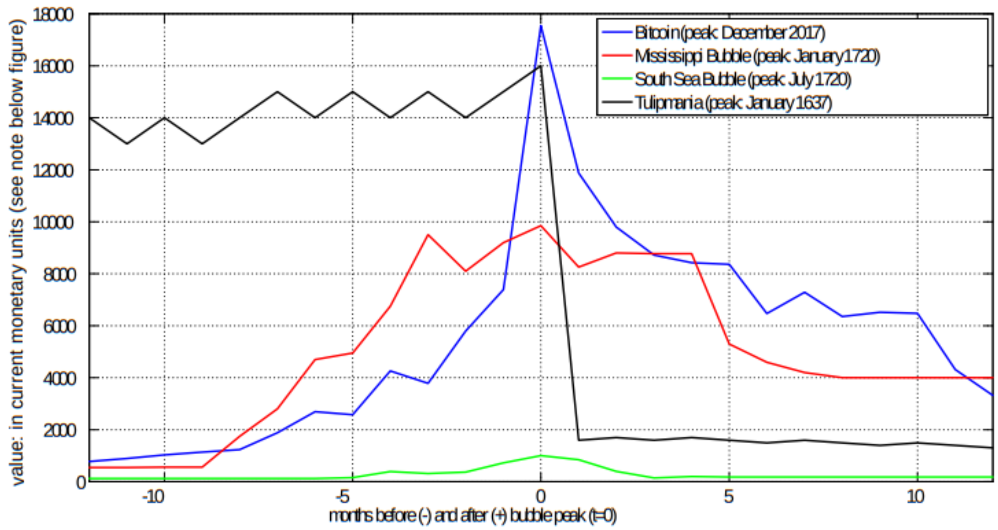

Figure 3.11: Scaling the Bitcoin Bubble into a Historical Perspective; approximate mid-month price (for Bitcoin) or approximate average month price (for the other assets); Bitcoin price in current USD Source: Bitcoin Price History Chart from www.buybitcoinworldwide.com; Mississippi Buble (1719-20): Compagnie des Indes stock price in Livres Tournois source: Fig. 1, p. 44, Garber (1990); South Sea Bubble (1719-20): South Sea Company share price in Pounds per fully paid share source: Fig. 3, p. 50, Garber (1990); Tulipmania Bubble (circa 1625-37): price of a Semper Augustus tulip bulb in current USD (converted from current Dutch guilders at USD 400 per ounce of gold) source: pp. 37-38, Garber [1990], Clark and Mihailov [2019].

3.5 The Functions of International Reserve Currencies

International or foreign reserves are cash or other reserve assets held by a central bank or other monetary authority to balance payments, maintain trust in the country's financial markets, and affect its currency exchange rate. Foreign reserves can take on many forms, most notably, gold, IMF SDRs[7], reserve positions with the IMF, foreign exchange depositors or short-term foreign treasury bills.

The earlier literature on international reserves focused on their role as a buffer stock, and the associated property of liquidity, in particular to finance trade deficits [Balogh, 1960, Caves, 1964]. Heller [1966] expanded this analysis into the motives to hold international reserves, in a way analogous to the much-discussed Keynesian tradition for holding money: (i) a transactions motive, (ii) a precautionary(savings) motive, and (iii) a speculative motive. Taking into consideration adjustment costs, he was the first to suggest that the "optimal" level of international reserve holdings depends on (i) the marginal propensity to import, (ii) the opportunity cost of reserves, and (iii) the balance of payments (BoP) volatility. Clark [1970] similarly examined "optimum" international reserves and this problem has been modeled in an increasingly sophisticated set-up ever since, e.g., in Alfaro and Kanczuk [2009] more recently. Following the East Asian financial crisis of 1997-98, researchers and policymakers have further stressed the issue of "reserve adequacy", in particular as a safeguard against sudden stops of capital inflows.

International reserves are used for:

1. International settlements as a medium of exchange

2. Foreign currency interventions in financial markets to manage exchange rate policies

3. Assets accumulated by central banks as current account surpluses

To fulfill their key functions as summarized above, international reserves must fulfill the following primary attributes:

1. Price stability

2. Liquidity, the ability to exchange readily exchange for another asset

3. Sufficient quantity in circulation

[7]SDRs were created by the IMF in the 1960s as a basket of member currencies to remove the USD as the single means of settling international accounts

Currently, the USD is the main international reserve currency, solidifying its place after the 1944 Bretton Woods agreement. Yet since 1999 the EUR (inheriting the similar roles of the DEM, GBP, and FRF) is increasing in the global share of reserve currencies, with the USD and the EUR consisting of over 80% of the international reserve currency shares [Ito and McCauley, 2019]. Beyond fiat money issued by the central banks in the most powerful and credible economies over the past centuries, the other common international reserve assets include gold [8], and SDRs.

3.5.1 Presentation and Discussion of CBDC Initiatives Currently Underway by Central Banks

In 2019, the Bank for International Settlements (BIS) began an annual survey of central banks' engagement in CBDC research and application. The most recent survey which was published on the BIS's website in January 2021 by Boar and Wehrli [2021] shows an increasing interest in central banks in researching CBDCs with 60% of central banks (up from 42% in 2019) conducting proofs-of-concept with 14% working towards pilot implementations. Boar and Wehrli [2021] research shows that in general, emerging market and developing economies, as a whole, are more interested in CBDC most likely due to their stronger motivations of efficiency of payments and financial inclusion. Accordingly, the first nationwide CBDC is from the Bahamas, called the Sand Dollar, and fully launched in October 2020 [Atlantic Council, 2021]. On March 31, 2021, the Eastern Caribbean Central Bank launched its currency Dcash in Saint Kitts and Nevis, Antigua, and Barbuda, Saint Lucia, Grenada, 4 of its 8 member states. It is a retail CBDC that consumers and merchants can use via the DCash App on their smartphones or via participating financial institutions [Atlantic Council, 2021]. Boar and Wehrli's (2021) work suggests, however, that the majority of central banks are unlikely to launch CBDC's in the foreseeable future, with a few notable exceptions, such as Sweden's Riksbsank's testing of the e-krona, and the People's Bank of China's e-CNY [Atlantic Council, 2021].

The People's Bank of China (PBOC) is the first major economy to pilot a CBDC with the e-CNY. In April 2020, the PBOC rolled out the pilot CBDC in four cities, enabling commercial banks to run internal conversion tests. In August 2020, the program expanded to 28 major cities. The PBOC is aiming for widespread domestic use by 2022 and allows athletes and visitors to use the e-CNY by the Beijing Winter Games in 2022. The PBOC has begun working on using

[8] High volumes of gold purchases recently undertaken by several central banks in large economies, such as Russia [GoldHub, 2018] and China [BullionStar, 2020].

the digital yuan in cross-border transactions.

Although still in the research phase, the US Federal Reserve has been actively researching CBDCs. The Federal Reserve Bank of Boston is collaborating with the Massachusetts Institute of Technology (MIT) on a prototype, and the US Federal Reserve is expected to release a major research paper in the late summer of 2021 [Atlantic Council, 2021].

3.5.2 Comparison of the characteristics of CBDCs and private cryptocurrencies

Although implicitly discussed throughout this chapter, in this section, the characteristics of CBDCs and Private Cryptocurrencies will be stated and compared.

CBDCs

CBDC's are central bank-issued digital money denominated in their national unit of account as a liability of the central bank, as defined in the Bank for International Settlements [2021] annual economic report, chapter 3. CBDC's offer the same guarantees as physical cash or demand deposits as they have the full backing of their respective government, essentially making them "riskless'. CBDCs are centralized, using a permissioned distributed ledger with trusted partners or a centralized system doing away with distributed ledgers altogether. CBDCs could be used by end consumers in a 'retail' setting or as 'wholesale' for large, commercial interbank settlements.

Private cryptocurrencies

Private cryptocurrencies, in contrast, are for the most part are decentralized, as described in section 3.1.1 vs the permissioned or centralized structure described in the previous subsection. Private cryptocurrencies, use their unit of account, such as Eth in Ethereum, with Stablecoins being an exception — see section 3.1.2 for a specific discussion of stablecoins. The Bank for International Settlements in their 2021 Annual Economic Report and CBDC annual survey both have strong opinions, which agree with the conclusions of this chapter, that private cryptocurrencies do not meet the true definitions of money, as described in section 3.3.1. The Bank for International Settlements [2021] Annual Economic Report states that: "...it is clear that cryptocurrencies are speculative assets rather than money, and in many cases are used to facilitate money laundering, ransomware attacks, and other financial crimes." while the 2021 CBDC survey by Boar and Wehrli [2021] states that: "Many cryptocurrencies experienced a surge in their values in 2020, true to their form as speculative assets. This increase was not matched by any change in the perceived usage in payments. Indeed, most central banks continue to see cryptocurrencies as niche products". Stablecoins, a subset of private cryptocurrencies, do provide stability, but the BIS holds to the opinion that they have promise in "extraordinary situations where trust in public institutions is low, leading to more widespread or significant use for domestic payments"[Boar and Wehrli, 2021].

Schilling and Uhlig [2019] argue in their fundamental pricing equation, that price volatility does not invalidate the medium-of-exchange function of Bitcoin. However, Schilling and Uhlig [2019] do not specifically address Bitcoin as a unit of account or store of value. The authors state in their introduction: "The analysis does not apply to gold, sugar, utility tokens such as ether and binance coin, equity tokens or stablecoins".

In Proposition 1 of their fundamental pricing equation, Schilling and Uhlig [2019] state that: "Due to the currency competition, sales against both Bitcoins and Dollars implies seller indifference." Their analysis assumes that a central bank has recognized Bitcoin, at least implicitly, as a currency. Jerome Powell, the current Federal Reserve Chairman, said the following during a July 14, 2021, House Financial Services Committee congressional hearing: "You wouldn't need stablecoins; you wouldn't need cryptocurrencies, if you had a digital U.S. currency"Sigalos [2021]. Based on this quote and the Federal Reserve's investigations into a CBDC, as outlined in section 3.5.1, it does not appear probable that the Federal Reserve will recognize Bitcoin or any other private cryptocurrency as a currency in the foreseeable future. Schilling and Uhlig [2019] argue that under their equilibrium assumptions, that price volatility, by itself, does not invalidate the medium-of-exchange function of Bitcoin. Assuming the equilibrium conditions they propose are held, that a central bank supports both Bitcoin and USD, and no Bitcoin speculation exists, then price volatility does not invalidate the medium-of-exchange function of Bitcoin. The author agrees that with the stated assumptions, that price volatility does not invalidate the use of Bitcoin as a currency, however for the scope of this analysis and the current policy environment surrounding private cryptocurrencies, the author believes that unless recognized by a central bank, Schilling and Uhlig [2019] work does not invalidate this chapter's conclusions.

3.5.3 Why Private Cryptocurrencies Fail to Perform the Functions of Money and International Reserves

To be used as international reserves, as well as money, private cryptocurrencies or entral Bank Digital Currency (CBDCs), need to satisfy the necessary attributes outlined and briefly discussed above in the two preceding subsections concerning the three central functions of money section 3.3 and the four main functions of international reserves in section 3.5. As we have shown in sections 3.1.3 and 3.2.2, the current generation of private cryptocurrencies fail abysmally in the stability attribute and, hence, the necessary role of trust. With the broad range of cryptocurrencies, and the relatively small market capitalization they represent, the difficulty of use, and the lack of assets denoted in cryptocurrencies, private cryptocurrencies fail in meeting the other essential properties we outlined to be able to function at present as an international reserve currency as well. However, arguably the most important way they fail to meet the basic needs of a reserve currency, or currency in general is the detachment of their money supply growth to forecasted or estimated money demand growth, for some private cryptocurrencies such as Bitcoin. This mismatch resulted in the exorbitant rise of Bitcoin before the collapse on Christmas 2017, due to its fixed, computationally determining supply, it is not agreeing with the money stock needs of the economy arising from the demand side. The underpinning of trust in cryptocurrencies is believed to be, by their noneconomist engineers and promoters, the inability of anybody (beyond the computational algorithm) to expand their supply after finite mining is completed, save for the potential introduction of fractional reserve banking, which would undermine trust in the medium. Economic growth is naturally inflationary, so the money supply should grow at least as fast as GDP to provide enough liquidity to help ward off deflation; moreover, modern central banking has defined price stability as about 2% per inflation per year, which is stationary and with low variation, enhances production and growth without overheating the economy into hyperinflationary pressures [Federal Reserve, 2020]. Of course, such monetary frameworks and strategies are now well understood even by the noneconomist public, due to the communication by central banks of their targets, instruments, forecasts, and their transparency and accountability to society, e.g., in the modern benchmark of inflation targeting monetary policy frameworks around the globe.

From a historical perspective, much can be learned from the analogy of the erratic or arbitrary money supply, detached from and unmatching money demand, by the long and turbulent history of the gold standard. Indeed, one needs to look no further than the ill-fated return to the gold standard of the UK in the 1920s under Sir Winston Churchill to see the deflationary effects of a constrained, or mispriced, money supply [K, 1925, Keynes, 1919, Bemanke and James, 1991]. We are setting aside the lack of ability of a central monetary authority to conduct open market operations as necessary to promote a stable fiat or CBDC.

Another important point to return to, and reiterate, is the general and absolute trust inherent in a monetary system for payments, and credit, to flow quickly and smoothly, as in modern digitalized and automated real-time gross settlement (RTGS) systems interlinked across the world through the banks. Instead of accountable central bankers acting under institutional frameworks of "constrained discretion" to preserve social trust, such as the popular inflation targeting monetary policy regime nowadays, that has evolved after centuries of monetary history and institutional learning, cryptocurrencies are governed by primarily anonymous groups of "techies" without deep knowledge of monetary economics, theory, and policy. This same point is often touted as the strength of cryptocurrencies, namely their decentralized structure governed by groups of Silicon Valley personalities, but it may as well become cryptocurrency's Achilles heel. Trust is an integral and inherent aspect of any monetary system and what gives society the assurance that these decentralized networks are not an improvement over the existing paradigm, although fraught with challenges, is an amalgamation of centuries of economic scholarship.

The network did not result in a breach, a smart contract had a bug that was exploited.

As one prominent example, a smart contract in the Ethereum the network had a bug that was exploited, which was resolved a group of developers rolled back days of transactions to fix the hack, and retrieve stolen assets [Siegel, 2016]. They then created a hard fork of the currency, which infuriated parts of the community, and led to a fork of Ethereum to Ethereum Classic. The minor occasional disturbances and annoyances with the traditional central bank activities appear as minor trivialities compared to the types of risks and volatile decisions that are common in the cryptocurrency space. And even huge and persistent shocks such as the global financial crisis have been mitigated by measured and concerted central bank actions, even if excessive and nontraditional, such as "quantitative easing" and "forward guidance", plus strengthened commercial bank supervision minimizing risks via the BIS and its network of central banks and bank supervision regulators.

3.5.4 Why Central Bank Digital Currencies Could Perform the Functions of Money and International Reserves

Berentsen and Schar [2018] argue that "there is a large unmet demand for a liquid asset that allows households and firms to save outside the private financial sector" and suggest that "central banks could offer such an asset by simply allowing households and firms to open accounts with them' (abstract, p. 97). This possible role of a "pseudo-cryptocurrency" issued by a central bank directly to the private sector, via newly introduced accounts of individuals and business firms with the central bank itself, is a different – and radically new for central banks – potential use of central bank digital currency (CBDC). However, while such a new task of the central bank may undergo some development and, possibly, even implementation, at least in a few countries exploring currently this option, such money will be not cryptocurrency in the precise and true sense of this new definition, but CBDC instead. The reason is that CBDC will be issued in a centralized and non-anonymous way by the central bank, and it will not therefore be a permissionless asset, maintaining user anonymity.

Although CBDCs could perform the functions of money and international reserves, they raise the question of why they are necessary, the additional overhead of a distributed network, and the lack of a clear benefit to justify the cost on behalf of central bank constituents (see chapter 5 of the Bank for International Settlements [2018] Annual Economic Report). As has been previously discussed in this chapter, blockchain-based cryptocurrencies have slower transaction times and depending on the consensus mechanism, can be more energy inefficient than fiat money. With faster peer-to-peer payment systems already existing, such as Venmo (PayPal) and Zelle (a consortium of banks), CBDCs are a solution looking for a problem. Central banks should not be in the business of using technology to try to keep up with Silicon Valley, but only use technology when the social benefits outweigh the social costs in implementing them.

Another one of the common reasons cited for the introduction of CBDCs is to escape the zero lower bound (ZLB) on nominal interest rates. However, the introduction of CBDCs is irrelevant concerning this point: end-users would convert their CBDCs to cash (see again chapter 5 of the Bank for International Settlements [2018] annual economic report)). To escape the ZLB, a cashless and goldless society would need to exist, which is theoretically possible with or without a CBDC. However, negative interest rates have been proven to be ineffective in practice, which yields this point moot [Takami, 2018, Danthine, 2018]. Highly negative interest rates, would cause individuals in a cashless society to buy stocks or other financial instruments, or establish some sort of barter economy.

The CBDCs could potentially be a significant improvement in the the financial system if they allowed end consumers to access the central bank's balance sheet, essentially cutting out the middle man of commercial banks. This may reduce some risks of retail and commercial banks becoming insolvent, but would introduce substantial additional risks, exacerbating the "too big to fail" phenomena but replacing the existing hub-and-spoke model with one single source for all monetary matters. As argued, in Bank for International Settlements [2018] annual economic report, chapter 5, this would stifle competition, and decimate the existing retail and the commercial banking industry and consist of an unprecedented power grab by central banks. However, to retain market competition and increase liquidity in the market, central banks could offer lower interest rates than commercial banks, providing a form of virtual cash, reflecting the difference in risk.

Due to these key objections raised above, we would, for the time being, focus on (and limit) any immediate role of CBDCs to facilitating international reserves transactions by augmenting existing or replacing fiat assets with their digitalized equivalents, backed by the central banks which hold them.

3.6 Possible Uses of Blockchain and FinTech Technologies

Looking beyond the hype of cryptocurrencies, it is hard to identify a specific economic problem that they currently solve better than traditional sources. Transactions can be slow and costly, prone to congestion, and aren't always designed to scale [Bank for International Settlements, 2018]. However, there are many areas of potential utility of blockchain-based technology, and extensions and applications that have become denoted as "FinTech", three of which are outlined next.

3.6.1 Digitization and Facilitation of International Trade Credit

The World Trade Organization estimates that 80-90% of global trade relies on trade finance [World Trade Organization, 2020]. The current process implemented via letters of credit and the related correspondence, documentation, verification, and validation is time-consuming and costly, involving much paperwork and many parties, namely: the importer, the exporter, the importer's bank, the exporter's bank, credit agencies, freight insurance, customers agencies, etc. The process requires preparing multiple documents as well, many times with manual components [Bank for International Settlements, 2018]. Smart contracts, which are self-executing contracts, with algorithmically programmed logic could significantly speed up this process.

3.6.2 Enhancement of Clearing and Payment within the Global Banking System

The SWIFT system and other cross-border payment settlement systems can sometimes take days for transactions to clear and have a single point of failure. A private blockchain implementation with nodes managed by trusted parties may provide an improvement in the speed of transactions and potentially enhance the security of the system by adding resilience [Bank for International Settlements, 2018]. SWIFT has already completed its first proof of concept, which showed promising signs. Cryptocurrency platforms such as Stellar and Exchange Union potentially provide this type of benefit for retail users [Stellar Development Foundation, 2014, Union, 2019].

Yet, the above three are very particular possible applications of smart contracts, and of blockchain and FinTech technologies more generally. There remains a wise skepticism regarding wider use, and a wider benefit, of the latter. To quote Andolfatto [2018]: "The promise of the blockchain protocol is that it is invulnerable to human foibles. Novel, for sure; but is it worth all the effort?" (abstract, p. 87)

3.6.3 Security Token Offerings

Security Token Offerings (STO) are an innovation in the cryptocurrency space responding to regulatory scrutiny of Initial Coin Offerings (ICO), and because of the pernicious scams that have perpetrated under the guise of an ICO, i.e., fake companies raising money with no intention of building a business. In July 2017, the US Security and Exchange Commission (SEC) published a document declaring that Decentralized Autonomous Organization tokens on the Ethereum network are treated as securities, under the Supreme court ruling in SEC vs W. J. Howey Co (1946)., to determine whether a transaction qualifies as an investment contract, which is a form of security [Clayton, 2017]. In June 2018, the SEC clarified their position to say that they would not classify all ether sales (the currency on the Ethereum network) as securities [Division of Corporation Finance, Division of Investment Management, and Division of Trading and Markets, 2018].

To provide legal recourse for investors in the case that tokens will be considered securities, the cryptocurrency community created STOs so if sales and organizations would be forced under SEC laws, a structured financial instrument reminiscent of traditional equity existed, also giving investors close to the same legal protection. Security tokens can be used to turn real assets into financial instruments by selling anything from shares to a Picasso painting, for instance, essentially via securitization of real, or “hard”, assets and recording them automatically on a blockchain. STOs would have all of the same ownership, voting, dividend, etc., rights of a traditional equity investor. It is commonly talked of as another way of “leap-frogging” the traditional banking and financial industry, much as the way that cryptocurrencies were spoken of. Some estimates, e.g., Tuwiner [2018], boldly “project” that STOs will be a 10 trillion USD market by 2020 – but these numbers seem far from credible[9].

Some of the pros that have been discussed for STOs include:

1. Increased liquidity of relatively illiquid assets, e.x., high-value real estate, art, etc. McKeon [2018].
2. Fractional ownership of previously unattainable assets, such as the aforementioned Picasso.
3. Rapid settlement of transactions, due to the nature of a blockchain architecture. However, as Auer [2019] recently claimed, when the incentive for miners in the current “Proof of Work” paradigm is diminished after all available currencies have been minted on a given network, such as Bitcoin, the transaction settlement volume may slow dramatically. Networks such as Ethereum are experimenting with “Proof of Stake” instead of “Proof of Work”; however, this paradigm has yet to be deployed on a large scale.
4. Reduced costs, by bypassing the traditional investment banking system.
5. 24/7/365 “over the counter” (OTC) markets.

The economic community has yet to fully analyze this emerging asset class in the decentralized financial world; however, it is the author’s opinion that STOs will never break out of marginality. It appears to offer some potential, but it is very early for a definite and conclusive assessment, with no large-scale examples of STOs so far, to our knowledge. However, despite the potential of this financial medium in some areas of finance by providing smart contracts and securitization of “hard” assets, the author does not believe that it will have the liquidity to come close to rivaling the traditional financial markets, as is “projected” by Tuwiner [2018]. The the benefit to finance and society of ideas like this is that the fundamental tenets,

[9]This original text estimate was published in Spring of 2018 and subsequently used in the author’s discussion paper Clark and Mihailov [2019] The author validated this claim on December 8, 2020, and found that the sector’s market cap was $390,526,495.21, a far cry away from the bold estimate [Security Token Market, LLC, 2020]

faster transaction times, lower costs, smart contracts, and securitization of “hard” assets will be integrated into the existing financial infrastructure, improving asset markets, meeting investors’ needs, and increasing liquidity.

3.7 Conclusion

Network externalities in a currency or means of payment are vital for their success, and reduce the cost per transaction, but with private cryptocurrencies, with an increase in transactions, processing time slows down and the cost per transaction does not decrease. More importantly, lack of trust in cryptocurrencies as a stable currency, as well as the many occasions of fraud observed so far, will hamper their use as a substitute or even as a complement, to fiat money and international reserves. The most effective trust mechanism behind money and international reserves have not changed with the advent of cryptocurrencies, but still is the good faith of a democratic government with checks and balances. The most probable and effective implementation of cryptocurrencies, or rather of the positive aspects of the blockchain technology behind them, will be most likely be with the active involvement of a credible central bank.

Through a counterfactual analysis of the BoE’s holdings, along with a thorough statistical examination of private cryptocurrency prices and volatility, the author concludes that private cryptocurrencies cannot currently effectively serve as either money or as international reserves. However, central bank digital currencies could conceivably work in both of these related roles, given the trust element of government backing, but there lacks a compelling reason for why they are needed.

Chapter 4

Complex System Modeling of Community Currencies

4.1 Introduction

Since the beginning of time, humans have used various means to represent value for commerce and wealth preservation. These mediums of exchange, whether rocks, cigarettes, gold bars, or paper currency, have been able to provide liquidity for trade[1][Radford, 1945]. What all of these variations of a medium of exchange has in common is trust among their users to represent value, at least in a limited sense. One such medium of exchange without extensive use is the community currency.

A relatively new form of such a medium of exchange, without wide-spread use or popularity thus far, has become known as 'community currency' or synonymously, 'complementary currency', 'parallel currency' and 'local currency' [Amato and Fantacci, 2020]. The purpose of this chapter is to present community currency's potential and to analyze its advantages and disadvantages, by focusing on a particular case study of *Grassroots Economics*'s Community Inclusion Currency (CIC) initiative developed by Will Ruddick in poverty-stricken regions of Kenya [Ruddick, 2020].

Community currency is a form of scrip (any substitute for legal money) issued by a group with a common bond. Its main objective is to maintain liquidity in a community when the national currency is in limited supply, and is designed to meet the specific needs of the users. Historically, community currencies have the following distinguishing characteristics [Ruddick, 2020]:

1. Are issued by a community organization;

[1]This chapter is adapted from a joint discussion paper Clark et al. [2021]

2. Cannot be used outside the community;
3. Bear zero interest rate (like money);
4. Encourage the community to help each other.

Community currencies meet two of the three functions of money, namely, medium of exchange and unit of account. However, they are not good stores of value, except in the near term, since their objective is to spend and generate activity in the local economy rather than for saving.

Scrip has a long history of use in many countries when legal tender was lacking or inadequate. In some instances, such as with US mining and logging towns, company scrip was acceptable at only company stores, and discounted at such a rate, that it made individuals entirely dependent on the company they worked for, ensuring their 'allegiance'. Scrip, if available for redemption to currency, was converted at an exchange rate significantly below face value. A well-known example in Austria during the Great Depression of the 1930s was the so-called Wörgl currency [Jr., 2002]. This scrip took its name from the town which began issuing it in July 1932, but was more precisely referred to as 'labor certificates'. The latter author bases his article on three original reports and concludes that the Wörgl currency improved the financial condition of the local (parish) government that issued it as well as the general health of the local economy while it was allowed to circulate. Scrip in modern times has had some less gloomy uses, specifically in the form of gift cards, Canadian Tire Dollars, and gift certificates. Canadian Tire dollars are a form of intermediation between government currency and interest-bearing assets that have been used successfully by customers [Eichenbaum and Wallace, 1985].

A long-lasting example of a large-scale successful complementary currency mutual credit clearing system is the WIR Bank, founded in 1934 in Zurich, Switzerland, formerly known as the Swiss Economic Circle [Lipton et al., 2020]. In 1998 University of Basel's Tobias Studer published a book on the WIR bank where he finds that the WIR systems help not only its members but the whole economy by supplementing economic trade and facilitating transactions that would not otherwise exist Studer [1998, 2006]. Although rigorous economic analysis around privately issued currency is lacking, the evidence that exists suggests that the public, at least in times without economic turbulence, will accept a privately issued currency as a substitute for government-issued currency without a discount.

After the financial crisis of 2007-2009, many people lost faith and trust in the global financial system, which contributed to the rise and popularity of private cryptocurrencies and of community currencies. A successful example from the UK is the Bristol Pound, created by financial activists in 2012 [Clark and Mihailov, 2019]. The Bristol Pound's thesis is that of a community interest currency, CIC, with a network of individuals and businesses circulating a community currency inside the specific group of individuals with a common bound to increase liquidity within the regional and local economy [Bristol Pound CIC, 2018].

Hundreds of community currencies have been created like the Bristol Pound, however the vast majority of these currencies have ceased to be sustainable due to the lack of market acceptance, similar to many blockchain projects [Lietaer et al., 2012]. Without a mechanism for redeeming the community currency back into a trusted means of exchange, the lack of trust in the currency and its utility is often a contributing factor in its demise. One of the other issues with community currency projects has been the inability to trade with other neighboring communities, limiting their ability to promote economic growth.

More recently, the Grassroots Economics Foundation has introduced a sustainable community currency that has shown that community currencies can be an effective means of fostering economic growth. Research by Stodder [2000] suggests that community currencies can counteract seasonal conditions and increase overall trade [Ruddick, 2020]. Started with an initial pilot in 2010 called Eco-Pesa, the project has moved from paper-based currency into digital CIC's [Ruddick, 2011]. The digital pilot was started in Q4 2018 and at the time of this writing, 24,000 registered users and an average of 1,000 transactions per day have been reached [Grassroots Economics, 2020a].

In developing economies, the availability of the national currency often has a low correlation with the local capacity or demand, but is to a large extent influenced by external factors, such as trade deficits, foreign interest rates, national debt, and IMF policies [Ruddick, 2020]). Instead of providing only aid-based programs to help alleviate poverty, using also markets to do so and contribute to achieving sustained growth in developing economies is becoming more common [Cooney and Shanks, 2010]. One of the issues with many aid-based development programs is the flow of aid funds to individuals in low-liquidity areas right back to city centers and financiers, creating a never-ending cycle of liquidity constraints. The goal of Community Inclusion Currencies (CIC) and other market-based approaches is to reduce poverty and liquidity constraints in poverty-stricken areas is to close the loop of net cash outflows by providing an incentives program that keeps the liquidity in local economies.

This chapter contributes to the applied blockchain currency literature from a perspective that combines computer science and systems engineering approaches to what those of monetary economics. Blockchain currency design has primarily occurred from within the computer science discipline without always knowledge of the original concepts, theory, or history from monetary economics. Often the same concepts use different terminology, sometimes even thought to be 'new' when ‘discovered’ but computer scientists. In this chapter, both sets of terminology, computer science/token economics definitions will be supplied along with their parallels in economics to help bridge the gap in how cryptocurrencies are discussed.

In this chapter, a simulation of Grassroots Economics Foundation’s Community Inclusion Currency implementation deployed in Kenya is provided, generalized as a graph-based dynamical system model that can provide a scaffold for macro-prudential economy planning for the project and similar projects.

4.2 Literature Review

The use of simulations for representing currency interactions is not new to economics Christian et al. [2018], Smets and Wouters [2003], Diebold et al. [1998], Rengs et al. [2019]. Other community currency simulations have been performed before Boik [2014], although using another modeling paradigm, systems dynamics stock-flow approach. The novelty of our work is the application of a bonding curve to a cryptographic currency and complex system subpopulation modeling of economic value flows, and implementation of a cryptoeconomic system design. Voshmgir and Zargham [2019] describe how systems theory provides the analysis tools for evaluating and designing the relationship and dependencies between cryptoeconomic systems parts, and how dynamic, adaptive, and multiscale socioeconomic systems can be created. Leaning heavily on the complex system theory, with an interdisciplinary lens, cryptoeconomic systems design is an amalgamation of heuristics and economics, engineering, operations research, control theory, and computer science, to name a few, of the multitude of components required to design a functioning cryptoeconomic economy. Bringing together these influences allows a more concrete and comprehensive few of developing a model, that transcends the traditional economic definition of a model, as the IMF describes as economic models are simplified descriptions of reality used to test a hypothesis about economic behavior and can be simple heuristics up to nonlinear, interconnected differential equations [Ouliaris, 2020]. Regardless of the complexity, the goal of economic modeling is the same: to explain hypotheses and answer questions. No model is a perfect representation of reality. However, as the statistician George E. P. Box once said: “All models are wrong, but some are useful”. Through the use of the cadCAD modeling tool, our simulation has been optimized to represent reality through the use of Monte Carlo simulations and parameter sweeping of values to better fit real-world data [BlockScience, 2018].

4.2.1 Simulation tools

When it comes to dynamic system simulation software, the leading software has been, arguably, MATLAB's Simulink [MathWorks, 1984]. Simulink has been around for over 30 years, and is used throughout industry and academia for digital twins, industrial processes, robotics, to name a few use use-case categories. Simulink provides a graphical user interface for model building, simulations, analysis, and verification of models. Simulink models can be exported to C and embedded systems code for use in industrial applications. There are even detailed books on Simulink, such as Klee and Allen [2011] "Simulation of Dynamic Systems with MATLAB and Simulink". However, as successful and widespread Simulink is, Simulink is a closed-source, proprietary tool. In the distributed ledger technology (DLT) paradigm and ecosystem, open-source software is at a distinct advantage, being able to be shared and integrated without vendor licenses. cadCAD (complex adaptive systems, computer-aided design), in comparison, as first discussed in chapter 2, is a Python-based, open-sourced, unified modeling framework for dynamical systems and differential equation simulations. It is capable of modeling systems at all levels of abstraction from Agent-Based Modeling (ABM) to System Dynamics (SD) with the integration of with existing data science workflows and paradigms [BlockScience, 2018]. Modeling in cadCAD, despite its relative immaturity, provided the benefits of the open-source community with the ability to seamless integrate with the robust Python ecosystem, as well as respecting the DLT ethos and community.

4.2.2 Community currencies, currency boards, and exchange rates

Community currencies operate in a fashion similar to currency boards. A currency board is a rule-based monetary policy that operates in a sort of autopilot to maintain a fixed exchange rate of a national currency with that of an identified reference foreign currency. To maintain this peg, the monetary authority needs to have 100%+ of the domestic currency backed with foreign reserve assets. A currency board, due to its limited capacity, cannot monetization fiscal deficits or lend to commercial banks, or perform any monetary inflationary policy standard across central banks. This allows the domestic currency to be fully backed by foreign asset reserves, which are designed to prevent depreciation of the currency, sometimes referred to in monetary economics as demurrage or debasement. Most often, currency boards use the US Dollar or Euro as the peg, however, any strong, global currency with ample liquidity and reach are sufficient to serve as pegs. Large-scale success stories of currency boards are Hong Kong (since 1983), Argentina (since 1991), and Bulgaria (since 1997) [Hanke, 2002]. Analogously, for community currencies, usually a private operator or local authority will act as the currency board and is responsible for the exchange, circulation, and redemption of their tokens or vouchers to the national or peg currency at par or the respective rate of the scheme.

The Grassroots CIC project has been created utilizing the emerging field of Tokenomics, which is a subset of Cryptoeconomics to build a type of currency board [Ruddick, 2020, Voshmgir and Zargham, 2019]. The studied implementation of the CIC system, which the simulations in this paper are a scaffolding of, use the Bancor protocol, named after Keynes' 1944 Bretton Woods international reserve currency proposal, for the underlying bonding curve and smart contracts [Hertzog et al., 2018]. Under the Bancor protocol, a bonding curve, a curve that defines the relationship between price and token supply, is used to automatically control the redemption rate of a token into the underlying reserve asset, essentially an automated currency board [Zargham et al., 2019]; see Figure 4.1. In the CIC implementation, xDai, a stable coin backed by the USD at a 1:1 stable exchange rate, serves as the reserve with CIC's being minted at a 4:1 basis [Barinov, 2018]. CICs are created, or minted at a 4:1 however redemption occurs on a 1:1 basis. The CIC white paper proposes the ability to link the Grassroots Sarafu CIC implementation with other CICs with potential different reserves to create a flexible, larger system of interoperability community currencies [Ruddick, 2020]. Using a blockchain system, the ability of interoperability is increased, automated governance by smart contracts; and an open, public ledger for validation are all factors that could help contribute to the CIC project, and other subsequent related community currencies a success.

According to Ruddick [2020], the new main sources of CIC price stability are market price arbitrage and collateral systems. In the case of market price arbitrage, by taking advantage of market inefficiencies with the bonding curve, traders, and investors can obtain profits while creating price stability for CIC users. By connecting the CIC system indirectly to the USD, the reserve is steady to reduce fluctuations in the value of the CIC, when, under certain conditions, users can withdraw their CIC at the defined rate to a national currency. NGOs, such as the Red Cross, can distribute funds to a CIC contract to increase the underlying reserve pool, thus funding an increase in market efficiency with distribution in rural communities vs humanitarian aid without as high of a multiplier potential, as previous research has indicated, an increase in national currency does not reflect to an extent, an increase in actual productive capacity [Ryan-Collins, 2011]. Estimates from Grassroots Economics is that a roughly 20x leverage on donated funds into CIC reserves is possible [Ruddick, 2020].

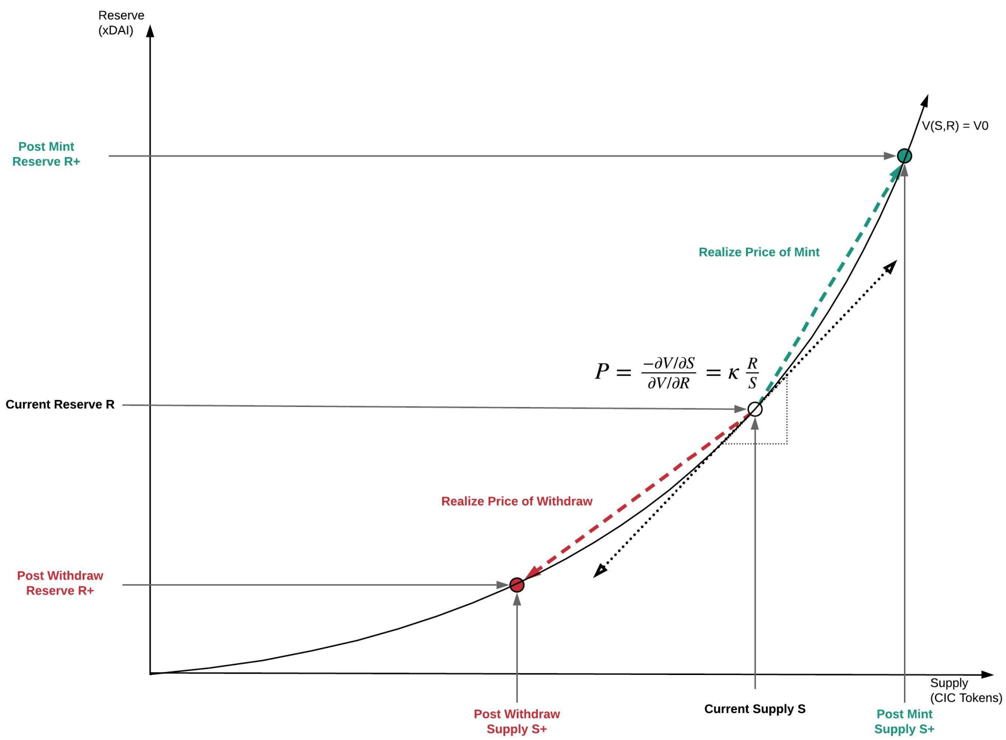

Figure 4.1: Bonding Curve Illustration of CIC Bancor Implementation

4.2.3 Development Aid Programs

Within the standard development aid programs, little literature exists on new aid innovations, comparable to the community currencies outlined thus far. A paper Udvari and Ampah [2018] states that not all aid is created equal, with some aid not directly beneficial in driving economic growth, while some targeted aid given to drive innovation and create infrastructure has been shown to drive economic growth. Their literature review of aid effectiveness literature showed that good governance of the receiving country and the institutional background of the facilitator are two leading indicators for aid effectiveness. Udvari and Ampah [2018] also found that innovation funding is currently a small proportion of total aid, but that its impacts on economic growth were positive.

The United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA) operates a Cash and Voucher Assistance (CVA) program, that has expanded as a result of COVID-19 [OCHA, 2021]. The program is using technology such as voice ID, for fund verification, delivery, evaluation, and monitoring. However, this program does not appear to have any local economy-building incentives built-in. Aker [2015] research shows that cash transfers are more effective than in-kind transfer, from a randomized experiment in the Democratic Republic of Congo. Hidrobo et al. [2014] research from a randomized experiment in Ecuador shows that cash, food vouchers, and food transfers are all effective at improving the quality and quantity of food consumed, however food transfers had the largest increase in calories consumed. The emphasis of community currencies on growing local economies is unique among aid organizations, although as outlined by Udvari and Ampah [2018], there are programs, such as the World Bank's Digital Economy Initiative for Africa (DE4A) that aim to grow developing economies through digital economy innovation [World Bank, 2021].

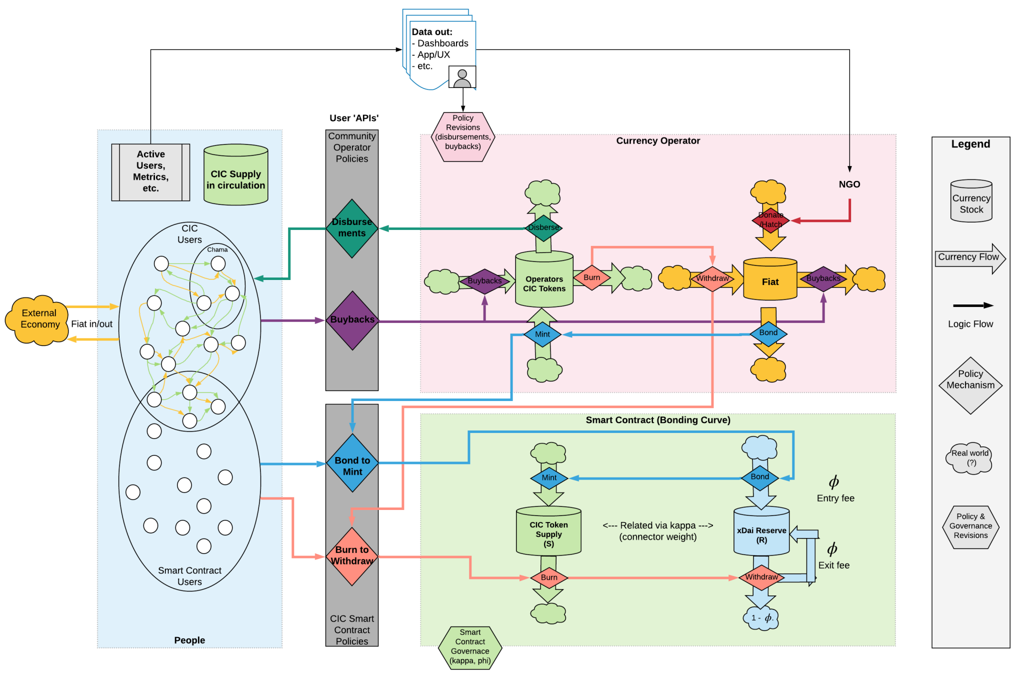

Figure 4.2: General Model

This chapter is organized as follows: Section 4.3 explains the modeling approach. Section 4.4 walks the reader through the model's components, with their internal structure and external connections. Section 4.5 summarizes and interprets the main results from our simulation runs, and section 4.6 concludes.

4.3 Formalized Model

The model proposed by this paper for studying community inclusion currencies within a complex system approach is described in Figure 4.2[2]. The model described here is generalized, which contributes to the build-up of a framework for developing currency simulations. with the system, We will layer in the specific case of *Grassroots Economics* in our simulation construction, as illustrated in Figure 4.5. The blue box shows the mixing process of subpopulations interacting with each other, and their interactions with the external economy, symbolized by the orange cloud, and with the pink box, or currency operator. The pink box is the meso-level local economic operator who is created as an institute in the support of blue box health economic growth. The pink box economic regulator (or in economic terms, policymaker) supports the health of the blue box (local) economy by allocations to individual agents and subpopulations when they join the economy, provides them the mechanisms of converting allocations, as well as providing governance policies to help to create a healthy blue box. The green box is an algorithmic monetary policy rooted in a bonding curve, as described by Zargham et al. [2019]. The green box is a regulator of the pink box, which is offering policies in the blue box. The goal of our simulations and modeling is to help guide the pink box (currency operator, policymaker) in managing the economy to keep the blue box healthy and promote economic growth. All parts of the environment/ecosystem must be working in harmony to create homeostasis (or equilibrium) in the system and a means for easing the liquidity constraints prevalent in failed local economies. We describe each section more thoroughly in the subsequent subsections.

4.3.1 Mixing Process

The community mixing model, as shown in the blue box in Figure 4.2 and 4.5, is a topological object representation of the interactions of subpopulations in a local economy. By modeling the trends and interactions of subpopulations clusters in an economy, we can observe system metrics from a macro level to help drive policy decision and economic interventions.

To represent the stochastic process that connects the implementation economy to the wider economy, we describe our mixing process of intra and inter subpopulations interacting into a networked, graph model evolving over time. Assuming we have a directed graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$ with subpopulations as vertices or nodes, $\mathcal{V} = \{1...\mathcal{V}\}$ and edges as $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$. Demand, utility, and spend are edges connecting the subpopulations, with demand used to denote desired flow between agents, as $i, j \in \mathcal{E}$. Technically, the graph is a weighted, directed multigraph with more

[2]See the appendix for a full mathematical specification of the system

than one edge, $i \longrightarrow j$ for any pair of vertices $i, j \in \mathcal{V}$ with $w_{i,j}$. A meso structure was chosen instead of the more standard Agent-based Model (ABM) technique, as the purpose of this simulation is to represent subpopulation movements for the optimization of the local economic currency system. Although theoretically, an ABM approach could be constructed for this purpose, it would be computationally intractable without specialized hardware; and the benefits do not outweigh the costs. Based on the behavior of the system in question the heterogeneity of clusters of agents, as further described in section 4.3.1, a subpopulation meso structure is most fitting for the use case [Voshmgir and Zargham, 2019, Dopfer et al., 2004].[3]. ABM models are interpretable, providing granularity of agents' behavior. However, ABMs, depending on the use case, can be computationally intractable for realistic agent-based modeling. Due to the computational intractability, and complexity of producing realistic, representative agents, for this use case, meso layer modeling was selected instead as it provided enough detail of the economic complexity while reducing computational overhead. Meso layers focus on change, whereas traditional micro and macro models focus on equilibrium and do not as readily account for the evolution and acceptance of rule changes [Dopfer et al., 2004].

In the next section, we describe the node types represented in our topographical model, as well as the edges within our multi-graph.

Node Types

- **Agent** is a user of the system. In the case of our applied simulation, agents are subpopulation representations of the real system data.
- **Cloud** is a representation of the open boundary to the world external to the model.
- **Contract** is the smart contract of the bonding curve.

Edges between agents

The edge weight $\mathcal{G}_{i,j} > 0$ takes on non-binary values, representing the intensity of the interaction, so we refer to (N, g) as a weighted graph. $\mathcal{E}$ is the set of directed edges, i.e., $i, j \in \mathcal{E}$

- **Demand** is the amount a subpopulation wants to interact in a given time step.

[3]Agent-based modeling (ABM) is a well-known modeling paradigm to simulate the interaction of autonomous agents and their results on the underlying system[Bonabeau, 2002, Turrell, 2016]

- **Fraction of demand in community currency** is the amount in a given transaction, the subpopulation wants to interact in token, with 50% being in community currency and 50% of the transaction being in the native currency, in this case, shilling.

- **Utility** is the subpopulation's utility for the transaction. For the spend calculations described later, we stack ranking the utilities to determine, given a liquidity constraint, which subpopulations will interact with. We describe the utility types and the ranking mechanism in the section 4.3.1.

- **Spend** records the amount of community currency and shilling that was exchanged in a given time step.

- **Fraction of actual spend in community currency** records the percentage of the transaction that was in community currency, for example, with 50% being in community currency and 50% of the transaction being in the native currency, in this case, shilling.

Subpopulation Modeling

As described in section 4.3.1, our desire to model at the meso-layer has driven the decision to use subpopulation modeling to model the blue box, or mixing process [Dopfer et al., 2004]. To use subpopulation, we are taking a graph zoom operation, bundling agents together based off their likeness. Nodes are constant, with edges being transitive. The algorithm we use for this graph zoom operation is Kmeans Clustering, as first described by Lloyd [1982].

To compute the clusters, we take Grassroots Economics [2020b] CIC implementation actual transactional data from January – May 11, 2020 (See Table 4.1 for the computed clusters). The data has the following features:

- Payer individual location
- Payer individual business type
- Receiver individual location
- Receiver individual business type
- Weight, which is tokens, exchange amount
- Payer individual CIC wallet balance
- Receiver individual CIC wallet balance

Based on our descriptive statistical analysis and use of the Gap Statistic, first described by Tibshirani et al. [2001], we determined that fifty clusters are representative of the subpopulations, see Figure 4.3. Fifty clusters were decided as our upper bound that we put into the gab statistic due to computational limits and the desire to model on a subpopulation vs agent-based level. All the flows inside the bundle become part of the self-loop flow. For example, within cluster 1, agent a can transaction with other agents; however these 'intra' transactions will not be explicitly recorded by our simulations as our model is representative of inter-cluster interactions.

cluster	median_source_balance	1st_quartile_source_balance	3rd_quartile_source_balance
0.00	150.00	56.00	403.96
1.00	340.00	118.46	506.60
2.00	250.00	105.00	592.96
3.00	20.00	64,767.51	64,767.51
4.00	330.00	251,652.00	251,652.00
5.00	320.00	124.50	1,501.41
6.00	240.00	4,139.28	7,214.90
7.00	300.00	146.10	869.82
8.00	300.00	1,002.50	1,557.01
9.00	50.00	17,145.78	18,304.36
10.00	900.00	52,676.20	55,142.93
11.00	120.00	100.00	419.96
12.00	400.00	121,082.43	121,082.43
13.00	180.00	112.00	816.30
14.00	300.00	28,849.43	38,653.54
15.00	6,000.00	27,619.22	37,106.89
16.00	132.50	66.36	770.65
17.00	130.00	251,652.00	251,652.00
18.00	160.00	148.00	838.46
19.00	5,000.00	38,653.54	38,653.54
20.00	150.00	67.22	315.00
21.00	10,000.00	121,082.43	121,082.43
22.00	200.00	6,429.46	9,074.79
23.00	10,000.00	555.04	5,726.66
24.00	200.00	104.48	602.02
25.00	200.00	96.43	437.96
26.00	35,000.00	52,676.20	63,234.80
27.00	20,000.00	251,652.00	251,652.00
28.00	100.00	64.73	425.00
29.00	500.00	36,824.50	40,953.15
30.00	425.00	15,182.03	17,145.78
31.00	13,320.00	485.94	6,349.27
32.00	500.00	21,660.89	25,695.83
33.00	500.00	11,210.00	13,156.46
34.00	1,000.00	100,579.18	100,579.18
35.00	390.00	100.46	819.33
36.00	150.00	2,845.01	4,158.50
37.00	250.00	3,338.98	5,597.38
38.00	45,000.00	1,274.91	2,823.81
39.00	36,300.00	6,724.88	20,030.91
40.00	960.00	38,653.54	51,710.52
41.00	120.00	114.50	537.94
42.00	200.00	68.00	542.92
43.00	100.00	100.00	415.43
44.00	220.00	20.93	895.66
45.00	600.00	14,050.30	18,304.36
46.00	62,000.00	63,145.96	63,145.96
47.00	500.00	9,276.23	14,050.30
48.00	900.00	63,234.80	64,767.51
49.00	486.00	64,767.51	64,767.51
Aggregated values			
Median	325.00	5,284.37	8,144.85
1st Quartile	185.00	112.63	817.06
3rd Quartile	900.00	38,653.54	49,021.18

Table 4.1: Descriptive statistics of the CIC historical data from January – May 11, 2020

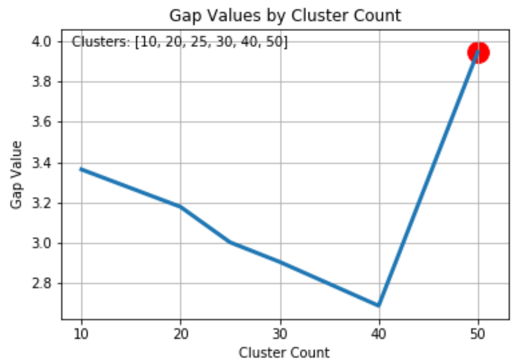

Figure 4.3: Gap Statistic of tested clusters

The starting native currency of the subpopulations was calculated from the 1st to 3rd quartile of cluster source balances. Starting tokens are the cluster's median source balance.

Utilities were calculated off of actual transaction data, and ordered by their types and probability within each cluster. Below are types and probability for cluster 2:

```
* Utility Types Ordered
 * Savings Group
 * Farming/Labour
 * Food/Water
* Utility Types Probability
    * 0.64
    * 0.25
    * 0.11
```

Figure 4.4: Utility Types and their Probability

Based on these subpopulation calculations, we can drive the blue box mixing process from actual agent-level interactions zoomed out to the subpopulation level.

4.3.2 Currency Operator

The pink box, as described above in section 4.3, is the meso-level economic operator whose purpose is to promote a healthy economy in the blue box. The Currency

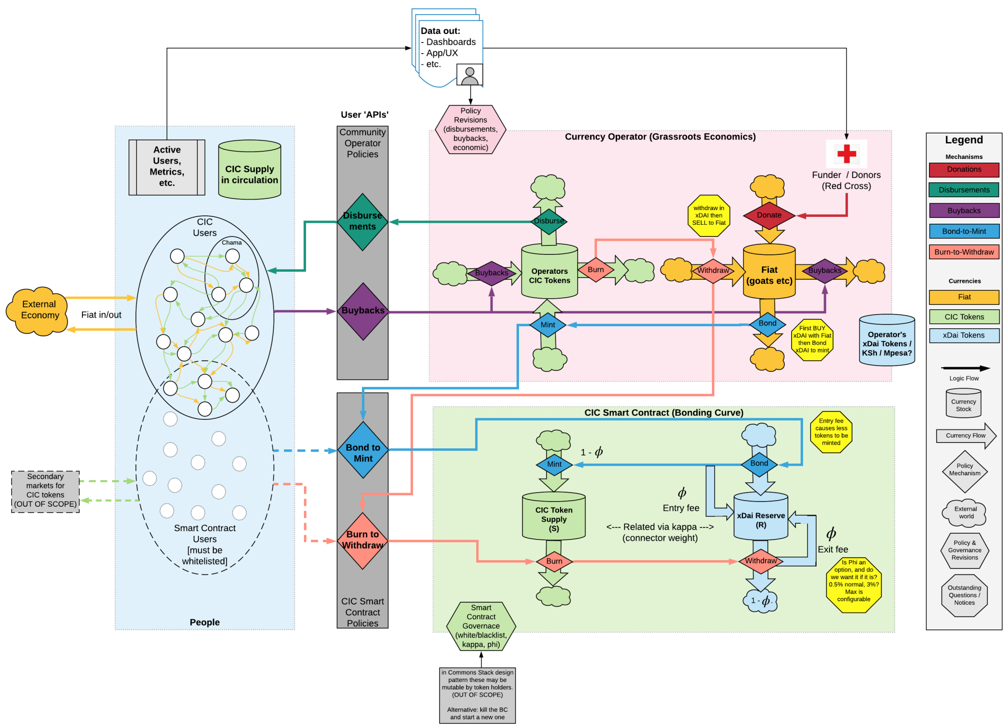

Figure 4.5: System dynamics model of CIC system representation

Operator, in this case, Grassroots Economics as of May 2020, issued CIC to new users, set at 400 CIC per each new agent, provides a mechanism for conversion at 1:1 into Kenyan Shilling, as well as drives monetary policy and structure [Ruddick, 2020]. In a general form, there is a net outflow to the system caused by the Currency Operator giving CIC's to agents, and allowing the redemption of their tokens. This causes a classic inventory control problem of managing that enough CIC and fiat exists to manage the Currency Operator's operations and provide the outflow of liquidity into the system. There are several mechanisms to manage net outflow, such as external donor drip, which is the current process, and illustrated in Figure 4.5, as well as the introduction of transaction fees. Below, we will describe both the mechanisms for the inventory control problem that is embedded into our simulation model and the disbursement and buyback policies.

The *inventory_controller* policy addresses the inventory control problem of the system. There is a natural tension between the operator CIC balance and operator's fiat balance, as the system has a natural net outflow. Conceptually, we can think of this as a heuristic conservation allocation policy between fiat and CIC

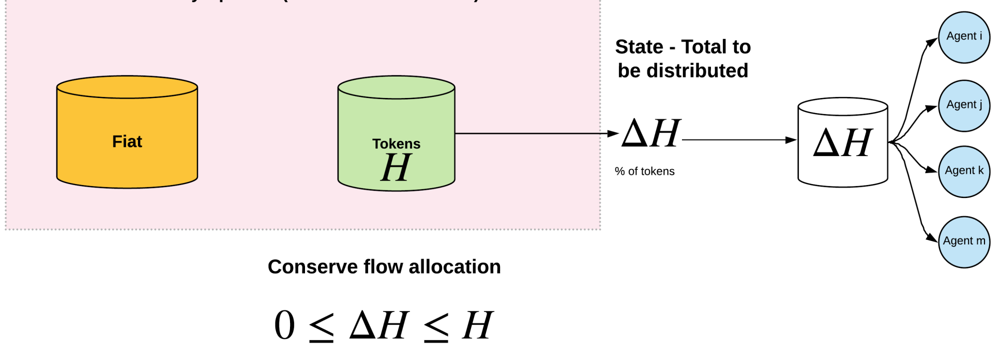

Figure 4.6: Subpopulation CIC Disbursement

reserves. We've created an inventory control function to test if the current balance is an acceptable tolerance. For the calculation, we use the following 2 variables, current CIC balance and current fiat balance, along with 2 parameters, desired CIC and variance, see Figure 4.7 for the allocation policy. For our model's purposes, we are assuming that the operator begins with 100,000 of Fiat and CIC, in our simulation initialization.

If the controller wants to mint, the amount decided from the inventory controller, ΔR is inserted into the minting equation, as described above in more detail in the bonding curve section 4.3.3.

There is a built-in process lag of 15 days before the newly minted or burned CIC is added to the respective operator accounts. This lag is a result of the financial lag time of bonding/minting funds and clearing this funds through the traditional banking system. The result of the *inventory_controller* behavior policy are directives to mechanisms to update the system variables according to whether any minting or burning occurred.

For disbursement, we assume that every subpopulation has already started with their CIC's, and we distribute a total of 1,000 to each subpopulation every 30 days. There is also a potential for allocation to occur based on a measure of individual agent centrality. Internal velocity is better than the external velocity of the system. Point of leverage to make more internal cycles. Can be used for tuning system efficiency. To improve system efficiency, as a fiscal multiplier, CIC could be distributed based on individual agent network centrality. Supply side economics method of increasing internal system velocity by providing more liquidity to the most active agents in the network.

```
if idealFiat - varianceFiat <= actualFiat <= idealFiat + (2*varianceFiat):
        decision = 'none'
        amount = 0
    else:
        if (idealFiat - varianceFiat) > actualFiat:
            decision = 'burn'
            amount = (idealFiat + varianceFiat) - actualFiat
        else:
            pass
        if actualFiat > (idealFiat + varianceFiat):
            decision = 'mint'
            amount = actualFiat - (idealFiat + varianceFiat)
        else:
            pass

    if decision == 'mint':
        if actualCIC < (idealCIC - varianceCIC):
            if amount > actualCIC:
                decision = 'none'
                amount = 0
            else:
                pass
    if decision == 'none':
        if actualCIC < (idealCIC - varianceCIC):
            decision = 'mint'
            amount = (idealCIC-varianceCIC)
        else:
            pass
```

Figure 4.7: Pseudocode representation of the heuristic inventory control algorithm

4.3.3 Currency Regulator — Bonding Curve

A bonding curve is a mechanism of market making and liquidity provider in token economies; and is similar in function to a currency board. In this section, the CIC bonding curve is explained, which is similar to Zargham et al. [2019, 2020] work as well as the Bancor protocol by Hertzog et al. [2018].

Humpage and McIntire [1995] describe bonding curves and their primary pros and cons for developing economies. Currency boards provide developing economies credibility and price stability by pegging their currency to a foreign currency, such as the USD, as often a 1:1 exchange rate. To have a credible link to a foreign currency, greater than 100% foreign currency reserves must be held. Notes issued to the public and the countries banking sector cannot exceed the board's holding of foreign-exchange reserves. The credibility of a currency board rests on the notion of full convertibility to the linked foreign currency [Humpage and McIntire, 1995][4]. In turn, by having the monetary link, the developing economy's currency gains credibility.

How bonding curves and currency boards have a similarity is in the automatic

[4]When a developing country chooses which reserve currency to peg to, they need to be sure to choose a country, such as the United States that runs a consistent current account deficit, as to ensure there are adequate reserves available to acquire.

adjustment to maintain a fixed exchange rate. Bancor's bonding curve protocol assumes the function of a non-profit automated market maker, with a smart contract calculating supply and demand for two respective currencies. In the case of the CIC implementation, the economic operator holds both CIC's and xDai. When the economic operator wants to increase the supply of CIC, they need to obtain enough xDai reserves to support the 'mint'.

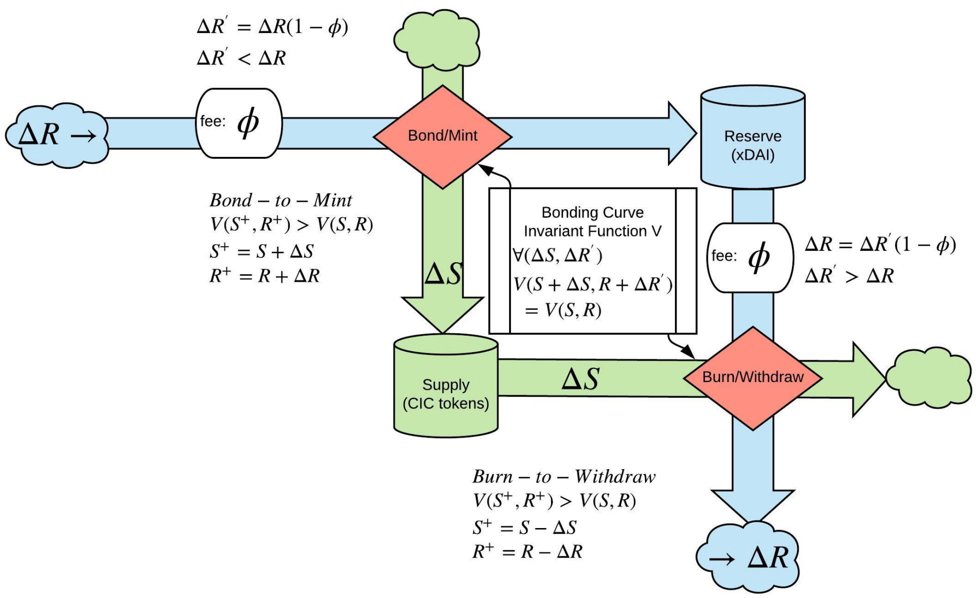

Figure 4.8: CIC Bonding curve

An important component of a bonding curve is its conservation function, a measure of a property that is an invariant, which means that the value of the conservation function remains unchanged under the allowable system transitions. For our model, the conservation function is:

$$V(S,R) = \frac{S^\kappa}{R}$$

with R being the xDai in Reserve and S as the Total Supply of CIC tokens in the system.

The deposit to mint equations are deposit ΔR xDAI to mint ΔS CIC tokens

$$\Delta S = mint\big(\Delta R; (R,S)\big) = S\big(\sqrt[\kappa]{(1+\frac{\Delta R}{R})} - 1\big)$$

The burn to withdraw equations are burn ΔS CIC tokens to withdraw ΔR xDAI

$$\Delta R = withdraw\big(\Delta S; (R, S)\big) = R\big(1 - (1 - \frac{\Delta S}{S})^{\kappa}\big)$$

System level initialization parameters shown below were determined based on simulation, analytical methods, and discussions with the Grassroots Economics team.

- $R_0 = 40000$ xDAI to generate S_0 initial supply
- The 'Connector Weight' in Bancor terms maps to the concept 'Target Reserve Ratio' $\rho = \frac{1}{\kappa} = \frac{R}{P \cdot S}$
- Conversion rate between USD and Kenyan Shilling is approximately 1:100
- Assume $P_0 = 1/100$ to ensure spot price is the right order of magnitude
- Leveraged applied to the bonding curve $\kappa = 4$
- Above implies $S_0 = 4 \times 100 \times 40000 = 16\,Million$ for the initial supply of CIC tokens

Figure 4.9 shows the base bonding curve case as determined by the originally suggested values by Grassroots Economics.

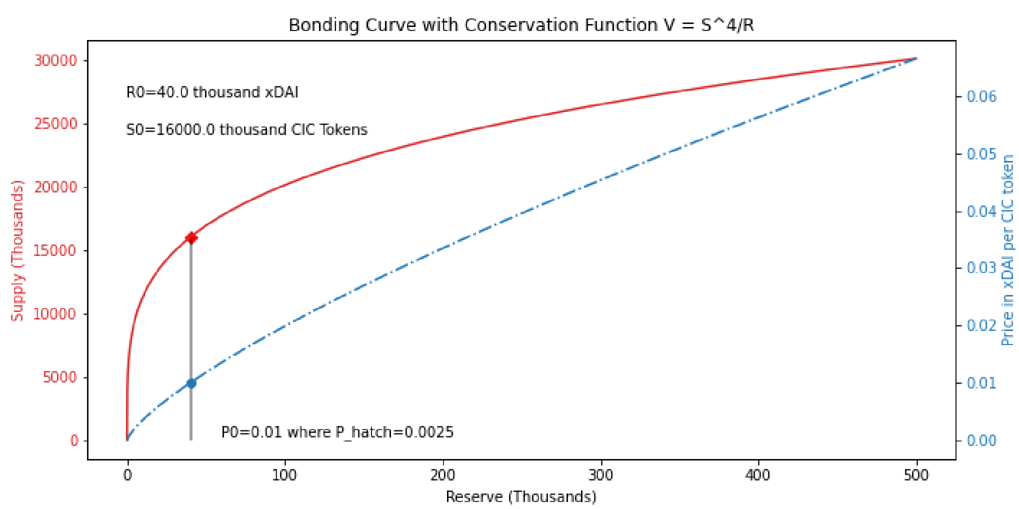

Figure 4.9: CIC Bonding Curve with initialization values

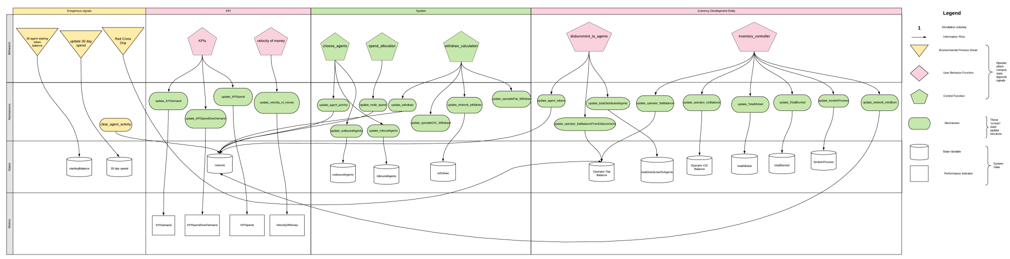

Figure 4.10: Differential Specification of the System

The bonding curve mathematics are relatively new but not novel in this project, with widespread deployment not prevalent. In the developmental economic context, the success of the Grassroots Economics project could be the first deployment of a bonding curve outside a pure token economy implementation. In traditional economics, bonding curves can be compared to currency boards.

4.4 System Walkthrough

In the cadCAD simulation methodology, we operate on four layers: **Behavior Policies, Mechanisms, States, and Metrics**. We can describe the interaction of these four layers through a differential specification using system modeling syntax, described by Zargham [2019]. Information flows do not have an explicit feedback loop unless noted in Figure 4.10. **Policies** determine the inputs into the system dynamics and can come from user input, observations from the exogenous environment, or algorithms. **Mechanisms** are functions that take the policy decisions and update the States to reflect the policy level changes. **States** are variables that represent the system quantities at the given point, and **Metrics** are computed from state variables to assess the health of the system. Metrics can often be thought of as KPIs, or Key Performance Indicators. See 4.11 for a snippet of the partial state update blocks and Table 4.2 for a listing of the states of the system.

4.4.1 Order of Events

In the system Figure 4.10 differential specification, we have 4 separate parts of the model, *Exogenous signals, KPI, System, and Currency Development Entity.* Each part is composed of 1 or more partial state update blocks, which when taken in sequence, create a state update, or one increment of a time step. **Exogenous** signals are a substep of the system with mechanisms that do not have policies.

```
partial_state_update_block = {
    # Users
    'Behaviors': {
        'policies': {
            'action': choose_agents
        },
        'variables': {
        'network': update_agent_activity,
        'outboundAgents': update_outboundAgents,
        'inboundAgents':update_inboundAgents
        }
    },
```

Figure 4.11: Example Partial State Update Blocks

System is the Figure 4.5 blue box, or mixing process interactions. **Currency Development Entity** is the policies and mechanisms for the Currency Operator, or Figure 4.5 pink and green boxes, whereas **KPI** are the system metrics. Below, we enumerate the substeps of a system time step.

1. Calculate the starting balance of the individual subpopulations every 30 days, the subpopulations actual 30 days spend, as well the periodic donor shilling drip[5], and clearing out the previous simulation step network mixing process activity. The starting balances and 30 days spend mechanisms are used to create variables that serve as a basis to simulate the aggregated agent withdraw off the Grassroots Economics CIC withdraw policy.

2. The System is the graph mixing process. Individual subpopulations will interact with each other to simulate inter-subpopulation value flows. With the graph structure discussed in 4.3.1, the first behavior, *choose_agents*, takes a uniform random sample of 46 from the 51 subpopulations (50 clusters plus external economy) for the payer subpopulations and another uniform random sample for the receiver subpopulations. The behavior policy then calculates the payer demands based on a Gaussian distribution computed from the μ actual CIC transactions involving the subpopulation and the σ of the actual transactions, as described in section 4.3.1. If the payer is the external economy node, we compute a Gaussian distribution based on average

[5]The basic model is an issuer with goods or services on offer (such as goats). The donor side of this was only bootstrapping and future donations will go into the bonding curve

of the average subpopulation μ and σ. To calculate the payer subpopulation's utility, we take a uniform distribution of the source subpopulation's business types and use their probability of occurrence, i.e., Food and Water-type occur 41% of the time in subpopulation 1 inter-cluster interactions, so we will choose this utility type 41% of the time. Note that for the scope of our simulations, we are assuming each subpopulation interacts once with one utility type for each time step. As the result of this behavior policy, we update the mixing graph with the edges that are interacting, their demand, utility, and the fraction of demand in CIC. For simulation purposes, we are assuming that the fraction of demand for a transaction is 50% fiat, 50% CIC, with 100% fiat if the subpopulation is interacting with the external environment.

3. The second behavior of the system, *spend_allocation*, we calculate, based off the desired interacting subpopulation's demand, utility, and liquidity constraints, i.e., the amount of CIC and shilling each subpopulation has available. We iterate through the desired demand and allocate based on a stack ranking of utility $v_{i,j}$ over demand $\frac{v_{i,j}}{d_{i,j}}$ until all demand for each subpopulation is met or the subpopulation i runs out of CIC and shilling. In the mechanisms, we then update the graph with the actual spend between agents.

4. The third and final behavior in the System section is the *withdraw_calculation*. Per Grassroot Economic policy, individual users can withdraw up to 50% of their CIC balance if they have spent 50% of their balance within the last 30 days at a conversion ratio of 1:1, meaning that for every one token withdraw, they receive 1 in Shilling [Ruddick, 2020]. For our subpopulation model, we are assuming that the agents want to withdraw as much as they can. One generalization we make from the system is that agent will have their 30-day clocks starting when they have joined the system. For simplification, in our model, we are assuming that each subpopulation is on the same 30-day clock. This produces jagged withdrawal graphs, but the net flows of the system are the same. This is one of the most important control points for Grassroots Economics. The more people withdraw CIC from the system, the more difficult it is on the system. The more people can withdraw, the better the adoption, however. The inverse also holds: the fewer individuals can withdraw, the lower the adoption. 30,000 is the max allowable amount to be withdrawn per 30 days. The mechanisms based on the behavior policy update the operator Fiat and CIC balances, the aggregated withdraw state, as well as the individual subpopulations, based on their activity.

5. The next sequence in our partial state update blocks is the Currency Development Entity. This sequence has two behaviors, *disbursement_to_agents* and *inventory_controller*, as described above in 4.3.2. In *disbursement_to_agents*, CIC is distributed to the subpopulations as a means of Universal Basic Income, or UBI.

6. The final section of our system model is the KPI's partial state update blocks. This policy group has two behaviors, *kpis* and *velocity_of_money*. The *kpis* behavior policy iterates through the network model edges to ascertain the subpopulation edge weights of demand and spend for the current time step. The policy function aggregates the spend and demand for a system level view of how much spend and demand occurred on the network during the time step, as well as spend over demand, to see how much of the demand was fulfilled. A spend over demand of 1 means that not all demand was satisfied, whereas a value of 1 denotes that all subpopulation demand was met. The behavior policy has three subsequent mechanisms that update the metrics variables of KPIDemand, KPISpend, and KPISpendOverDemand with the timestep results.

   - Behavior policy *velocity_of_money* calculates the velocity of money per timestep via indirect measurement. Research by de la Rosa and Stodder [2015] has shown that the velocity of local currencies can be as much as five times higher than their corresponding national currencies.

     $$V_t = \frac{PT}{M}$$

     Where V_t is the velocity of money for all agent transaction in the period examined, P is the price level, T is the aggregated real value of all agent transactions in the period examined, and M is the average money supply in the economy in the period examined. The *velocity_of_money* mechanism updates the metric variable of VelocityOfMoney.

4.5 System Run and Results

cadCAD provides the ability for Monte Carlo runs. Due to the stochastic nature of our system, Monte Carlo runs will provide an averaged readout on how a system will perform. As a result of the size and complexity of the model with the subpopulations, we will run 5 Monte Carlo runs over 100 time steps to produce time series quartile charts of Subpopulation Spend, KPISpendOverDemand, VelocityOfMoney, and operator CIC and fiat balances. As a result of the simulations, see

State Variables	Purpose
network	Multi-directed graph in NetworkX objectHagberg et al. [2008]
KPIDemand	Subpopulation demand from the timestep in dictionary format
KPISpend	Subpopulation spend from the timestep in dictionary format
KPISpendOverDemand	Subpopulation spend divided by demand in dictionary format
VelocityOfMoney	Velocity of money from the timestep
startingBalance	The starting subpopulation CIC balance in dictionary format
30_day_spend	Subpopulation spend over the last thirty timesteps
withdraw	Subpopulation actual withdraw, in dictionary format
outboundAgents	Subpopulation agents that are paying during the timestep.
inboundAgents	Subpopulation agents that are receiving during the timestep
operatorFiatBalance	Currency operator Fiat balance.
operatorCICBalance	Currency operator CIC balance
fundsInProcess,	Dictionary of Dictionaries that records funds awaiting settlement
totalDistributedToAgents	Total amount of CIC distributed to agents during the simulation
totalMinted	Total amount of CIC minted during the simulation
totalBurned	Total amount of CIC burned during the simulation

Table 4.2: State variables for the economic system simulation

Figures 4.12, 4.13, 4.14, 4.16, and 4.15, we can observe the predicted net outflow of fiat from the system, or enable some sort of fee structure [Clark, 2020a]. For this illustration, and the desire for this sort of simulation model to not be completely 'driverless' the rough heuristic inventory control algorithmic policy defined above was turned off for the simulations run. As has been illustrated in this paper, the potential for system level decision-making regarding the withdrawal policies, liquidity requirements of the currency development operator, the introduction of transaction fees, the ability of traders and investors to interact with the network to provide liquidity and interact with the bonding curve, calculating the fiscal multiplier of an external liquidity development investment are all examples of subsequent work that could be performed for a specific currency development use case based off the network-based framework we have enumerated above.

4.5.1 Main Findings and Contributions

This chapter examined what community inclusion currencies are, based on the simulation application performed regarding the *Grassroots Economics* CIC's project in Kenya, as of May 2020. Furthermore, in this chapter a network-based complex systems model of subpopulation interactions was described, and a simulation of the performance of the economic system given some hyperparameters was performed.

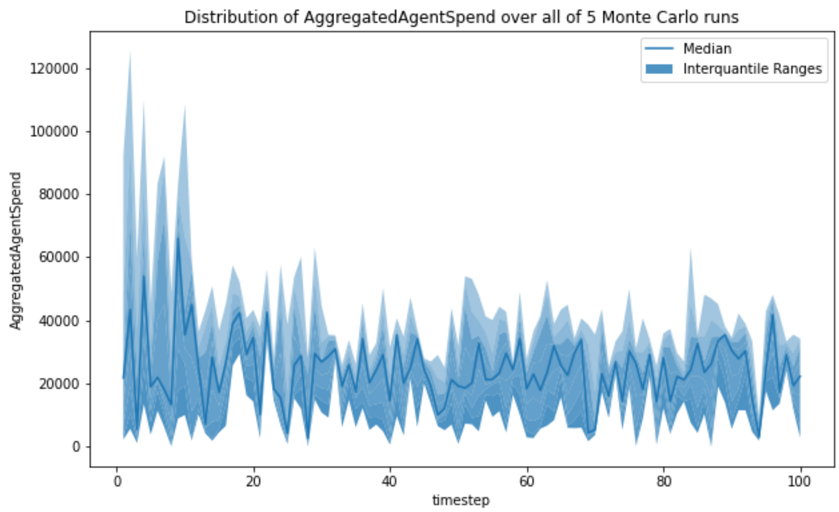

Figure 4.12: Aggregated inter-subpopulation spend. This figure shows the aggregated inter-subpopulation spend per time step of the simulation. After the system initialization of agent spend and economy outflows, the spend stays relatively constant, despite no new agents introduced.

Contributions to the economic literature, in particular on new forms of money and cryptoeconomics, was a novel meso-economic approach, in-between the standard extremes of micro and macro in modeling the local economy and its use of a CIC.

The contribution of this chapter to the computer science, and tokeneconomics communities are:

- Providing a scaffold for modeling community currency viability and net flows.
- Implementing a network-based dynamical systems modeling approach that is more grounded in economic and monetary theory, to simulate a subpopulation mixing processes.
- Applied computational modeling of complex systems embodying key economic principles.

By utilizing complex systems modeling and modern computational simulations, modeling of economic systems can be accomplished to aid development efforts and guide monetary policy decisions.

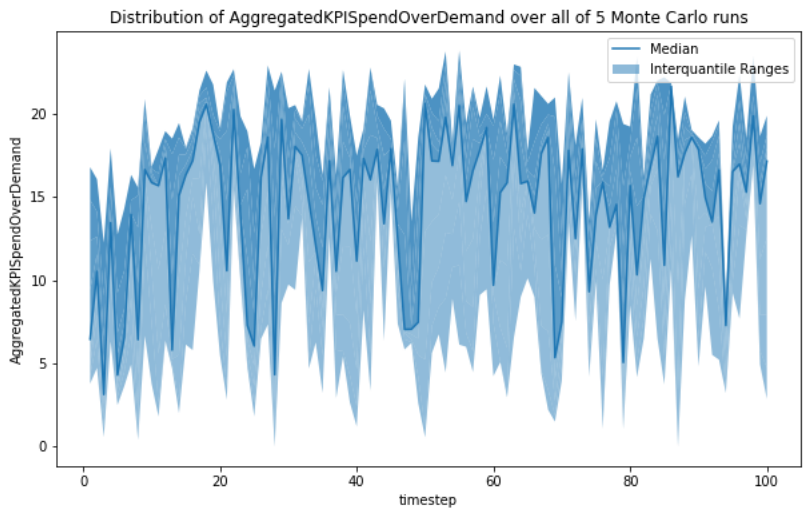

Figure 4.13: Aggregated inter-subpopulation KPI spend over demand. A value of 1 means that all demand is fulfilled, while a value of less than 1 shows us that not all subpopulation wants were met, based off our stochastic demand function.

4.5.2 Future Research

In our paper, we have created a meso-subpopulation model for modeling the Grassroots Economics CIC project, but can be configured for other economic modeling use cases. The model we have created was designed to be leveraged for making decision about how to govern the economy and manage monetary and fiscal policy. Future research on this model includes adding more detailed adoption processes, the introduction of fees, and the execution of simulation experiments to drive operational decision-making. Enumerated below are the recommended modeling next steps:

- User adoption and randomized withdrawal
    - Poisson Distribution — fractions of CIC in subpopulations (change withdraw and distribution policies)
        - Add new subpopulation adoption
        - to randomize when subpopulations withdraw. They each have a separate '30 day' clock.

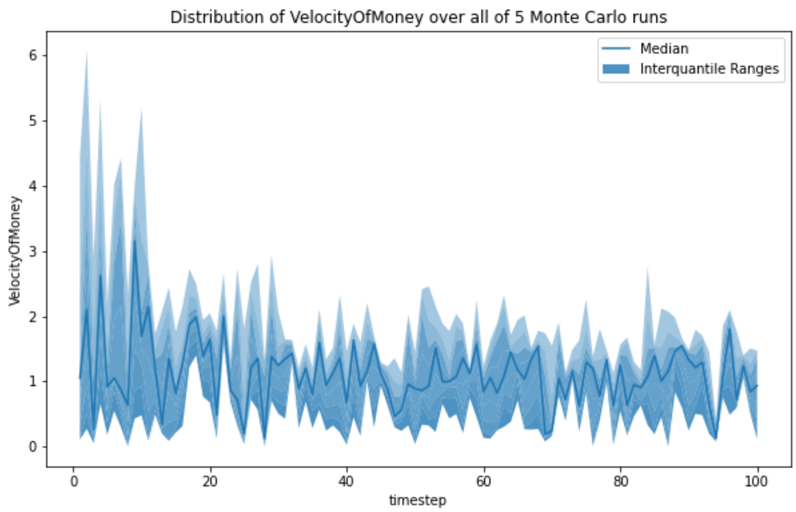

Figure 4.14: Aggregated inter-subpopulation velocity of money. Very similar to trend and insight from figure 4.12

    * Cash-outs are discrete events in continuous time. Time between events is a flow weighted exponential distribution. Generate time between events, with the amount to disburse based on the mixing process.
    * Lower bound is 30 days. There is a max of 30k withdraw per 30 days for the system. Some cash out at every time step. We want to pull the conditional exponential distribution given the subpopulation.
    * Poisson's distribution for each subpopulation for new arrivals.
    * For each subpopulation, we will represent these arrivals by the percentage of CIC that is available for withdrawal.

- Weighted edges for choosing probability of subpopulations interacting. I.e., subpopulations interact with the same 5 subpopulations primarily
- provide an ability to derive the fiscal multiplier of NGO buy ins, which would enable us to evaluate the amount of lift these liquidity injections can provide.
- Fee mechanisms

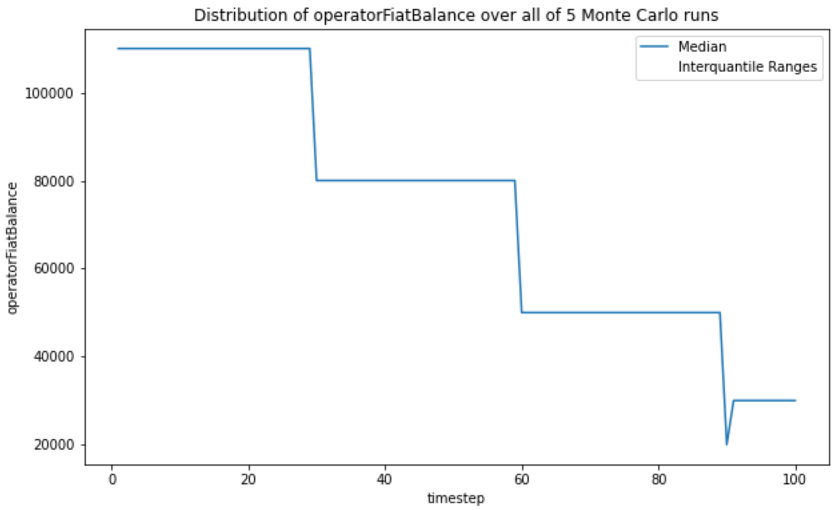

Figure 4.15: Operator fiat balance. Since the CIC system in this simulation is a net outflow, relying on donations, the balance is downward trending, per expectation. The subsequent introduction of fees, see section 4.5.2, will be focused on making this balance static or trending slightly positive.

  - Parameter sweeps on fee percentages, and which actors to impose them, i.e., traders, investors, or general users via transaction fees.

- Payer and receiver needs to have separate amount of CIC demanded. Payer wants to pay in 100% fiat, whereas receiver may only want 5% fiat. Need to reconcile the two and track the difference.
  - Create 'negotiator' policy and separate generator functions.
  - Fraction of demand in CIC edge type to dictionary of type payer key value and receiver key value
- Move to closed loop model without external drips or new buy ins.
- Advanced algorithmic inventory allocation
  - If scarcity on both sides, add feedback to reduce percentage able to withdraw, frequency you can redeem, or redeem at less than par.
- Percentage of k cycles centrality- for rewards feedback/basic income

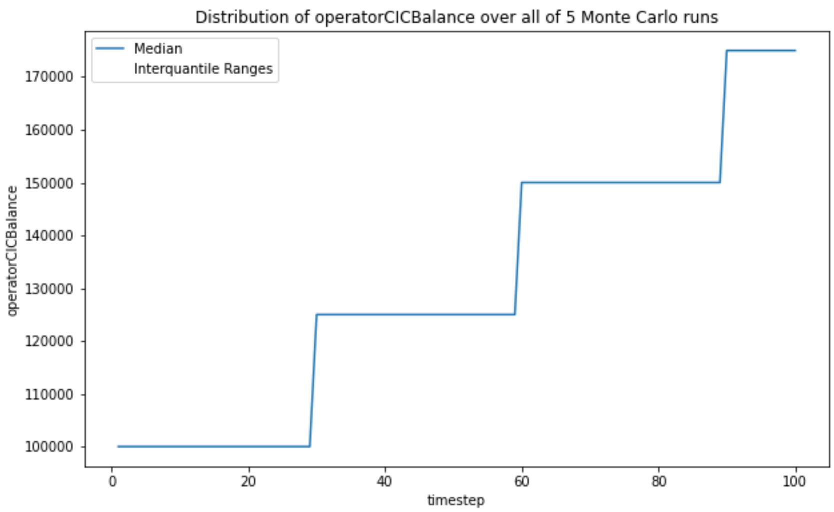

Figure 4.16: Operator CIC balance. As a result of minting and buybacks, the CIC balance is increasing, as expected.

4.5.3 Reproducibility

To replicate the simulation results we presented here, we direct the reader to visit `https://www.anaconda.com/products/individual` to download Python 3.7+ for the specific version of operating system, i.e., Linux, macOS. To install cadCAD and download the source code, we direct the reader to run the commands shown in Figure 4.17 in their command line:

```
# Install cadCAD
pip install cadCAD==0.3.1

# Download code
git clone -b paper https://github.com/BlockScience/Community_Inclusion_Currencies.git

# Access the repository
cd Community_Inclusion_Currencies

# Run a notebook server
jupyter notebook
```

Figure 4.17: Bash shell commands to download simulation code

4.6 Conclusion

In our paper we have examined what community currencies are, enumerated the Grassroots Economics CIC project in Kenya, as of May 2020, created a network-based complex systems model of subpopulation interactions, and a simulation of the performance of the economic system given some hyperparameters. The contribution to economic literature from our model is three-fold:

- a Scaffold for modeling community currency viability and net flows.
- A theoretically grounded network-based modeling approach to simulate subpopulation mixing processes.
- Applied computational modeling of complex systems utilizing economic principles.

By utilizing complex systems modeling and modern computational simulations, modeling of economic systems can be accomplished to aid development of economic efforts and guide monetary policy decisions.

Chapter 5

Conclusion

5.1 Economic Policy Implications

The three preceding chapters have shown where computational techniques can be used to look at long-standing or emerging economic phenomena with a fresh lens, using practitioner technology. In chapter 2, the concept of using complex dynamic systems as the basis for economic forecasting was introduced and illustrated how a dynamic system model could provide a path to accurate forecasts. Chapter 3 outlines the motivation behind private cryptocurrencies, how they function, and why they are in their early stages and not ready to be used as an asset or form of money, specifically, as an international reserve asset. Chapter 4 describes community currencies, provides historical context, and outlines a novel meso-layer dynamic simulation model as a new paradigm for modeling economic systems. In the next sections, specific concepts and computational techniques are examined in more detail for their impact on economic policy.

5.1.1 Forecasting and Machine Learning

The utilization of ML in economics and specifically for economic modeling is a relatively new development, but when strict global interpretability and casualty are not the key driving points of the model, such as in forecasting, ML provides a lot of promise [Athey, 2018]. ML is sometimes conflated with 'p-value hacking' and 'Big Data Mining' where correlation and casualty are sometimes intermingled. However, advanced ML models and methodologies, when correctly constructed and applied, in the appropriate contexts, can provide more accuracy and provide richer, more complex analysis than generalized linear models.

ML, in areas such as NLP, has a lot of potential in economic policymaking by providing a means to filter vast amounts of data for actionable insight. For instance, as illustrated in chapter 2, NLP can be used for sentiment analysis of news articles, Twitter feeds, and the like for insights into what consumers or the public are thinking, and make inferences on their behavior. Data provided by these refined data streams can greatly improve existing policy frameworks and economic models. With the different types of NLP available, and the increasing accuracy of transfer learning models, historical economic research can be drastically changed by the inclusion of unsupervised and transfer learning topic modeling, for instance, to examine old texts for insights, when supervised training sets are not available.

Computer Vision (CV) has many applications in development economics, microeconomic modeling, macroeconomic modeling by the analysis of satellite images, and stock market forecasting [Donaldson and Storeygard, 2016, Partnoy, 2019, Yao, 2019]. In a developmental context, a country's night lights provide information, especially over time, to its level of economic growth. As a country develops from poverty to a more robust economy, it is brighter at night. However, when a country reaches a certain level of development, productivity increases turn from factories and commercial and residential development to knowledge increases [Yeh et al., 2020]. Hedge funds have used the alternative data from satellites to augment their fundamental analysis models to forecast company earnings for years [Partnoy, 2019].

5.1.2 Cryptocurrencies

In chapter 3, the motivation behind Bitcoin and the grassroots push for non-centralized, means of exchange and storage of value were explored, along with an analysis of the top 10 cryptocurrencies by market cap, as of June 2020. Additionally, an alternative history counterfactual of what would have happened to the Bank of England's foreign exchange reserves if they had held a percentage of private cryptocurrencies is developed. In this section, policy implications of cryptocurrencies will be discussed, primarily as an overview of recommendations for central banks.

Central Bank Digital Currencies (CBDC)

1. In free, dynamic economies, such as the US and the UK, CBDC lack a strong reason for being and could introduce more centralization and risk to the already extremely centralized international financial system. Central banks issuing currency directly to consumers would interfere with the segregation of duties in the financial system and the 'lender of last resort' function of central banks, not to mention the enormous risks involved with cybersecurity

and the impact on the economy by potentially eliminating commercial and retail banking functions. In economies such as the US, there is still a large demand for physical cash, especially among the elder population, and a fear of government and government overreach. The adoption of a CBDC may not be high enough to justify the expense of issuing it. In centrally managed economies such as China, CBDC may make more sense.

2. One argument in favor of CBDC is the potential to reach more non-banked people, but as this dissertation has shown, in chapter 4, the use of more targeted, local, community currencies, which could be cryptographically based, would be better suited to the task than a large, centralized option.

3. An argument could be made that CBDC's could reduce criminal activity if implemented exclusively to replace all physical cash. In technocratic circles, this idea is gaining traction. However, this should not be a decision made without public discourse and the democratic voting processes, as state surveillance and management would go to a yet unfathomable place in the free world [Gnan et al., 2018]. An argument could also be made for fully digital CBDC to allow for negative interest rates, a topic many central banks are drawn to overcome the interest rate zero bound. However, as has been shown in many instances, negative interest rates are not very effective at increasing the velocity of money [Bank, 2020, Arteta et al., 2016].

CBDC's do not have a clear benefit in a free, democratic society, and any implementation in the Western World should not be decided in the shadows but by a public referendum. Enhancing regulation of private cryptocurrencies can be implemented to help prevent money laundering and other illicit activities by taking a technology-neutral approach and enforcing existing same KYC, AML, etc., regulations. However, if implemented too aggressively without adaptation, existing regulations could hamper financial innovation.

5.1.3 Complex System Models

Complex systems are systems that combine many elements that interact with each other in unique and complex ways. Complex system behavior isn't easily modeled due to properties that include nonlinearity, adaption, feedback loops, emergence, and spontaneous order [Voshmgir and Zargham, 2019]. Complex system theory is very interdisciplinary, with heavy influences from economics, control theory, engineering, and physics, in an attempt to holistically understand the system. Complex systems models are applied in cryptoeconomic or tokeneconomic modeling, as chapter 4 contributes to, and have interesting applications as Digital Twins, modeling the impact of CBDCs, and as a potential enhancement for Dynamic Stochastic General Equilibrium (DSGE) models. Having more accurate models and modeling paradigms such as cadCAD will enable central banks and economics to create more realistic representations of economic phenomena to learn about their interconnectedness and, as discussed early, enhance their predictive accuracy [BlockScience, 2018].

5.2 Future Research

Based on the research conducted for this dissertation, and the research conducted during my professional career, my subsequent research areas will focus along with the following areas:

1. Complex system modeling of economic systems, methods, and applied. Research on modeling existing systems more closely as decision support software, and developing supporting methodologies along with using complex systems modeling to help design cryptoeconomic implementations. An example of a recent project I worked on is modeling a cryptoeconomic voting system [Zargham and Clark, 2020].

2. Using satellite imagery for economic forecasting. As discussed earlier in this chapter, advancements in computer vision have provided a rich and unmanageably large dataset that can be applied to many applications in economics. Using this rich set of data in a macroeconomic context for finding correlations or causality with standard macroeconomic metrics. To what extent, combined with complex systems modeling, can image data provide policymakers with early warning actionable insight on economic phenomena, and provide richer information for decision-making will be my primary research objectives.

3. ML model validation. Through the company I've co-founded, Monitaur.ai, an ML assurance start-up, methods to verify that under a given range of assumptions, a model non-biased against protected classes and performs as expected, within a reasonable range of assurance, is of paramount importance [Habayeb and Clark, 2019]. Using an interdisciplinary approach, taking the current academic literature from model checking, formal verification, behavioral economics, and computer science, defining an approach for validating that a model is performing as expected will provide a useful service to Monitaur's customers, as well as provide some key research papers that will be helpful in not only the computer science field, but also the field

of economics for verifying assumptions and stress testing of economic models. A speech by Federal Reserve Governor Brainard [2021] talked about the risks of AI and ML models for making decisions that affect consumers and calls for increased diligence by banks for ensuring bias-free and explainable models. The work my company does and the research I will be conducting directly supports these initiatives.

5.2.1 Thesis limitations and potential future expansion

With the future, adjacent research interests outlined, below are actionable steps for revising the existing dissertation chapters and related discussion papers for journal submissions.

A Pound-Centric look the Pound vs. Krona Exchange Rate Movement from 1844 to 1965 — Chapter 2

1. Convert yearly data to monthly for more granular analysis.
2. Create a financial newspaper-specific training data set for sentiment analysis instead of using the modern IMDB dataset by using data generation techniques.
3. Experiment with adding more macroeconomic variables such as interest rates and money supply.

Why Private Cryptocurrencies Cannot Serve as International Reserves but Central Bank Digital Currencies Can — Chapter 3

1. Include a discussion about institutions and their role in money, specifically as they pertain to organizations behind private cryptocurrencies.
2. Under which circumstances, a public (rather than private) cryptocurrency could rise to be a valid parallel currency on the scale of a national currency, but not necessarily as a substitute for a national currency.

Complex System Modeling of Community Currencies — Chapter 4

1. Add behaviors and mechanisms for user adoption and randomized CIC withdrawal.
2. Add behavior and mechanisms for various fee regimes, such as transaction fees. Perform parameter sweeps and simulations to determine the ideal fee levels optimized for platform goals.
3. Conduct formal stress testing to determine where the network breaks down, such as not enough network activity.

5.3 Conclusion

"Money and Exchange Rates from a Computational Perspective" has contributed to the computational monetary policy literature by linking ML, complex systems, and emerging cryptocurrency paradigms to existing methodologies and techniques, through the lens of practitioner technology.

Chapter 2 has shown that a complex system ML forecasting model outperforms a random walk during the World Wars. "New" ML modeling techniques are not and cannot be a replacement for data quality, causal modeling, and understanding the linkages between variables. Throwing more data at a problem is not always the best solution and domain expertise in determining feature design and cannot be overstated.

Chapter 3 provides a literature review, analysis, and discussion on private cryptocurrencies, highlights their limitations, and shows their instability and volatility for use as an international reserve asset. Through the analysis, it was determined that central bank digital cryptocurrencies could be viable, but there lacks a strong case for why they are needed.

Chapter 4 contributes to the economics literature by providing an overview, discussion, and analysis of community currencies, and a novel, meso-level complex system model implementation. The chapter helps to bridge the gap between monetary economics and computer science/token economics. By utilizing complex system modeling and modern computational simulations, modeling economic systems can be accomplished to aid development economic efforts and guide monetary policy decisions.

Bibliography

The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 1969. URL https://www.nobelprize.org/prizes/economic-sciences/1969/summary/. Last visited 2021-01-22.

Alan Akbik, Duncan Blythe, and Roland Vollgraf. Contextual string embeddings for sequence labeling. In *COLING 2018, 27th International Conference on Computational Linguistics*, pages 1638–1649, 2018.

Jenny C. Aker. Comparing Cash and Voucher Transfers in a Humanitarian Context: Evidence from the Democratic Republic of Congo. SSRN Scholarly Paper ID 2684219, Social Science Research Network, Rochester, NY, October 2015. URL https://papers.ssrn.com/abstract=2684219.

Laura Alfaro and Fabio Kanczuk. Optimal reserve management and sovereign debt. *Journal of International Economics*, 77(1):23–36, February 2009. URL https://ideas.repec.org/a/eee/inecon/v77y2009i1p23-36.html.

Massimo Amato and Luca Fantacci. *Complementary Currencies*, pages 501–522. Springer Singapore, Singapore, 2020. ISBN 978-981-13-0596-2. doi: 10.1007/978-981-13-0596-2_50. URL https://doi.org/10.1007/978-981-13-0596-2_50.

David Andolfatto. Blockchain: What It Is, What It Does, and Why You Probably Don't Need One, 2018. URL https://research.stlouisfed.org/publications/review/2018/02/13/blockchain-what-it-is-what-it-does-and-why-you-probably-dont-need-one. Last visited 2020-12-08.

Carlos Arteta, Ayhan Kose, Marc Stocker, and Temel Taskin. Negative interest rate policies : sources and implications. *Policy Research working paper - World Bank Group*, (WPS 7791), 2016. URL https://documents.worldbank.org/en/publication/documents-reports/documentdetail/235551470834953672/Negative-interest-rate-policies-sources-and-implications.

Susan Athey. *The Impact of Machine Learning on Economics*, pages 507–547. University of Chicago Press, January 2018. doi: https://doi.org/10.7208/chicago/9780226613475.001.0001. URL http://www.nber.org/chapters/c14009.

Susan Athey and Guido Imbens. Machine learning methods economists should know about, 2019.

Atlantic Council. Central Bank Digital Currency Tracker, 2021. URL https://www.atlanticcouncil.org/cbdctracker/. Last visited 2021-08-15.

Raphael Auer. Beyond the doomsday economics of "proof-of-work" in cryptocurrencies. January 2019. URL https://www.bis.org/publ/work765.htm. Last visited 2020-12-08.

T. Balogh. International Reserves and Liquidity. *The Economic Journal*, 70(278): 357–377, 06 1960. ISSN 0013-0133. doi: 10.2307/2228736. URL https://doi.org/10.2307/2228736.

European Central Bank. Going negative: the ECB's experience. August 2020. URL https://www.ecb.europa.eu/press/key/date/2020/html/ecb.sp200826~77ce66626c.en.html.

Bank for International Settlements. Triennial Central Bank Survey of foreign exchange and OTC derivatives markets in 2016. December 2016. URL https://www.bis.org/publ/rpfx16.htm. Last visited 2020-11-05.

Bank for International Settlements. V. Cryptocurrencies: looking beyond the hype. June 2018. URL https://www.bis.org/publ/arpdf/ar2018e5.htm. Last visited 2020-12-07.

Bank for International Settlements. III. CBDCs: an opportunity for the monetary system. June 2021. URL https://www.bis.org/publ/arpdf/ar2021e3.htm. Last visited 2021-08-09.

Bank of England. Real Gross Domestic Product at Market Prices in the United Kingdom, January 2019. URL https://fred.stlouisfed.org/series/RGDPMPUKA. Last visited 2021-02-12.

Igor Barinov. *xDai STAKE*, 2018. URL https://www.xdaichain.com/. Last visited 2020-06-14.

Marta Bańbura, Domenico Giannone, Michele Modugno, and Lucrezia Reichlin. Chapter 4 - now-casting and the real-time data flow. In Graham Elliott and

Allan Timmermann, editors, *Handbook of Economic Forecasting*, volume 2 of *Handbook of Economic Forecasting*, pages 195–237. Elsevier, 2013. doi: https://doi.org/10.1016/B978-0-444-53683-9.00004-9. URL https://www.sciencedirect.com/science/article/pii/B9780444536839000049.

Ben Bemanke and Harold James. The Gold Standard, Deflation, and Financial Crisis in the Great Depression: An International Comparison. Technical Report c11482, National Bureau of Economic Research, January 1991. URL https://www.nber.org/books-and-chapters/financial-markets-and-financial-crises/gold-standard-deflation-and-financial-crisis-great-depression-international-comparison.

Pierpaolo Benigno. Monetary Policy in a World of Cryptocurrencies. CEPR Discussion Papers 13517, C.E.P.R. Discussion Papers, February 2019. URL https://ideas.repec.org/p/cpr/ceprdp/13517.html.

Aleksander Berentsen and Fabian Schar. The Case for Central Bank Electronic Money and the Non-case for Central Bank Cryptocurrencies, 2018. URL https://research.stlouisfed.org/publications/review/2018/02/13/the-case-for-central-bank-electronic-money-and-the-non-case-for-central-bank-cryptocurrencies. Last visited 2020-12-07.

Aleksander Berentsen and Fabian Schär. A short introduction to the world of cryptocurrencies. *Review*, 100:1–16, 01 2018. doi: 10.20955/r.2018.1-16.

Aleksander Berentsen and Fabian Schär. *Stablecoins: The quest for a low- volatility cryptocurrency*, pages 65–71. 03 2019.

David Bholat, Stephen Hans, Pedro Santos, and Cheryl Schonhardt-Bailey. *Text mining for central banks.* Number 33 in Handbooks. Centre for Central Banking Studies, Bank of England, December 2015. URL https://ideas.repec.org/b/ccb/hbooks/33.html.

BIS Monetary and Economic Department. Foreign exchange turnover in April 2019. September 2019. URL https://www.bis.org/statistics/rpfx19_fx.htm. Last visited 2020-11-25.

Bitcoin Association. Bitcoin SV: Build on the only public blockchain designed for Enterprise, 2018. URL https://bitcoinsv.io/. Last visited 2020-06-07.

BlockScience. cadCAD – A Python package for designing, testing and validating complex systems through simulation, 2018. URL https://cadcad.org.

Codruta Boar and Andreas Wehrli. Ready, steady, go? - Results of the third BIS survey on central bank digital currency. January 2021. URL https://www.bis.org/publ/bppdf/bispap114.htm. Last visited 2021-08-09.

Jan Bohlin. *Historical Monetary and Financial Statistics for Sweden: Exchange rates, Prices and Wages, 1277–2008*, volume I, chapter 7 - From appreciation to depreciation-the exchange rate of the Swedish krona, 1913-2008, pages 340–411. Svergies Riksbank, 2010. URL https://www.riksbank.se/globalassets/media/forskning/monetar-statistik/volym1/7.pdf. Last visited 2021-11-28.

John Boik. First micro-simulation model of a ledda community currency-dollar economy. *International Journal of Community Currency Research*, 18(A):11–29, 10 2014.

Eric Bonabeau. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, 99(suppl 3): 7280–7287, May 2002. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas.082080899. URL https://www.pnas.org/content/99/suppl_3/7280.

Lael Brainard. Speech by Governor Brainard on supporting responsible use of AI and equitable outcomes in financial services, 2021. URL https://www.federalreserve.gov/newsevents/speech/brainard20210112a.htm. Last visited 2021-01-13.

Bristol Pound CIC. Bristol Pound – More than money, 2018. URL https://bristolpound.org/. Last visited 2021-01-04.

BullionStar. Central Bank Gold Policies - People's Bank of China - Gold University - BullionStar, 2020. URL https://www.bullionstar.com/gold-university/central-bank-gold-policies-peoples-bank-china. Last visited 2020-12-04.

Bitcoin Cash. Bitcoin cash, 2017. URL https://www.bitcoincash.org/. Last visited 2020-06-07.

Richard E. Caves. International liquidity: Toward a home repair manual. *The Review of Economics and Statistics*, 46(2):173–180, 1964. ISSN 00346535, 15309142. URL http://www.jstor.org/stable/1928183.

Chiranjit Chakraborty and Andreas Joseph. Machine learning at central banks. Bank of England working papers 674, Bank of England, September 2017. URL https://ideas.repec.org/p/boe/boeewp/0674.html.

Bruce Champ. Private Money in our Past, Present, and Future. *Economic Commentary*, (January 1, 2007), January 2007. URL https://www.clevelandfed.org/newsroom-and-events/publications/economic-commentary/economic-commentary-archives/2007-economic-commentaries/ec-20070101-private-money-in-our-past-present-and-future.

Tianqi Chen and Carlos Guestrin. Xgboost: A scalable tree boosting system. *CoRR*, abs/1603.02754, 2016. URL http://arxiv.org/abs/1603.02754.

Brandon Chez. Global Charts, 2013. URL https://coinmarketcap.com/charts/. Last visited 2018-12-20.

Lawrence J. Christian, Martin S. Eichenbaumand, and Mathias Trabandt. On dsge models. *Journal of Economic Perspectives*, 32(3):113–40, August 2018. doi: 10.1257/jep.32.3.113. URL https://www.aeaweb.org/articles?id=10.1257/jep.32.3.113.

Andrew Clark. CIC modeling. https://gitlab.com/grassrootseconomics/cic-modeling, 2020a. Last visited 2021-11-28.

Andrew Clark. A pound centric look at the pound vs. krona exchange rate movement from 1844 to 1965. Economics Discussion Papers em-dp2020-22, Department of Economics, Reading University, October 2020b. URL https://ideas.repec.org/p/rdg/emxxdp/em-dp2020-22.html.

Andrew Clark and Alexander Mihailov. Why private cryptocurrencies cannot serve as international reserves but central bank digital currencies can. Economics Discussion Papers em-dp2019-09, Department of Economics, Reading University, May 2019. URL https://ideas.repec.org/p/rdg/emxxdp/em-dp2019-09.html.

Andrew Clark, Alexander Mihailov, and Michael Zargham. Complex Systems Modeling of Community Inclusion Currencies. Economics Discussion Papers em-dp2021-06, Department of Economics, Reading University, January 2021. URL https://ideas.repec.org/p/rdg/emxxdp/em-dp2021-06.html.

Peter B. Clark. Optimum international reserves and the speed of adjustment. *Journal of Political Economy*, 78(2):356–76, 1970. URL https://EconPapers.repec.org/RePEc:ucp:jpolec:v:78:y:1970:i:2:p:356-76.

Jay Clayton. SEC.gov | Statement on Cryptocurrencies and Initial Coin Offerings, 2017. URL https://www.sec.gov/news/public-statement/statement-clayton-2017-12-11. Last visited 2020-12-08.

Kate Cooney and Trina R. Williams Shanks. New approaches to old problems: Market-based strategies for poverty alleviation. *Social Service Review*, 84(1): 29–55, 2010. ISSN 00377961, 15375404. URL http://www.jstor.org/stable/10.1086/652680.

A. Cowles. Can stock market forecasters forecast. *Econometrica*, 1:309, 1933.

Crypto.com Chain. Crypto.com Chain, 2020. URL https://chain.crypto.com. Last visited 2020-06-07.

CryptoCompare. The Best Free CryptoCurrency Price and Historical Data API for Developers | CryptoCompare API (trades, news, streaming and toplists also available), 2020. URL https://min-api.cryptocompare.com. Last visited 2020-06-07.

CryptoSlate. Stablecoin Cryptocurrencies, 2020. URL https://cryptoslate.com/cryptos/stablecoin/. Last visited 2020-11-25.

Jean-Pierre Danthine. Negative interest rates in Switzerland: What have we learned? *Pacific Economic Review*, 23(1):43–50, 2018. ISSN 1468-0106. doi: https://doi.org/10.1111/1468-0106.12251. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/1468-0106.12251.

Joshua Davis. The Crypto-Currency, 2011. URL https://www.newyorker.com/magazine/2011/10/10/the-crypto-currency. Last visited 2021-11-28.

Nikhilesh De. Tether Lawyer Admits Stablecoin Now 74% Backed by Cash and Equivalents, April 2019. URL https://www.coindesk.com/tether-lawyer-confirms-stablecoin-74-percent-backed-by-cash-and-equivalents. Last visited 2020-11-25.

Josep Lluís de la Rosa and James Stodder. On velocity in several complementary currencies. 2015. URL https://ijccr.files.wordpress.com/2015/02/ijccr-2015-rosa-stodder.pdf.

Francis Diebold and Roberto Mariano. Comparing predictive accuracy. *Journal of Business Economic Statistics*, 13(3):253–63, 1995. URL https://EconPapers.repec.org/RePEc:bes:jnlbes:v:13:y:1995:i:3:p:253-63.

Francis X. Diebold, Lee E. Ohanian, and Jeremy Berkowitz. Dynamic equilibrium economies: A framework for comparing models and data. *The Review of Economic Studies*, 65(3):433–451, 1998. ISSN 00346527, 1467937X. URL http://www.jstor.org/stable/2566933.

Division of Corporation Finance, Division of Investment Management, and Division of Trading and Markets. SEC.gov | Statement on Digital Asset Securities Issuance and Trading, 2018. URL https://www.sec.gov/news/public-statement/digital-asset-securites-issuuance-and-trading. Last visited 2020-12-08.

Dave Donaldson and Adam Storeygard. The View from Above: Applications of Satellite Data in Economics. *Journal of Economic Perspectives*, 30(4):171–198, November 2016. ISSN 0895-3309. doi: 10.1257/jep.30.4.171. URL https://www.aeaweb.org/articles?id=10.1257/jep.30.4.171.

K. Dopfer, J. Foster, and J. Potts. Micro-meso-macro. *Journal of Evolutionary Economics*, pages Springer–Verlag, 2004.

Rodney Edvinsson. *House Prices, Stock Returns, National Accounts, and the Riksbank Balance Sheet, 1620–2012*, volume II, chapter 4 - The Gross Domestic Product of Sweden within present borders, 1620–2012, pages 101–182. Svergies Riksbank, 2014. URL https://www.riksbank.se/globalassets/media/forskning/monetar-statistik/volym2/chapter4_-volume2_140613.pdf. Last visited 2021-11-28.

Martin S. Eichenbaum and Neil Wallace. A shred of evidence on public acceptance of privately issued currency. *Quarterly Review*, Winter:2–4, 1985. URL https://reinventingmoney.files.wordpress.com/2016/09/qr911-canadiantiremoney.pdf.

Steve Ellis, Ari Juels, and Sergey Nazarov. Blockchain Oracles for Connected Smart Contracts | Chainlink, 2017. URL https://chain.link/. Last visited 2020-06-07.

Ethereum. Ethereum, 2014. URL https://ethereum.org. Last visited 2020-06-07.

Eugene F. Fama. The Behavior of Stock-Market Prices. *The Journal of Business*, 38(1):34–105, 1965. ISSN 0021-9398. URL https://www.jstor.org/stable/2350752.

Eugene F. Fama. Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2):383–417, 1970. ISSN 0022-1082. doi: 10.2307/2325486. URL https://www.jstor.org/stable/2325486.

Federal Reserve. The Fed - Why does the Federal Reserve aim for inflation of 2 percent over the longer run?, 2020. URL `https://www.federalreserve.gov/faqs/economy_14400.htm`. Last visited 2021-10-22.

Sergio Focardi. Is economics an empirical science? if not, can it become one? *Frontiers in Applied Mathematics and Statistics*, 1:7, 2015. ISSN 2297-4687. doi: 10.3389/fams.2015.00007. URL `https://www.frontiersin.org/article/10.3389/fams.2015.00007`.

Aidan Fuller, Zhong Fan, Charles Day, and Chris Barlow. Digital Twin: Enabling Technologies, Challenges and Open Research. *IEEE Access*, 8:108952–108971, 2020. ISSN 2169-3536. doi: 10.1109/ACCESS.2020.2998358.

G7 Working Group on Stablecoins. Investigating the impact of global stablecoins. October 2019. URL `https://www.bis.org/cpmi/publ/d187.htm`. Last visited 2020-11-25.

Peter M. Garber. Famous first bubbles. *Journal of Economic Perspectives*, 4(2): 35–54, June 1990. doi: 10.1257/jep.4.2.35. URL `https://www.aeaweb.org/articles?id=10.1257/jep.4.2.35`.

David Gelernter. *Mirror worlds, or the day software puts the universe in a shoebox-: how it will happen and what it will mean.* Oxford University Press, New York Oxford, 1991. ISBN 9780195079067. OCLC: ocm27933410.

Matthew Gentzkow, Bryan Kelly, and Matt Taddy. Text as Data. *Journal of Economic Literature*, 57(3):535–574, September 2019. ISSN 0022-0515. doi: 10.1257/jel.20181020. URL `https://pubs.aeaweb.org/doi/10.1257/jel.20181020`.

Edward Glaessgen and David Stargel. The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles. In *53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference
20th AIAA/ASME/AHS Adaptive Structures Conference
14th AIAA*, Honolulu, Hawaii, April 2012. American Institute of Aeronautics and Astronautics. ISBN 9781600869372. doi: 10.2514/6.2012-1818. URL `http://arc.aiaa.org/doi/abs/10.2514/6.2012-1818`.

Ernest Gnan, Donato Masciandaro, Fabio Panetta, Ruth Judson, Ruth Judson, Walter Engert, Ben S. C. Fung, Alessandra Cillo, Mario Bergara, Jorge Ponce, Paul Pichler, Martin Summer, Dirk Niepelt, Itai Agur, Michael D. Bordo, and Andrew T. Levin. Do We Need Central Bank Digital Currency? Economics, Technology and Institutions, SUERF Conference Proceedings and Studies .:. SUERF - The European Money and Finance Forum, 2018. URL https://www.suerf.org/studies/7025/do-we-need-central-bank-digital-currency-economics-technology-and-institutions. Last visited 2021-02-14.

GoldHub. Central Banks and other institutions, 2018. URL https://www.gold.org/goldhub/research/gold-demand-trends/gold-demand-trends-q3-2018/central-banks-and-other-institutions. Last visited 2020-12-04.

Grassroots Economics. *Community Inclusive Currencies Dashboard*, 2020a. URL https://dashboard.sarafu.network. Last visited 2021-01-04.

Grassroots Economics. January to May 11th 2020 xDAI Blockchain Data, 2020b. URL https://www.grassrootseconomics.org/research. Last visited 2020-06-28.

Anthony Habayeb and Andrew Clark. Monitaur.ai - Machine Learning Assurance, 2019. URL https://monitaur.ai/machine-learning-assurance. Last visited 2021-01-12.

Aric A. Hagberg, Daniel A. Schult, and Pieter J. Swart. Exploring network structure, dynamics, and function using networkx. In Gaël Varoquaux, Travis Vaught, and Jarrod Millman, editors, *Proceedings of the 7th Python in Science Conference*, pages 11 – 15, Pasadena, CA USA, 2008.

Steve H. Hanke. Currency boards. *The ANNALS of the American Academy of Political and Social Science*, 579(1):87–105, 2002. doi: 10.1177/000271620257900107. URL https://doi.org/10.1177/000271620257900107.

Ty Haqqi. 15 Biggest Companies That Accept Bitcoin, 2021. URL https://finance.yahoo.com/news/15-biggest-companies-accept-bitcoin-165115491.html. Last visited 2021-03-09.

Heinz Robert Heller. Optimal International Reserves. *The Economic Journal*, 76(302):296–311, 06 1966. ISSN 0013-0133. doi: 10.2307/2229716. URL https://doi.org/10.2307/2229716.

Eyal Hertzog, Guy Benartzi, and Galia Benartzi. Bancor protocol whitepaper. 2018. URL https://storage.googleapis.com/website-bancor/2018/04/01ba8253-bancor_protocol_whitepaper_en.pdf.

Melissa Hidrobo, John Hoddinott, Amber Peterman, Amy Margolies, and Vanessa Moreira. Cash, food, or vouchers? Evidence from a randomized experiment in northern Ecuador. *Journal of Development Economics*, 107:144–156, March 2014. ISSN 0304-3878. doi: 10.1016/j.jdeveco.2013.11.009. URL https://www.sciencedirect.com/science/article/pii/S0304387813001715.

Owen Humpage and Jean M. McIntire. An introduction to currency boards. *Economic Review*, (Q II):2–11, 1995. URL https://EconPapers.repec.org/RePEc:fip:fedcer:y:1995:i:qii:p:2-11.

Invictus. Invictus Capital - Grow your wealth with innovative investment funds, 2018. URL https://invictuscapital.com/en/hyperion. Last visited 2020-06-07.

Hiro Ito and Robert N. McCauley. The currency composition of foreign exchange reserves. December 2019. URL https://www.bis.org/publ/work828.htm. Last visited 2020-12-04.

Gareth Jenkinson. Untethered: The History of Stablecoin Tether and How It Has Lost Its $1 Peg, 2018. URL https://cointelegraph.com/news/untethered-the-history-of-stablecoin-tether-and-how-it-has-lost-its-1-peg. Last visited 2020-11-25.

Thomas H. Greco Jr. Comment on the wörgl experiment with community currency and demurrage. *online*, 5 2002. URL https://reinventingmoney.com/greco-comment_on_worgl/. Last visited 2021-11-28.

Project Jupyter. Project Jupyter, 2014. URL https://www.jupyter.org. Last visited 2021-06-08.

J. M. K. The Gold Standard Act, 1925. *The Economic Journal*, 35(138):311–313, 1925. ISSN 0013-0133. doi: 10.2307/2222707. URL https://www.jstor.org/stable/2222707.

R. E. Kalman. A New Approach to Linear Filtering and Prediction Problems. *Journal of Basic Engineering*, 82(1):35–45, March 1960. ISSN 0021-9223. doi: 10.1115/1.3662552. URL https://asmedigitalcollection.asme.org/fluidsengineering/article/82/1/35/397706/A-New-Approach-to-Linear-Filtering-and-Prediction.

John Maynard Keynes. *The Economic Consequences of the Peace*. Number keynes1919 in History of Economic Thought Books. McMaster University Archive for the History of Economic Thought, 1919. URL https://ideas.repec.org/b/hay/hetboo/keynes1919.html.

Harold Klee and Randal Allen. *Simulation of Dynamic Systems with MATLAB and Simulink, Second Edition*. CRC Press, Boca Raton, FL, 2nd edition edition, February 2011. ISBN 9781439836736.

Elliott Krause. A Fifth of All Bitcoin Is Missing. These Crypto Hunters Can Help. *Wall Street Journal*, July 2018. ISSN 0099-9660. URL `https://www.wsj.com/articles/a-fifth-of-all-bitcoin-is-missing-these-crypto-hunters-can-help-1530798731`. Last visited 2018-07-05.

Andrew M. St Laurent. *Understanding Open Source and Free Software Licensing: Guide to Navigating Licensing Issues in Existing & New Software*. "O'Reilly Media, Inc.", August 2004. ISBN 9780596553951. Google-Books-ID: 04jG7TTLujoC.

Libra Association. Libra White Paper | Blockchain, Association, Reserve, 2020. URL `https://libra.org/en-US/white-paper/`. Last visited 2020-11-25.

Bernard Lietaer, Christian Arnsperger, Goerner, and Stefan Brunnhuber. *Money and sustainability : the missing link ; a report from the Club of Rome - EU Chapter to Finance Watch and the World Business Academy*. 01 2012.

Alexander Lipton, Aetienne Sardon, Fabian Schär, and Christian Schüpbach. From tether to libra: Stablecoins, digital currency and the future of money, 2020.

S. Lloyd. Least squares quantization in pcm. *IEEE Transactions on Information Theory*, 28(2):129–137, 1982.

Håkan Lobell. *Historical Monetary and Financial Statistics for Sweden: Exchange rates, Prices and Wages, 1277–2008*, volume I, chapter 6 - Foreign exchange rates 1804–1914, pages 291–339. Svergies Riksbank, 2010. URL `https://www.riksbank.se/en-gb/about-the-riksbank/the-tasks-of-the-riksbank/research/historical-monetary-statistics-of-sweden/volume-i-exchange-rates-prices-and-wages-1277-2008/`. Last visited 2021-11-28.

Tim Loughran and Bill McDonald. When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks. SSRN Scholarly Paper ID 1331573, Social Science Research Network, Rochester, NY, March 2010. URL `https://papers.ssrn.com/abstract=1331573`.

Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. Learning word vectors for sentiment analysis. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 142–150, Portland, Oregon, USA, June 2011. Association for Computational Linguistics. URL `http://www.aclweb.org/anthology/P11-1015`.

Maker Foundation. Maker - Whitepaper, 2014. URL `https://makerdao.com/en`. Last visited 2020-11-25.

Benoit Mandelbrot. The Variation of Certain Speculative Prices. *The Journal of Business*, 36(4):394–419, 1963. ISSN 0021-9398. URL `https://www.jstor.org/stable/2350970`.

MathWorks. Simulink - Simulation and Model-Based Design, 1984. URL `https://www.mathworks.com/products/simulink.html`. Last visited 2021-08-26.

Stephen McKeon. The Security Token Thesis | Hacker Noon, 2018. URL `https://hackernoon.com/the-security-token-thesis-4c5904761063`. Last visited 2020-12-08.

Richard A. Meese and Kenneth Rogoff. Empirical exchange rate models of the seventies: do they fit out of sample? *Journal Of International Economics*, 14: 3–24, 1983.

Winston Moore and Jeremy Stephen. Should cryptocurrencies be included in the portfolio of international reserves held by central banks? *Cogent Economics & Finance*, 4(1):1147119, 2016. doi: 10.1080/23322039.2016.1147119. URL `https://doi.org/10.1080/23322039.2016.1147119`.

Al-Naji Nader. Basis | A stable, algorithmic cryptocurrency protocol, 2018. URL `https://www.basis.io/`. Last visited 2020-11-25.

Satoshi Nakamoto. Bitcoin: A peer-to-peer electronic cash system. *Cryptography Mailing list at https://metzdowd.com*, 03 2009. URL `https://bitcoin.org/bitcoin.pdf`. Last visited 2021-11-28.

OCHA. Cash and Voucher Assistance | Global Humanitarian Overview, 2021. URL `https://gho.unocha.org/delivering-better/cash-and-voucher-assistance`. Last visited 2021-08-22.

Lawrence H. Officer and Samuel H. Williamson. The price of gold, 1257-present, 2019. http://www.measuringworth.com/gold/.

Sam Ouliaris. Economic models: Simulations of reality - imf finance & Development, 2020. URL `https://www.imf.org/external/pubs/ft/fandd/basics/models.htm`. Last visited 2020-07-01.

Frank Partnoy. Stock Picks From Space, April 2019. URL https://www.theatlantic.com/magazine/archive/2019/05/stock-value-satellite-images-investing/586009/. Last visited 2021-01-12.

Wouter Penard and Tim van Werkhoven. On the secure hash algorithm family, chapter 1 in gerard tel (ed.),. *Cryptography in Contex, Utrecht University*, 2008. URL https://webspace.science.uu.nl/~tel00101/liter/Books/CrypCont.pdf. Last visited 2021-11-28.

Daniel Phillips. What Will Happen to Bitcoin After All 21 Million are Mined?, February 2021. URL https://decrypt.co/33124/what-will-happen-to-bitcoin-after-all-21-million-are-mined. Last visited 2021-03-09.

Author removed at request of original Publisher. 9.1 What Is Money? In *Principles of Macroeconomics*. University of Minnesota Libraries Publishing edition, 2016. This edition adapted from a work originally produced in 2011 by a publisher who has requested that it not receive attribution., December 2016. URL https://open.lib.umn.edu/macroeconomics/chapter/9-1-what-is-money/.

R. A. Radford. The economic organisation of a p.o.w. camp. *Economica*, 12(48): 189–201, 1945. ISSN 00130427, 14680335. URL http://www.jstor.org/stable/2550133.

Bernhard Rengs, Manuel Scholz-Wäckerle, and Jeroen van den Bergh. Evolutionary macroeconomic assessment of employment and innovation impacts of climate policy packages. *Journal of Economic Behavior Organization*, 169, 12 2019. doi: 10.1016/j.jebo.2019.11.025.

Ripple. XRP, 2012. URL https://ripple.com/xrp/. Last visited 2020-06-07.

Jesus Rodriguez. Bitcoin Cash vs. Bitcoin SV: What Data Tells Us 10 Months After the Hash Wars | Hacker Noon, 2019. URL https://hackernoon.com/bitcoin-cash-vs-bitcoin-sv-what-data-tells-us-10-months-after-the-hash-wars-s2r434cn. Last visited 2020-06-07.

Will Ruddick. Community inclusion currencies (cics) documentation. https://gitlab.com/grassrootseconomics/cic-docs/-/tree/master, 2020. Last visited 2021-11-28.

William O. Ruddick. Eco-pesa: An evaluation of a complementary currency programme in kenya's informal settlements. 2011.

J. Ryan-Collins. *Where Does Money Come from: A Guide to the UK Monetary and Banking System*. New Economics Foundation, 2011. ISBN 9781908506078. URL https://books.google.com/books?id=_agxuAAACAAJ.

Linda Schilling and Harald Uhlig. Some simple bitcoin economics. *Journal of Monetary Economics*, 106:16–26, 2019. ISSN 0304-3932. doi: https://doi.org/10.1016/j.jmoneco.2019.07.002. URL https://www.sciencedirect.com/science/article/pii/S0304393219301199. SPECIAL CONFERENCE ISSUE: "Money Creation and Currency Competition" October 19-20, 2018 Sponsored by the Study Center Gerzensee and Swiss National Bank.

Wolfgang Schneider. Analytical uses of Kalman filtering in econometrics — A survey. *Statistical Papers*, 29(1):3–33, December 1988. ISSN 0932-5026, 1613-9798. doi: 10.1007/BF02924508. URL http://link.springer.com/10.1007/BF02924508.

scikit-learn developers. 6.1. Pipelines and composite estimators — scikit-learn 0.23.2 documentation, 2020. URL https://scikit-learn.org/stable/modules/compose.html. Last visited 2020-10-09.

Security Token Market, LLC. Security Token Market - Home Page, 2020. URL https://stomarket.com. Last visited 2020-12-08.

Adam Hale Shapiro, Moritz Sudhof, and Daniel Wilson. Measuring News Sentiment. *Federal Reserve Bank of San Francisco, Working Paper Series*, pages 01–22, January 2017. doi: 10.24148/wp2017-01. URL http://www.frbsf.org/economic-research/publications/working-papers/2017/01/.

David Siegel. The DAO Attack: Understanding What Happened, June 2016. URL https://www.coindesk.com/understanding-dao-hack-journalists. Last visited 2021-06-06.

MacKenzie Sigalos. Why the Fed hates cryptocurrencies and especially stablecoins, July 2021. URL https://www.cnbc.com/2021/07/16/jerome-powell-promotes-cbdc-digital-dollar-warns-against-stablecoins.html. Last visited 2021-11-21.

Frank Smets and Raf Wouters. An Estimated Dynamic Stochastic General Equilibrium Model of the Euro Area. *Journal of the European Economic Association*, 1(5):1123–1175, September 2003. URL https://ideas.repec.org/a/tpr/jeurec/v1y2003i5p1123-1175.html.

Stellar Development Foundation. Stellar - an open network for money, 2014. URL `https://www.stellar.org`. Last visited 2020-12-08.

James Stodder. Reciprocal exchange networks: implications for macroeconomic stability. pages 540 – 545, 02 2000. ISBN 0-7803-6442-2. doi: 10.1109/EMS.2000.872562.

Tobias Studer. *WIR in unserer Volkswirtschaft*. WIR Bank, Basel, 1998.

Tobias Studer. *WIR and the Swiss National Economy, translated by Philip H. Beard*. Sonoma State University, Rohnert Park, California, 2006.

Synced. Tree Boosting With XGBoost – Why Does XGBoost Win "Every" Machine Learning Competition?, October 2017. URL `https://syncedreview.com/2017/10/22/tree-boosting-with-xgboost-why-does-xgboost-win-every-machine-learning-competition/`. Last visited 2020-10-09.

Torsten Söderström and Petre Stoica. *System identification*. Prentice Hall International series in systems and control engineering. Prentice Hall, New York, 1989. ISBN 9780138812362.

Kosuke Takami. BOJ's negative rate policy has not worked as hoped, 2018. URL `https://asia.nikkei.com/Politics/BOJ-s-negative-rate-policy-has-not-worked-as-hoped2`. Last visited 2020-12-08.

Tether Limited. Tether | Stable digital cash on the Blockchain, 2014. URL `https://tether.to/`. Last visited 2020-06-07.

The Open Foundation. The Open Application Network, 2017. URL `https://theoan.com/`. Last visited 2020-06-07.

Robert Tibshirani, Guenther Walther, and Trevor Hastie. Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society Series B*, 63:411–423, 02 2001. doi: 10.1111/1467-9868.00293.

John Tsang. johntwk/Diebold-Mariano-Test, October 2020. URL `https://github.com/johntwk/Diebold-Mariano-Test`. original-date: 2017-12-07T15:33:38Z.

Arthur Turrell. Agent-based models: understanding the economy from the bottom up, 2016. URL `https://www.bankofengland.co.uk/quarterly-bulletin/2016/q4/agent-based-models-understanding-the-economy-from-the-bottom-up`. Last visited 2021-08-29.

Austin Tuwiner. Introduction to Polymath (POLY) - The Ultimate Security Token Platform, March 2018. URL https://cryptoslate.com/polymath/. Last visited 2020-12-08.

Beata Udvari and Isaac Ampah. Impacts of aid for innovation on economic growth in the sub-saharan african countries. *Mediterranean Journal of Social Sciences*, 9:99–108, 07 2018. doi: 10.2478/mjss-2018-0119.

Exchange Union. Exchange union, 2019. URL https://www.exchangeunion.com/landing/general?locale=en-gb. Last visited 2020-12-08.

Chris Veness. SHA-256 Cryptographic Hash Algorithm implemented in JavaScript | Movable Type Scripts, 2019. URL https://www.movable-type.co.uk/scripts/sha256.html. Last visited 2021-11-28.

Shermin Voshmgir and Michael Zargham. Foundations of cryptoeconomic systems. Working Paper Series / Institute for Cryptoeconomics / Interdisciplinary Research 1, Research Institute for Cryptoeconomics, Vienna, November 2019. URL https://epub.wu.ac.at/7309/.

Stephen Williamson. Is Bitcoin a Waste of Resources?, 2018. URL https://research.stlouisfed.org/publications/review/2018/02/13/is-bitcoin-a-waste-of-resources. Last visited 2020-12-03.

World Bank. Digital Economy for Africa Initiative, 2021. URL https://www.worldbank.org/en/programs/all-africa-digital-transformation. Last visited 2021-08-24.

World Trade Organization. WTO | The WTO and Word Customs Organization - The challenges of trade financing, 2020. URL https://www.wto.org/english/thewto_e/coher_e/challenges_e.htm. Last visited 2020-12-08.

Jiaxiong Yao. Illuminating Economic Growth Using Satellite Images – IMF F&D, 2019. URL https://www.imf.org/external/pubs/ft/fandd/2019/09/satellite-images-at-night-and-economic-growth-yao.htm. Last visited 2021-01-12.

Christopher Yeh, Anthony Perez, Anne Driscoll, George Azzari, Zhongyi Tang, David Lobell, Stefano Ermon, and Marshall Burke. Using publicly available satellite imagery and deep learning to understand economic well-being in Africa. *Nature Communications*, 11(1):2583, May 2020. ISSN 2041-1723. doi: 10.1038/s41467-020-16185-w. URL https://www.nature.com/articles/s41467-020-16185-w.

Michael Zargham. cadCAD Differential Specification Syntax Key, September 2019. URL https://community.cadcad.org/t/differential-specification-syntax-key/31. Last visited 2020-10-09.

Michael Zargham and Andrew Clark. 1Hive/conviction-voting-cadcad, 2020. URL https://github.com/1Hive/conviction-voting-cadcad. original-date: 2020-07-09T20:13:32Z.

Michael Zargham, Jamsheed Shorish, and Krzysztof Paruch. From curved bonding to configuration spaces. Working paper series / institute for cryptoeconomics / interdisciplinary research, WU Vienna University of Economics and Business, Vienna, December 2019. URL https://epub.wu.ac.at/7385/.

Michael Zargham, Krzysztof Paruch, and Jamsheed Shorish. Economic games as estimators. Working paper series / institute for cryptoeconomics / interdisciplinary research, WU Vienna University of Economics and Business, Vienna, January 2020. URL https://epub.wu.ac.at/7433/.

Chapter 6

Appendix

6.1 CIC Mathematical Specification

Assume we have a weighted, directed multigraph $\mathcal{G}(\mathcal{V}, \mathcal{E})$ with subpopulations as vertices, or nodes, $\mathcal{V} = \{1...\mathcal{V}\}$ and edges as $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$. 'Demand', 'utility', and 'spend' are edges connecting the subpopulations, with 'demand' used to denote desired flow between subpopulation agents, as $i, j \in \mathcal{E}$.

6.1.1 Node Types

Node types, $\mathcal{V}$, can take on the 3 types, *Agent, Cloud, or Contract*, and are enumerated below.

- **Agent** is a subpopulation of the system. Agents are subpopulation representations of the real system data and are represented by $\mathcal{V}_{A^n}$. Agents are unique subpopulations and stay constant throughout the simulation.
- **Cloud** is a representation of the open boundary to the external world; is unique, and is represented by $\mathcal{V}_{Cloud}$.
- **Contract** is the smart contract of the bonding curve; does not need to be unique, and is represented by $\mathcal{V}_{Contract}$.

6.1.2 Edges between Agents

The edge weight $\mathcal{G}_{i,j} \geq 0$ takes on non-binary values, representing the intensity of the interaction. $\mathcal{E}$ is the set of directed edges, i.e., $i, j \in \mathcal{E}$

- **Demand** is the amount a subpopulation wants to interact in a given time step (i.e., period, as most common usage in economics), represented by $\mathcal{E}_{D_{i,j}}$.
- **Fraction of demand in community currency** is the amount in a given transaction, the subpopulation wants to interact in token, with 50% of the transaction being in community currency and the remaining 50% of in the native currency. It is represented by $\mathcal{E}_{F^D_{i,j}}$.
- **Utility** is the subpopulation's utility (in economic sense) for the transaction. For the 'spend' calculations described later, we stack ranking the utilities to determine, given a liquidity constraint, which subpopulations will interact. It is represented by $\mathcal{E}_{U_{i,j}}$.
- **Spend** records the amount of community currency and shilling that was exchanged in a given time step. It is represented by $\mathcal{E}_{S_{i,j}}$.
- **Fraction of actual spend in community currency** records the percentage of the transaction that was in community currency, for example, with 50% being in community currency and 50% of the transaction being in the native currency, in this case, shilling. It is represented by $\mathcal{E}_{F^S_{i,j}}$.

At an intermediate step of the system, a node, such as subpopulation agent 10 $\mathcal{V}_{A^10}$ interacts with agent 12 $\mathcal{V}_{A^12}$, will have an edge weight at all edges types, such as $\mathcal{E}_{D_{10,12}} = 300$, $\mathcal{E}_{F^D_{10,12}} = 50\%$, $\mathcal{E}_{U_{10,12}} = Food/Water$, $\mathcal{E}_{S_{10,12}} = 200$, $\mathcal{E}_{F^S_{10,12}} = 50\%$

6.1.3 State Space

States or objects or points representing the current configuration of the system. $X \in \mathcal{X}$. Each of the states in this simulation are defined below.

Definition 20 ***Network****: A Multi-directed graph notated as $\mathcal{G}(\mathcal{V}, \mathcal{E})$. This state contains the multi-graph of nodes and their weighted edges of interaction.*

Definition 21 ***startingBalance****: The starting subpopulation CIC balance, notated as SB. $SB > 0$ for all $\mathcal{V}_{A^n}$.*

Definition 22 ***30_day_spend****: Subpopulation spend over the last thirty time steps; notated as DS. $DS >= 0$ for all $\mathcal{V}_{A^n}$.*

Definition 23 ***drip****: Amount of currency dripped into network by external parties during a time step; notated as D. $D >= 0$*

Definition 24 ***outboundAgents****: Subpopulation agents that are paying during the time step; notated as OA. $0A >= 0$*

Definition 25 ***inboundAgents****: Subpopulation agents that are receiving during the time step; notated as IA. $IA >= 0$*

Definition 26 ***withdraw****: Subpopulation agent actual withdraw, notated as W.*

Definition 27 ***fundsInProcess****: Funds awaiting settlement; notated as FIP.*

Definition 28 ***totalMinted****: Total amount of CIC minted during the simulation; notated as M. $M >= 0$*

Definition 29 ***totalBurned****: Total amount of CIC burned during the simulation; notated as B. $B >= 0$*

Definition 30 ***operatorFiatBalance****: Currency operator Fiat balance; notated as OBF. $OBF > 0$*

Definition 31 ***operatorCICBalance****: Currency operator CIC balance; notated as OCB. $OCB > 0$*

Definition 32 ***totalDistributedToAgents****: Total amount of CIC distributed to agents during the simulation; notated as D_A. $D_A > 0$*

6.1.4 Metric State Space

Definition 33 ***KPIDemand****: Subpopulation demand from the time step in per subpopulation, notated as KPI_D. $KPI_D > 0$*

Definition 34 ***KPISpend****: Subpopulation spend from the time step per subpopulation, notated as KPI_S. $KPI_S >= 0$*

Definition 35 ***KPISpendOverDemand****: Subpopulation spend divided by demand per subpopulation; notated as $KPI_{\frac{S}{D}}$. $KPI_{\frac{S}{D}} >= 0$*

Definition 36 ***VelocityOfMoney****: Velocity of money from the time step; notated as V_M. $V_M > 0$*

6.1.5 Mechanisms

Definition 37 ***update_agent_activity:*** *takes in outboundAgents, inboundAgents, stepDemands, and stepUtilities at each time step as determined by the* ***Choose_agents*** *action and updates the* $\mathcal{G}(\mathcal{V},\mathcal{E})$ $\mathcal{E}_{D_{i,j}}$,$\mathcal{E}_{F^D_{i,j}}$, *and* $\mathcal{E}_{U_{i,j}}$ *based off of the* ***Choose_agents*** *action.*

Definition 38 ***update_outboundAgents:*** *updates the* ***outboundAgents****,* OA *state based on the* ***Choose_agents*** *time step bound action.*

Definition 39 ***update_inboundAgents:*** *updates the* ***inboundAgents****,* IA *state based on the* ***Choose_agents*** *time step bound action.*

Definition 40 ***update_node_spend:*** *updates the* ***network****,* $\mathcal{G}(\mathcal{V},\mathcal{E})$ *state based on the* ***spend_allocation*** *time step bound action.*

Definition 41 ***update_withdraw:*** *updates the* ***withdraw****,* W *state based on the* ***withdraw_calculation*** *time step bound action.*

Definition 42 ***update_network_withdraw:*** *updates the* ***network****,* $\mathcal{G}(\mathcal{V},\mathcal{E})$ *state based on the* ***withdraw_calculation*** *time step bound action.*

Definition 43 ***update_operatorFiatBalance_withdraw:*** *updates the* ***operatorFiatBalance****,* OBF *state based on the* ***withdraw_calculation*** *time step bound action.*

Definition 44 ***update_operatorCICBalance_withdraw:*** *updates the* ***operatorCICBalance****,* OCB *state based on the* ***withdraw_calculation*** *time step action.*

Definition 45 ***update_agent_tokens:*** *updates the* ***network****,* $\mathcal{G}(\mathcal{V},\mathcal{E})$ *state based on the* ***disbursement_to_agents*** *time step bound action.*

Definition 46 ***update_operator_FromDisbursements:*** *updates the* ***operatorCICBalance*** OCB *state based on the* ***disbursement_to_agents*** *time step bound action.*

Definition 47 ***update_totalDistributedToAgents:*** *updates the* ***totalDistributedToAgents****,* D_A *state based on the* ***disbursement_to_agents*** *time step bound action.*

Definition 48 ***update_operator_fiatBalance****: updates the* ***operatorFiatBalance****, OCF state based on the* ***inventory_controller*** *time step bound action.*

Definition 49 ***update_operator_cicBalance****: updates the* ***operatorCICBalance****, OCB state based on the* ***inventory_controller*** *time step bound action.*

Definition 50 ***update_totalMinted****: updates the* ***totalMinted****, M state based on the* ***inventory_controller*** *time step bound action.*

Definition 51 ***update_totalBurned****: updates the* ***totalBurned****, B state based on the* ***inventory_controller*** *time step bound action.*

Definition 52 ***update_fundsInProcess****: updates the* ***fundsInProcess****, FIP state based on the* ***inventory_controller*** *time step bound action.*

Definition 53 ***update_KPIDemand****: updates the* ***KPIDemand****, KPI_D state based on the* ***kpis*** *time step bound action.*

Definition 54 ***update_KPISpend****: updates the* ***KPISpend****, KPI_S state based on the* ***kpis*** *time step bound action.*

Definition 55 ***update_KPISpendOverDemand****: updates the* ***KPISpendOverDemand****, $KPI_{\frac{S}{D}}$, state based on the* ***kpis*** *time step bound action.*

Definition 56 ***update_velocity_of_money****: updates the* ***VelocityOfMoney****, V_M, state based on the* ***velocity_of_money*** *time step bound action.*

Exogenous Processes

Definition 57 ***calculate_drip****: In our version of the simulation, as of May 2020, a periodic donor drift could occur. The logic that we have is that every 90 days, we calculate drift based off an initial amount of \$10,000 reduced by \$5,000 per 90 days, with a lower bound of 0. The amount calculated here determines the transient state D.*

Definition 58 ***startingBalance****: Calculate agent starting balance every 30 days and store in startingBalance dictionary state, SB.*

Definition 59 ***30_day_spend****: Aggregate agent spend, DS. Refreshed every 30 days.*

6.1.6 Actions

Definition 60 ***Choose_agents*** *is an action that determines which subpopulations, $\mathcal{V}_{A^n}$, will interact during the given time step; and create their respective $\mathcal{G}_{i,j}$ weights.*

Choose_agents takes a uniform random sample of 46 from the 51 subpopulations (50 clusters plus the external economy) for the payer subpopulations and another uniform random sample for the receiver subpopulations. The behavior then calculates the payer demands based on a Gaussian distribution computed from the μ actual CIC transactions involving the subpopulation and the σ of the actual transactions. If the payer is the external economy node, we compute a Gaussian distribution based on average of the average subpopulation μ and σ. To calculate the payer subpopulation's utility, we take a uniform distribution of the source subpopulation's business types and use their probability of occurrence, i.e., Food and Water-type occur 41% of the time in subpopulation 1 inter-cluster interactions, so we will choose this utility type 41% of the time. Note that for the scope of our simulations, we are assuming each subpopulation interacts once with one utility type for each time step. The output of this action is the outboundAgents, inboundAgents, stepDemands, and stepUtilities.

Definition 61 ***spend_allocation*** *is an action that takes the mixing subpopulation agents,$\mathcal{V}_{A^n}$, demand $\mathcal{E}_{D_{i,j}}$, and utilities $\mathcal{E}_{U_{i,j}}$ for a given time step and allocates subpopulation agent shillings and tokens based on utility and scarcity to determine for actual spend $\mathcal{E}_{S_{i,j}}$, and fraction of actual spend in community currency, $\mathcal{E}_{F^S_{i,j}}$.*

spend_allocation, is calculated based on the desired interacting subpopulation's demand, utility, and liquidity constraints, i.e., the amount of CIC and shilling each subpopulation has available. Iterate through the desired demand and allocate based on a stack ranking of utility $v_{i,j}$ over demand $\frac{v_{i,j}}{d_{i,j}}$ until all demand for each subpopulation is met or subpopulation i runs out of CIC and shilling. The action returns a list of the paying subpopulation agents, a list of the receiving subpopulation agents, and the list of the spend amounts.

Definition 62 ***withdraw_calculation*** *is an action that determines the number of shillings agents $\mathcal{V}_{A^n}$ can withdraw over 30 days.*

withdraw_calculation per *Grassroot Economics* policyRuddick [2020] at the time of this simulation, individual users were able to withdraw up to 50% of their CIC balance if they have spent 50% of their balance within the last 30 days at a conversion ratio of 1:1, meaning that for every one token withdraw, they would receive 1 in shilling. For simplification, it is assumed that each subpopulation agent,

$\mathcal{V}_{A^n}$, is on the same 30-day clock and withdraws the max amount available(30,000 is the max allowable amount to be withdrawn per 30 days). A dictionary of the agent and their withdrawal amount is returned from this action.

Definition 63 ***disbursement_to_agents*** *is an action that periodically distributes CIC to agents, $\mathcal{V}_{A^n}$. The action returns a boolean for distribute, and a dictionary with the agent as a key and the value as the amount.*

disbursement_to_agents is determined by a parameter, FrequencyOfAllocation, which for the simulations, which was set to 30. The amount is determined by a parameter unadjustedPerAgent, which was set to 100. unadjustedPerAgent was then multiplied by the agent allocation, a dictionary with agent as the key, centrality, and allocation value as the values. For the time being, the centrality and allocation value was set to 1 for all agents. A v2 of this model would gauge this allocation based on agent centrality to the network.

Definition 64 ***inventory_controller*** *is an action that as a monetary policy conservation allocation between the* ***operatorFiatBalance****, OBF and* ***operatorCICBalance****, OBC states.*

inventory_controller is in place to address the inventory control problem of the net outflow system by balancing the OBC and OBF states. The inventory control function tests if the current balances are within an acceptable tolerance. For the calculation, we use the following 2 states: current CIC balance, OBC and current fiat balance, OBF; along with 4 parameters: idealCIC, varianceCIC, idealFiat, and varianceFiat. If the balances are not within the acceptable tolerances, the function would return a decision to either mint or burn CICs, along with the amount to mint or burn. For this model's purposes and the initial simulations, the inventory_controller has been turned off to observe the system's performance under the net outflow condition. The action returns a string of burn, mint, or none; a float of the calculated change in fiat, a float of the calculated change in CIC, and a dictionary of the funds in process, which consists of a time step key, with a follow if the time step + a process lag parameter, currently set to 15 days, appended to a list embedded within the value, along with the decision, cicChange, and fiatChange.

Definition 65 ***kpis*** *is an action that calculates the system KPI's of: KPIDemand, KPISpend, and KPISpendOverDemand*

kpis iterates through the network $\mathcal{G}(\mathcal{V}, \mathcal{E})$ model edges to ascertain the subpopulation edge weights of demand, $\mathcal{E}_{D_{i,j}}$, and spend,$\mathcal{E}_{S_{i,j}}$, for the current time step. The policy function aggregates the spend and demand for a system level view of how much spend and demand occurred on the network during the time step as well as spend over demand, to see how much of the demand was fulfilled. A spend over demand of 1 means that not all demand was satisfied, whereas a value of 1 denotes that all subpopulation wants were met. The action has three subsequent mechanisms returns the dictionaries of KPIDemand, KPISpend, and KPISpendOverDemand with agent,$\mathcal{V}_{A^n}$, as the key and the KPI as the value.

Definition 66 ***velocity_of_money*** *is an action that calculates the velocity of money per timestep via indirect measurement.*

velocity_of_money

$$V_t = \frac{PT}{M}$$

Where V_t is the velocity of money for all agent transactions in the period examined, P is the average price level, T is the aggregated real value of all agent transactions in the time period examined, and M is the average money supply in the economy in the period examined.