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AI Driven Monetary Policy in the Era of Digital Currency

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Abstract

The use of Artificial Intelligence in monetary policy of digital currencies is a very new area. Although Machine learning is at the heart of Artificial Intelligence, new aspects like Reinforcement Learning (RL) and Recurrent Neural Networks have been created to train AI on complex macroeconomic events and make monetary policy decisions. This is a review paper based on multiple literature survey. Studies show that AI is trained on vast economic data can give accurate predictions of the economy based on the monetary policy. This can be used as a great tool for bureaucrats and economic advisors to help grow a nations GDP which aligns with people's interest thus having a win-win situation. Finally, some pros and cons have been mentioned with future scope of this technology.

Introduction

Central Bank Digital Currency

Central Bank digital currency (CBDC) has no proper definition, although it describes the regulation of digital currencies like Etherium, Block chain etc. by central banks. This type of Technology is not well known among the masses and therefore has a negative outlook, only few people with advance understanding of this technology are willing to accept this type of currency. The role of this paper is to help people understand how AI can be helpful in regulating the digital currency which would benefit the masses.

Use of CBDC in Monetary Policy

Some researchers want the CBDC to be only accessible to a specific segment in a society, which would make CBDC as a supplementary currency, it can be used by businesses which cannot access loans in traditional currency (Bech and Garratt 2017). Although few researchers (Fung and Halaburda 2016) and Bjerg (2017) believes that universal access to CBDC is its fundamental property. This is a cause of concern for some economists who believe that currency of any type should be accessible by anyone. Owing to this controversy the European Central Bank has opted to use the term "Digital base money" in place of CBDC, emphasizing the fact that this type of currency is available to all, although researchers use the term 'CBDC' acknowledging the slight misnomer.

The other parameter of CBDC is its potential for interest bearing capacity, an interest bearing CBDC can offer varying levels of interest rates ranging from positive to negative. It can be used by the government to stabilize inflation or manage the demand for CBDC. A non interest bearing CBDC can be equivalent to central bank notes also referred as "ecash". In figure 1 all the potential properties of CBDC is shown corresponding to the different types of CBDC.

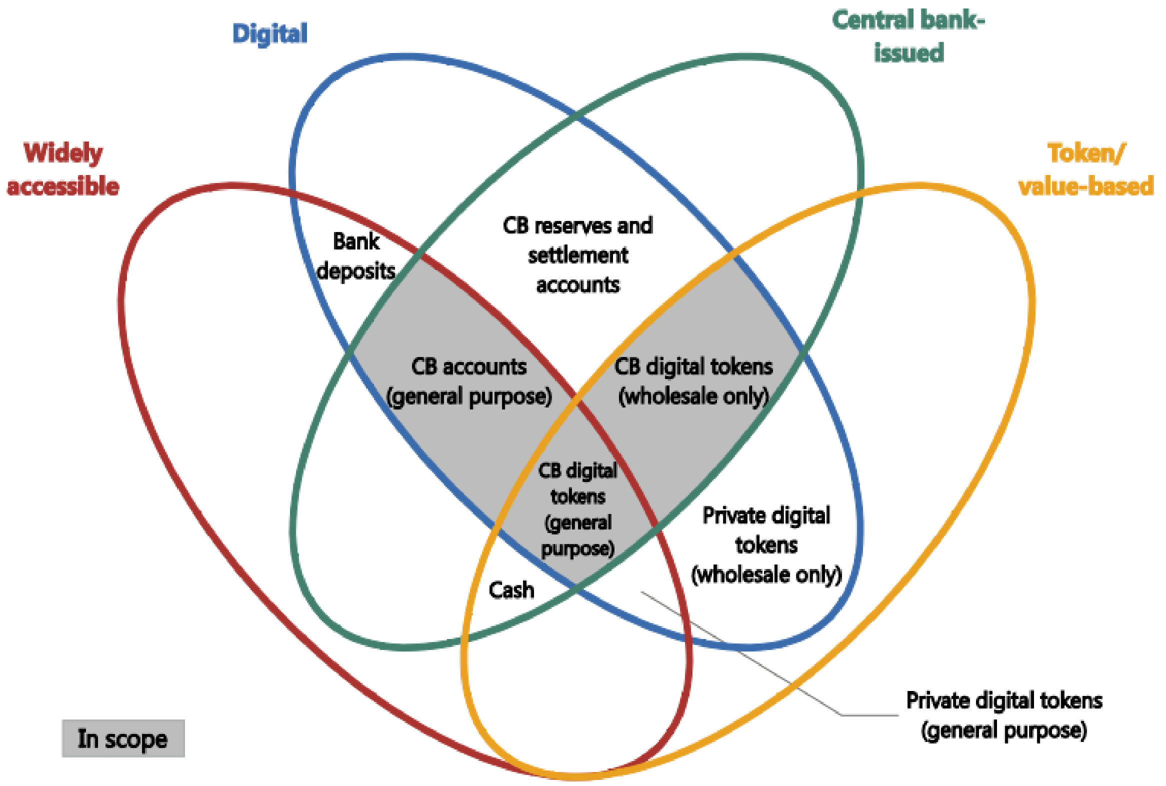

Figure 1. Taxonomy of money

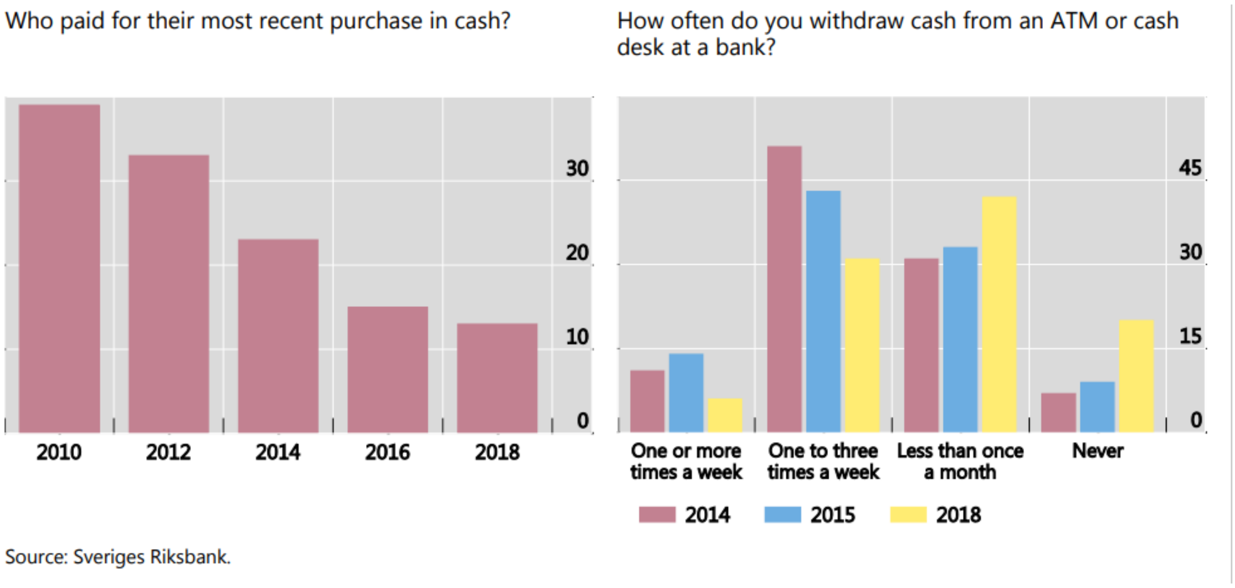

Figure 2. Survey regarding payment preference as a percentage of respondents

In parts of the world where banking facilities are not widely available, CBDC's can provide banking facilities on their phones. This allows people from remote parts of the world to participate in the financial system. Efficiency of CBDC transactions is higher than any other type of currency transactions, there is minimum room for errors, this makes it highly efficient in performing high volume transactions also facilitating cross border transactions without any time delays, whereas in traditional cross border transactions, intermediaries are required which delay the processing of the transaction.

Transparency and traceability are also enhanced with the use of CBDCs. It makes financial transactions more transparent, which helps in detecting and preventing illegal activities like money laundering, tax evasion, and other illicit behaviors.

CBDC's can also enhance the innovation in the financial sector, driving more people to be a part of it which in turn grows the economy and increases the GDP of a Nation. However, there are some disadvantages with using CBDC's since it is very transparent and traceable, this can allow the government to monitor all the transactions made by an individual or a company which raises concern over privacy.

Another problem might be the destabilization of the general banking sector due to the shift in using just the CBDC in the finance sector, this will make people leave the cash and only focus on the digital currency. It can have disastrous effects like the drop in the share price of publicly trading companies although that can be compensated by the use of digital currency if used wisely.

Literature of AI in regulating CBDC

Review of simple rules in monetary policy

From decades economists have been trying to device a monetary policy that would always result in positive economic growth but this does not happen in reality. This is where the use of AI comes which has been trained on vast amount of economic data sets and can be used to make impactful monetary decisions regarding decentralized crypto assets, this property of AI is being developed using data sets of crypto assets. However, it is unclear whether the AI trained on decentralized assets can be used in the realm of CBDC. It is because the type of data set required for CBDC is quite different than decentralized currencies. This is a challenge since the macroeconomic environment keeps on changing and the dependent variables associated with it. Although the AI can be trained on all of those variables and only then it can make correct policy decisions.

Reinforcement learning using AI

Reinforcement Learning (RL) is a part of Machine learning which uses trial and error method to find optimal solutions to a problem. Now since the real world has multiple levels of variables in the context of economics, AI tools use RL to train and come up with proposed solutions. This method is used in all the industries now a days, from manufacturing to design. Some researchers claim that RL is the method by which AI will achieve Singularity which means that it will have human like intelligence and reasoning ability. Discussed below are the modelling steps used to train the AI model for the monetary policy of CBDC.

Modeling Steps

The modeling process involves three key stages:

1. Generating Transition Equations: In this Stage the neural networks are laid out, all the data set is collected for the training of AI.
2. Training the AI model: RL is used to train the AI model and find the optimal monetary decisions and simulate the economic reaction.
3. Interpretation: This is the last stage, it is a kind of feedback stage where the results are simulated and checked, if the decisions results in a negative growth in the economy, the model is trained further until it starts giving correct results.

Stage 1 Generate transition equations

Stage 1 consists of making a sample space akin to a sand box environment in whish the AI model is going to learn about the economy and the variable that is dependent on. This data set requires a lot of data from the real world like the GDP data of previous decades, Job market, export, imports, FDI's etc. Using all this information a neural network is made where all the data is dependent on each other through various mathematical functions. Recurrent Neural Networks (RNN) and Gated Recurrent Units (GRU's) are used to train the AI better because they store the information overtime which makes the AI recall each set of data to make predictions. Below is the research methodology used by researchers to Train the AI model.

Since the Research was done in Georgia. Macro economic variables were used to train the AI. The necessary data for the research was retrieved from the database of the National Bank of Georgia. An assessment report of economic growth done by the National Statistics Office of Georgia was used a proxy for the real GDP growth. The date available starts from January 2010 and the last data retrieved is from March 2022. [11]

Stage 2 Training macro agent

The training dataset is briefly explained in this section. The AI model is trained on economic indicators like inflation rate, M2 annual growth rate, real effective exchange rate and current loss. The learning process in [11] was done using the datasets of Georgia. The time period was taken from March 2022 and simulated the next 8192 months. The AI model alters the policy each month which effects the macroeconomy in the sample space. Figure 3 shows a brief overview on the workings on RL method. We can see that the economic environment consists of indicators like policy rate, growth rate, REER, inflation etc, which is controlled by the GRU and the AI model. Also we can see a feedback loop which helps the AI correct its mistakes, the ultimate goal is to have the inflation rate low enough for a consistent number of years while increasing the growth rate and providing jobs to the people.

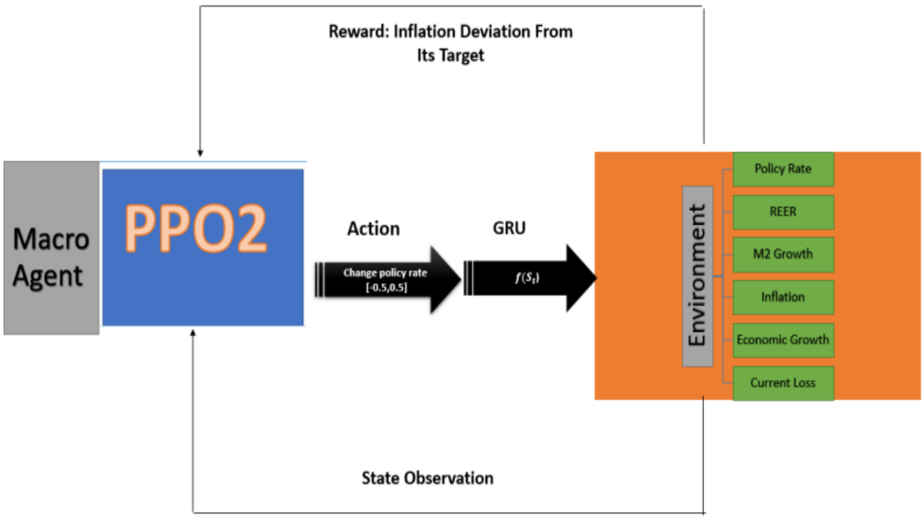

Figure 3. Overview of reinforcement learning based monetary policy decision

Stage 3 Making sense of training results

In this stage the simulation is run and the response of the AI is checked. A few economic variable are changed to check how accurate is the AI model, Each variable is changed positively and negatively for a period of six months and the simulation is run for 300 months. This type of sudden change in the variables gives the researcher better understanding of how the AI model is able to recover from a negative indicator. The results show that AI is better able to compute complex nonlinear equations found in Dynamic General Equilibrium (DGE) models. Unlike the traditional methods, the RL AI model is able to learn nonlinear decision structures and effectively manage any challenges caused by the complex higher order problems which are at the core of DGE models.

The researchers conclude that AI can certainly by used as an assistant in the monetary policy of digital currency because of its ability to go through vast amunts of data which humas will take years to compute. The AI is able to predict the outcome correctly using the RNN and GBR method.

Literature Review

Seyed (2021). Many central banks in the world are considering the introduction of CBDCs. CBDCs offer features like the possibility of earning interest. However, using a CBDC comes with with a cost. This study examines the optimal monetary policy when AI agents have access to only cash, only a CBDC, or both. If the cost of using a CBDC is relatively low, more efficient outcomes can be achieved, potentially reaching an optimal state. Offering both cash and a CBDC could lead to lower overall welfare compared to scenarios where only one is available. The study also estimates the welfare benefits of using CBDC in the United States and Canada. For instance, if the cost of using a CBDC relative to cash is about 0.25% of the transaction value, introducing a CBDC could result in a consumption increase of 0.12–0.21% in the United States and 0.04–0.07% in Canada [1].

Beniak (2019). The rapid digitalization of payments across the world has enhanced cost and time efficiency but the downside is that it may also introduce security risks, having the likelihood of weakening financial stability and reducing the effectiveness of monetary policy. To ensure the best security, central banks are exploring and testing new solutions that would allow the general public to do payments without having to worry about the security risks. One such solution is the central bank digital currency (CBDC), a digital version of cash. The proposed versions of CBDCs vary significantly, and depending on the design adopted by a particular central bank, a CBDC could influence central bank interest rate setting, the implementation of monetary policy, and the transmission mechanism [2].

Jack Meaning (2018). This paper explores the CBDC and its potential effects on the monetary transmission mechanism. Researchers have examined how CBDC could influence the different stages of transactions, from central bank money markets to the real economy. The results suggest that monetary policy could continue to function similarly to like it is now, by adjusting the price or quantity of central bank money, with the possibility that transmission could even become more effective for any given change in the monetary policy [3].

Serez Bozkus (2018). Artificial intelligence (AI) has recently become increasingly important and is now a dominating field within computer science category. AI aims to develop intelligent systems that mimic human behavior, including making judgments, solving problems, and understanding languages. There is a significant computational energy required to make AI this capable. Although AI is a relatively new, it is closely connected to other long-established fields, such as Philosophy, Mathematics, Computing, Cognitive Science, and Neuroscience. In this context, while the historical foundations of AI trace back to thinkers like Aristotle and Socrates, this paper review the history of evolution of intelligence and compares that with the evolution of AI intelligence, although AI is quite fast in learning new languages and has a vast memory capability. It still has not reached Human level reasoning ability and curiosity [4].

Hengjie Ai (2022). This paper talks about effect of monetary policy on the stock market. The researchers have used the option-implied variance reduction to assess the sensitivity of stock returns to monetary policy announcements, this paper demonstrates that monetary policy announcements demand substantial risk compensation across the cross section of equity returns. Researchers propose a simplified equilibrium model where FOMC announcements disclose the Federal Reserve's disclosure regarding its interest-rate target, which in turn influences the private sector's expectations about the economy's long-term growth rate. The model explains the dynamics of implied variances and the cross-sectional monetary policy announcement observed around FOMC announcement days [5].

Stephen D (2008).In this paper the Researchers study the effects of monetary policy on prices, interest rates, consumption, labor supply, and output. A segmented market model of monetary policy is developed, consisting of goods market segmentation and its connection to conventional asset market segmentation. The model also explores optimal monetary policy and the costs of inflation. Key characteristics of the model include consistent non-neutralities of money, relative price effects from increases in the money supply, persistent liquidity effects, and a negative Fisher effect resulting from a money supply increase. The analysis concludes that a Friedman rule is generally suboptimal [6].

Peterson (2023). The purpose of this paper is to provide insights into central bank digital currency (CBDC) research by reviewing recent advancements in the field. The goal is to assist researchers, policymakers, and practitioners in taking a closer look at CBDC. The study reveals a general consensus that a CBDC is a liability of the central bank and possesses cash-like attributes. It also highlights the motivations and benefits of issuing a CBDC, such as enhancing financial inclusion, improving the conduct of monetary policy, and promoting efficient digital payments. Furthermore, the researchers show that many central banks are exploring the potential of issuing CBDCs due to these benefits. However, several studies caution against excessive optimism regarding the potential advantages of CBDCs, pointing to the limitations of CBDC design and its inability to achieve multiple competing objectives simultaneously. The paper identifies areas for future research, including the need to determine the optimal CBDC design that balances all competing goals [7].

David Andolfatto (2020). In this paper the researchers have examined the potential impact of a central bank digital currency (CBDC) on a monopolistic banking sector. Their analysis combines the Diamond (1965) model of government debt with the Klein (1971) and Monti (1972) model of a monopoly bank. The findings suggest that the introduction of a CBDC does not negatively affect bank lending activity and may even encourage it under certain conditions. Competitive pressure resulting from the use of CBDC leads to a higher deposit rate in the monopolistic banking sector, which increases deposit funding by enhancing financial inclusion and encouraging desired saving. The study, concludes that a well-designed CBDC is unlikely to pose a threat to financial stability [8].

Jesus Fernandez (2021). In this study the researchers study the affect of Bank runs on the CBDC and the commercial banking sector. A central bank is not an expert in investments, it cannot directly invest in long-term projects and must rely on investment banks for that purpose. Researchers establish an equivalence result showing that, in the absence of a banking panic, the allocation outcomes achieved through private financial intermediation would also be achieved with a CBDC. However, during a bank run, the rigidity of the central bank's contract with investment banks has the potential to prevent bank runs. Therefore the central bank proves to be more stable than the commercial banking sector. People start to recognize this stability of CBDC, leading to the central bank becoming a deposit monopolist, drawing all deposits away from the commercial banking sector [9].

Adedoyin et al. (2020). In this review, the researchers present a comprehensive overview of AI applications within the blockchain domain. The development of Blockchain applications have been studied. Researchers have identified the challenges associated with integrating blockchain and AI techniques. The impact of cloud computing on these two technologies has also been reviewed in the context of having Blockchain and AI as a service. The integration of AI and blockchain is said to unlock numerous possibilities, offering scientists and professionals unparalleled research assistance [10].
Mariam (2022). In this study researchers propose a new approach in the formation of the monetary policy that uses the RL method. The analysis of AI-generated monetary policy rules reveals that these optimal rules tend to exhibit some nonlinearities due to the vast dataset that they are trained on. This finding may explain why simple monetary rules, which rely on traditional linear modeling tools, often lack the accuracy required for implementation or have many logical fallacies. By analyzing the generated transition equations, researchers were able to estimate the neutral policy rate, which was determined to be 6.5 percent. Researchers also explore the potential integration of this method with cutting-edge FinTech innovations in digital finance, such as DeFi and CBDC, and discuss the feasibility of a "MonetaryTech" approach to monetary policy [11].

Conclusions

In conclusion, the integration of artificial intelligence (AI) into monetary policy, particularly in the context of digital currencies is a significant step forward in central banking sector. By leveraging AI tools such as reinforcement learning (RL) and Recurrent Neural Networks (RNNs), central banks can better analyze and manage complex macroeconomic environments which have high level of nonlinearities and high-dimensional challenges. AI-driven models, trained on data and dynamic simulations, adapt to evolving economic conditions and provide more robust policy recommendations.
The application of AI in this domain aligns well with emerging financial technologies, such as decentralized finance (DeFi) and central bank digital currencies (CBDCs). By incorporating AI-driven policies, central banks can move towards semi-autonomous phase, ensuring more timely and accurate responses to economic fluctuations. This approach, termed "MonetaryTech," could offer a more resilient and adaptable framework for managing digital economies. As central banks explore the design and implementation of CBDCs, the insights gained from AI applications in monetary policy will be invaluable, paving the way for more sophisticated and effective monetary governance in the digital age.

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