# Worldwide CBDC designs: a perspective from macro indicators to further implications

**by**

Ran You

An honors thesis submitted in partial fulfillment

of the requirements for the degree of

Bachelor of Science

Business and Economics Honors Program

NYU Shanghai

May 2025

Professor Marti G. Subrahmanyam Professor Hanna Halaburda
Professor Christina Wang
Professor Wendy Jin

Faculty Advisers Thesis Adviser

## Preface

Although the world witnesses an increasing and diverse developing trend in CBDC issues, we are still curious about or even questioning the necessity of CBDC projects. Because there seems to be no obvious differences or immediate benefits from them to our daily life, compared to cash, cryptocurrencies or other digital payment methods. Different countries' central authorities propose CBDC projects with similar motivations and designs, each arguing that CBDC solves their specific problems. But they have different development status, and the CBDC motivations, sound not only too big, but also like excuses for central authorities to surveil people, increase centralization or replace private payment providers. Obviously, a gap exists between the government and public perception of CBDCs.

To find answers to these questions, we can move beyond the focus of usual CBDC research on certain countries' isolated cases to patterns and commonalities for global projects. And to make reasoning more plausible and comprehensible, we can switch to a more practical angle of specific CBDC design feature categories (not conceptual motivations), incorporating more objectively measured factors like macro development conditions. This brings commonly-used classical macro(economic) theories into explanation, links CBDCs with macro-level topics and provides further insights on economic growth, global competitiveness and geopolitics, etc.

Overall, CBDC is a topic worthwhile to explore and discuss even for daily life. Talking to people around in China, I found out that almost everyone is confused about the real differences between E-CNY and Wechat/Alipay, as well as the government's reasons for promoting E-CNY. Therefore, we need research to help us understand CBDCs better. But given controversies shown in existing literature focusing on specific CBDC cases, generated from subjective opinions and investigation methods, CBDC research needs to follow, or explore new forms and perspectives.

**Acknowledgements**

First and foremost, I would like to express my deepest gratitude to my thesis advisor Professor Hanna Halaburda, who guided me throughout this CBDC research project with her academic expertise and encouraging words. It was fortunate for me to take her course on FinTech at NYU Stern during my study away semester. That course gave me the initial idea of this research on CBDC projects and the opportunity to invite her to be my advisor. From the proposal stage to the completion of this research, we worked together to overcome every challenge.

Meanwhile, I am also immensely grateful to Professor Guillaume Haeringer and Chitra Marti for giving insightful suggestions from different perspectives with expertise, when I was struggling with the data analysis process. They patiently listened to me talking about my research aims and difficulties, discussing these problems with me and guiding me based on their rich research experience, despite the busy schedule.

I also want to express my special thanks to the program coordinators, Professor Marti G. Subrahmanyam, Professor Christina Wang, and Professor Wendy Jin, as well as our teaching assistant Xinyi Yang. Along with the seminar instructors, they ensured our research projects stayed on track, offering guidance, feedback and encouragement throughout the process.

Last but not least, I am always truly thankful to the people around me. My friends and family always listened to my ideas and concerns patiently, offering solutions and comfort whenever I felt overwhelmed.

I am incredibly fortunate to have such generous support during my first formal research project. Without all these people, I could not have reached my expectations, improved my research skills, or enriched my academic experience.

**Abstract**

Central bank digital currency (CBDC) seems to be only an economic or technological related topic, but opinions have been associating it with different fields. An increasing number of countries show interest in initiating CBDC projects, and discussions on CBDCs have evolved from expected benefits to developing choices and public views. Existing literature focuses either on specific CBDC cases or general CBDC related macro topics, but rarely tries to connect abstract theories to help evaluate practical cases. This research applies logistic regression to World Development Indicators (WDIs) and different design features of worldwide CBDC projects, to examine how countries' macro development conditions influence their choices of CBDC designs. By linking macro-level theories and indicators to countries' specific decisions, it provides practical justification for these choices, as well as a better understanding of government motivations and public opinions on CBDCs. Overall, this research enables us to non-abstractly explore not only CBDCs and reasons for countries' growing interest in them, but also the world's diverging developing trend toward CBDC issues.

**Keywords:** Central Bank Digital Currency (CBDC), CBDC design features, macro(economic) development indicators, digital currency and government motivations, digital currency and public opinions, global CBDC trend

**Contents**

## 1. Introduction

Central Bank Digital Currency, a digital form of a country or region's legal tender, issued and regulated by its central bank for the public, has gained global attention in recent years. Statistics show that over 100 countries have initiated a CBDC project, either for research purposes or aim at launching in the near future. CBDCs are granted with huge expectations, with discussions evolving from reasons and benefits for them to designs and development of them, as well as risks and challenges. Almost a decade since the world's first CBDC initiative, different countries' focuses and decisions on CBDCs gradually diverge. They choose different specific designs, developing timeline and stages, motivated by different policy goals and expected outcomes, as shown in the BIS survey on CBDCs and cryptos (Kosse, A. & Mattei, I., 2023). It compares advanced economies with emerging and developed economies and suggests that they tend to make different decisions on retail or wholesale CBDC initiatives.

Except for CBDC discussions mostly on these topics from central institutions and authoritative organizations, public surveys either initiated by the government or academics become more common. They investigate people's understanding, requirements and acceptance of CBDCs. However, there is a gap between government stances and public opinions. Though the government gives their explanation for motivations and design choices, the public seems still doubting or not interested in the concept of CBDC. Deutsche Bundesbank's survey (2021) shows that in German households' view, although a CBDC can help with digitization, existing payment methods are sufficient, and the less-monitored cash payment should not be abolished.

This gap in understanding is generated by the failure to link the abstract motivations and theories on CBDCs, to practical understanding based on their potential daily use. Some countries might have similar motivations (illustrated in **Appendix A**) and same design choices, which

makes it less justifiable that these decisions are based on their current developing status – but can it be that those countries have similar development conditions? Therefore, this research tries to bridge this gap and promote a better understanding of CBDC projects and discussions worldwide by incorporating macro indicators, to explore their influence on countries' CBDC design choices. Since government motivations and public opinions seem inherently subjective, macro indicators, more objective and measurable, can provide better justification that countries' choices of CBDC design features for their own initiatives, are based on practical considerations.

By categorizing design features of worldwide CBDC projects, and finding their relations with macro development indicators (economic, political, geographical and demographic ones), this research discovers that countries with similar development conditions tend to choose the same design category: higher inflation points to an account structure, larger land area points to an earlier announcement year, deeper credit information points to hesitation in DLT design, higher political stability points to a later announcement year, higher GDP points to a non-DLT design, more high-tech manufacturing value added points to a wholesale design, higher employment points to a launched status, higher GNI per capita points to a DLT design, and larger working population points to a both retail and wholesale design, etc. Moreover, by explaining possible reasons for these results incorporating theory and practice, we can see that design choices can relate back to motivations and also further with public opinions, giving implications on the world's interest and countries' diverging developing trends in CBDC related topics.

## 2. Literature Review

Except for official statements, whitepapers and media posts, there are many scholarly research articles that investigate different aspects of CBDCs – from theoretical reasons, designs and policy suggestions for them, to specific use cases, challenges and public attitudes on them.

The most basic studies state general background, developing processes and policy potentials of CBDCs. Soderberg et al. point out conceptual benefits of CBDCs such as promoting financial inclusion, improving payment efficiency, reducing illicit use of money and reinforcing monetary sovereignty (2022). While study from Tourpe et al. gives technical and methodological guidelines of "Five Phases of CBDC Project Management" – preparation, proof-of-concepts, prototypes, pilots and production (2023). And Das et al. dialectically discuss opportunities and challenges CBDCs might bring to monetary policy transmission in their research (2023).

For more specific studies discussing CBDC designs or trend displayed in countries' CBDC decisions, the one from Bilgen and Dutto (2023) describes CBDC design frameworks as a three-level parallel model, "economy and business, socio-political and legal, and technology and operation", each extended with sub-considerations. Together with the BIS survey above showing diverging design patterns and decisions emerging with increasing global interest in CBDCs (Kosse, A. & Mattei, I., 2023), these studies give us insights on how to explore CBDCs in general, understanding their concepts, design features and relevant discussions.

Apart from these neutral and general-perspective research, there is a second type of them voicing critical opinions on practical concerns and real-life impacts of CBDCs. Some studies pay attention to users' privacy needs in the CBDC ecosystem (Murphy, K. et al., 2024), others argue that there are preconditions and obstacles for achieving system interoperability and facilitating cross-border payments with CBDCs (World Bank Group, 2021). Or in addition, the overall CBDC benefits of promoting financial inclusion and stability are based on certain institutional and operational requirements for digital technology systems (Ozili, K., 2022).

The last group of studies are ones that exactly focus on investigating and understanding public attitudes. If CBDC is for the general public, then how public opinions are incorporated or

influences the whole landscape is important. Although an increasing number of countries show interest in CBDC research, very few of them have grown their projects into a launched stage. Public opinions, especially people's worries or objections, can be one of the possible reasons why many projects stop and stay at a pilot stage or never plan for real implementations.

Authoritative institutions are using surveys to study people's knowledge and attitudes on CBDCs, either with a larger focus on global respondents from different backgrounds (Deane, S. & Fines, O., 2023) or targeting specific groups or regions, such as the U.S. (Akana, T. et al., 2024), Canada (Bank of Canada, 2023) or Germany (Deutsche Bundesbank, 2021). People have different attitudes, but surprisingly similar design requirements for CBDCs – they usually value accessibility, security and data privacy. Besides, there are also scholarly articles diving deeper into reasons behind these attitudes, such as how personal characteristics and trust influences CBDC acceptance (Bijlsma, M. et al., 2021), or how 'design alignment with consumer preferences, effective information dissemination, and leveraging network effects from emerging payment technologies' drives adoption of CBDCs (Nocciola, L. & Pérez, A., 2024).

To conclude, these literature justify a possible research direction of connecting CBDC design choices with macro development conditions, to better understand reasons for CBDC initiatives and trends, as well as exploring specific use cases and different opinions on CBDCs from a new perspective with the help from general, commonly-used macro-level theories.

While considering the most relevant literature foundations for this research, namely ones that connect CBDCs with macro indicators, Makridis' research (2024) is an example. It investigates new patterns in CBDC determinants from 2021 to 2023 based on a group of countries, as well as how CBDC adoption contributes to GDP growth and inflation (to evaluate its real economic benefits). This research, based on the idea of exploring macro determinants of

CBDCs, expands the scope by incorporating more macro indicators and categorizing CBDC design features into different, specific classes. Its ultimate goal is not to evaluate the effectiveness of CBDCs by looking at changes in macro indicators, let alone the fact that this method cannot even fully exclude influences from other monetary changes. Instead, it tries to explain countries' choices of different CBDC designs with their specific macro-developing backgrounds, and explore how designs may reflect CBDC motivations and connect with public opinions. It aims not at giving subjective, case-specific suggestions for certain CBDC projects, but tries to investigate CBDC projects worldwide, especially the overlooked ones.

## 3. Methodology

To quantitatively explore the relationship between CBDC design choices and macro indicators, or more specifically, whether and how countries' macro development conditions influence their choices of CBDC design features, this research treats countries' macro development conditions as independent variables (continuous), and CBDC design feature categories, as dependent variables (namely categorical).

### 3.1. Data and Variables

This research gathers basic information of worldwide CBDC projects in launch, pilot, proof of concept and developing stages, from two online CBDC Trackers (Atlantic Council & CBDC Tracker, 2024), complementing each other with missing information. Then, it incorporates different projects' official whitepapers or initiating countries' central bank announcements, to gain more detailed information about their choices of CBDC design features, and to verify correctness of the information collected from online trackers.

Here, this research excludes CBDC projects that are still in research or early-developing stages, namely those without clear design choices stated or tested, because they do not provide

sufficient information relevant to this research's focus. It also excludes countries that have never expressed interest in CBDCs, as the aim is not to examine whether macro conditions influence a country's decision to have CBDCs or not, but how they relate to CBDC design choices.

While among the selected CBDC projects, this research separates the joint ones between countries or across regions. They either share the same set of design features with their countries' own CBDC projects, which are already included in the selected ones, or they have very similar (regardless of initiating country/region) or totally different motivations (country/region-specific backgrounds). As a result, for joint CBDC projects, it is difficult to find patterns between their design features and macro indicators. Working out a principle of aggregating macro development conditions for a group of countries is demanding, and their design choices can also be overdriven by other factors such as regionally collective goals. Moreover, for several cancelled projects, it is also better to analyze them separately in future studies, qualitatively with different angles such as initial goals, reasons for cancellation, designs and possible problems behind, etc. Since cancelled projects are now inactive, including them alongside active ones in the analysis causes disruption.

After collecting the feature information of CBDC projects (45 qualified), this research breaks down and categorizes raw descriptions in sentences into following features: Announcement Year, Status, Structure, Type and DLT Choice (see detailed description in **Table 1**). Then, it shortens and standardizes these categorized descriptions into simplified words or phrases, and encodes them with numbers to prepare for quantitative analysis.

**Table 1** Descriptions of dependent variables

| **Dependent Variables** | **Description** |
|---|---|
| Announcement Year<br>(Before 2020 - 1, After 2020 - 2) | It is when countries officially state their interest on CBDC, no matter they aim at only researching or launching a CBDC in the future. Reasons for choosing 2020 as a splitting point for two classes are as follows: 1) the time point chosen for data of macro indicators is 2019, to exclude the Covid-19 influence; 2) the |

| | |
|---|---|
| | earliest CBDC projects worldwide were initiated around a decade ago, so 2020 is a middle point. |
| Status<br>(Launched - 1, Pilot - 2, PoC - 3) | It is the most recently updated information on a country's CBDC project stage. 'Launched' means the CBDC has been in daily use on a large scale, as an official payment method. 'Pilot' means the CBDC, with a certain set of designs, runs in real-life simulated environments, to test its scalability and performance. This involves a larger group of end-users, either domestic or partnered with another country. 'POC' means small, controlled tests that are held to validate certain design choices of CBDCs, or more generally, an idea of CBDC and preconditions required for it. |
| Structure<br>(Account - 1, Token - 2, Undecided - 3) | It is how a CBDC manages ownership and transactions. 'Account' is similar to traditional banking systems, verifying transactions based on user identity through intermediaries. 'Token' is similar to digital cash or cryptocurrencies. The transaction verification is based on cryptographic proof like private keys. 'Undecided' means the country has not specified on a certain CBDC structure, or has not considered/mentioned this. |
| Type - Retail<br>(Yes - 1, No - 0) | It is the intended usage for the CBDC project. 'Retail' means that the CBDC mainly aims at daily transactions between the general public, at individual or merchant's level. 'Yes' means choosing a retail design and 'No' means the opposite. |
| Type - Wholesale<br>(Yes - 1, No - 0) | 'Wholesale' means the CBDC is used at an institutional level, between banks or across regions and countries. 'Yes' means choosing a wholesale design and 'No' means the opposite. |
| Type<br>(Both - 1, Wholesale - 2, Retail - 3) | 'Retail' and 'Wholesale' mean exactly the same as above. 'Both' means a CBDC aims at both wholesale and retail functions. |
| DLT Choice<br>(DLT - 1, non-DLT - 2, Undecided - 3) | It is the technological infrastructure for a CBDC project. 'DLT' is a decentralized system where multiple nodes validate and record transactions (e.g. blockchain platforms). 'Non-DLT' is a centralized system managed by central authorities, with transactions recorded also in a centralized database. 'Undecided' means the country has not decided on a certain DLT choice for its CBDC yet, or not providing information/mentioning this. |

Apart from CBDC design features, the categorical dependent variables, this research gathers data representing independent variables from World Bank, namely macro development

conditions for initiating countries (for 45 selected projects). At first selection, it chooses 40 macro indicators under World Development Indicators collection, which are more likely to influence CBDC design choices. Then, considering the small dataset, the categorical nature of dependent variables, and the feasibility of a possible regression analysis, this research selects 15 of the WDIs in the end. These indicators have fewer missing values, more intuitive relation with CBDC design choices and well-established theoretical foundations (see detailed description in **Table 2**), covering different macro(economic) aspects.

**Table 2** Descriptions of independent variables

| **Independent Variables** | **Description** |
|---|---|
| Employment to population ratio, 15+, total (%) (national estimate) | The proportion of a country's population that is employed. Employment is defined as persons of working age who were engaged in any activity to produce goods or provide services for pay or profit. It includes those who are at work during a short reference period or not at work due to temporary absence, or working-time arrangements. |
| GDP (constant 2015 US$) | Represents the sum of value added by a country or region's all resident producers. Value added is the value of gross output less intermediate goods and services consumed in production, plus product taxes and minus subsidies excluded in the product value. GDP is calculated without deductions for depreciation and depletion of natural resources. |
| GNI per capita (constant 2015 US$) | Gross national income divided by mid-year population. GNI is the sum of value added by a country or region's all resident producers, plus product taxes (less subsidies) not included in the valuation of output, and net receipts of primary income from abroad (employee compensation and property income). |
| Inflation, consumer prices (annual %) | Measured by CPI. It reflects the annual percentage change in the cost for an average consumer, to acquire a basket of goods and services that are fixed or changed at specified intervals. |
| Land area (sq. km) | A country's total area, excluding inland water bodies such as major rivers and lakes, national claims to continental shelf, and exclusive economic zones, but including areas of former states. |

| | |
|---|---|
| Medium and high-tech manufacturing value added (% manufacturing value added) | The share of medium and high technology industries in the total value added to the manufacturing sector. These industries are defined according to OECD classification, based on International Standard Industrial Classification of All Economic Activities (ISIC), Revision 3 and Revision 4 Division. |
| Population ages 15-64 (% of total population) | The percentage of a country's total population that falls within the 15-64 age group. The age structure is based on estimates from the United Nations Population Division's World Population Prospects. The total population includes all residents, regardless of their legal status or citizenship. Values are mid-year estimates. |
| Political Stability and Absence of Violence/Terrorism: Estimate | Measures perceptions of the likelihood of political instability or politically-motivated violence, including terrorism. The estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, ranging from about -2.5 to +2.5. |
| Depth of credit information index (0=low to 8=high) | Measures 1) rules affecting the scope, accessibility, and quality of credit information available through public or private credit registries; 2) whether banks and financial institutions can access credit information via an online platform or system-to-system connection; and (3) whether credit scores are offered as a value added service to help financial institutions to assess borrowers' creditworthiness. If the credit bureau or registry is not operating or covers less than 5% of the adult population, the index is 0. |

As stated in the description of Dep. Variable *Announcement Year - Before 2020/After 2020*, this research chooses year 2019 as the reference point for WDI data. This choice helps avoid abnormal values and reporting gaps in subsequent years due to Covid-19 effects, while still using as recent data as possible. We do not need to worry a lot about the influence of relying on a specific year's data rather than applying a time-aggregation method, because effects from macro development conditions on CBDC designs are more likely to be gradual and need time to reflect.

**3.2. Model Selection**

The data features are as follows: 1) a small dataset with five dependent variables, each having 45 observations and divided into two to four different classes, and 15 independent variables, each also with 45 observations, but some with few missing values; 2) categorical

dependent variables and continuous independent variables. Therefore, after several trials of different regression models, this research eventually proceeds on with binomial/multinomial logistic regression (depends on the number of classes for each dependent variable) to analyze how countries' macro development conditions influence their choices of CBDC design features.

For **Binomial logistic regression**:

$$log\left(\frac{P(Y=1)}{1-P(Y=1)}\right)=\beta_0+\beta_1X_1+\beta_2X_2+\cdots+\beta_nX_n$$

Here, P (Y=1) is the probability of choosing the predicted class. 1-P (Y=1) is the probability of choosing the reference/baseline class. $\beta_0$ is the intercept, and $\beta_1$, $\beta_2$, ..., $\beta_n$ are the coefficients for each independent variable. $X_1$, $X_2$, ..., $X_n$ represent the standardized independent variables.

For **Multinomial logistic regression**:

$$log\left(\frac{P(Y=j)}{P(Y=1)}\right)=\beta_{0j}+\beta_{1j}X_1+\beta_{2j}X_2+\cdots+\beta_{nj}X_n$$

Here, P (Y=j) is the probability of choosing the predicted class j. P(Y=1) is the probability of choosing the reference/baseline class. $\beta_{0j}$ is the intercept for class j, and $\beta_{1j}$, $\beta_{2j}$, ..., $\beta_{nj}$ are the coefficients for class j for each independent variable. $X_1$, $X_2$, ..., $X_n$ represent the standardized independent variables.

In the first trial of logistic regression, all 15 WDIs are included simultaneously in the model to find how macro development conditions influence CBDC design choices. However, when this research applies the model across different dependent variables, their performances are poor overall, whether judging from different model fit measures (i.e. Omnibus likelihood ratio test, AIC, BIC and Pseudo $R^2$) or coefficient estimates (i.e. P-value, 95% confidence interval of odds ratio and Standard error). The model either does not fit the data well, not performing better than a null model, or the relationship indicated between variables is far from being statistically

significant. Only binomial logistic regressions converge, while the multinomial ones fail to converge, with completely volatile and untrustworthy predictions. Though this first regression trial is unsuccessful, it still gives important insights on issues to be addressed: 1) there is high multicollinearity between independent variables; and 2) the class distribution of some dependent variables are imbalanced or sparse.

To solve the collinearity problem, this research conducts a Variance Inflation Factor (VIF) test to explore how much the variance of estimated coefficient of each variable increases, due to the collinearity of itself with others. It uses a VIF threshold of five to identify problematic variables with high multicollinearity, thus excluding four independent variables from the model: *Government Effectiveness: Estimate*, *Final consumption expenditure (% of GDP)*, *Gross savings (% of GDP)*, and *Voice and Accountability: Estimate* (see full output in **Appendix B**).

For **VIF test**:

$$VIF\left(Xi\right) = \frac{1}{1 - R_i^2}$$

Here, $R_i^2$ is the coefficient of determination obtained from regressing the independent variable $X_i$ on all the other independent variables. It represents the proportion of variance in $X_i$ explained by other independent variables. In the model application, VIF calculation is based on standardized independent variables, which are scaled to have a mean of zero and a standard deviation of one, without changing the correlation structure and VIF values. The standardization is to ensure that variables are on the same scale, and none of them dominates the model due to large units of measurement, since independent variables here (WDIs) are in different units.

Then, after taking out four WDIs based on collinearity, logistic regression is applied again for the five dependent variables. However, the convergence failure remains the same. To solve this problem, this research conducts a second VIF test, accompanied by a correlation

matrix. It excludes WDIs from the highest correlation pairs and those with higher VIF values (see full output in **Appendix C**). As a result, *Net migration* in *GDP* and *Net migration* pair, and *Individuals using the Internet* in *GNI per capita* and *Individuals using the Internet* pair are taken out. After these adjustments, models for all dependent variables converge, with nine WDIs left.

Meanwhile, this research reconsiders and reclassifies instances within certain feature categories, to reduce their class imbalance. It also makes specific adjustments to the basic logistic regression implementation in Python. These includes selecting a solver best suited for a small dataset (finally 'bfgs'), increasing the maximum number of iterations (finally 10000) to give the algorithm more time to refine estimates, and imputing missing values in independent variables with means of each, since dropping rows leads to even a smaller dataset. In addition, as stated previously, this research standardizes independent variables and computes model fit measures for each dependent variable to evaluate the performance.

### 3.3. Relation Hypotheses

The relationship between macro development conditions and CBDC design features can be hypothesized as follows: For *Depth of credit information index (0=low to 8=high)*, this indicator reflects the robustness of financial institutions and credit information collection, relating to needs like improving existing credit systems and facilitating financial services providing. Therefore, a higher index may point to CBDC design features of **a wholesale Type and non-DLT Choice**, suggesting that CBDCs prioritize institutional efficiency, and safer, traditional designs.

For *Employment to population ratio, 15+, total (%) (national estimate)*, this indicator reflects employment and people's living conditions, relating to factors like financial system design requirements for daily consumption, money transfer and wage payments. Therefore, a

higher ratio may point to CBDC design features of **an earlier Announcement Year, fast-moving Status, token Structure and retail Type**, suggesting that CBDCs are urgent, with cash-like structures and serving individuals.

For *GDP (constant 2015 US$)*, this indicator reflects stability of the socioeconomic environment, relating to factors like resources for developing financial service infrastructures and improving existing systems, as well as consumer confidence and behavior. Therefore, a higher number may point to CBDC design features of **a later Announcement Year, slow-moving Status, retail Type and DLT Choice**, suggesting that CBDCs require careful exploration, are consumer-based and provide technological support for existing infrastructures.

For *GNI per capita (constant 2015 US$)*, this indicator reflects people's income, relating to factors like purchasing power, access to digital technology and public opinions on financial system designs. Therefore, a higher number may point to CBDC design features of **a later Announcement Year, slow-moving Status, token Structure, retail Type and DLT Choice**, suggesting that CBDCs require careful developing processes and decentralization, with public focus and high-tech design.

For *Inflation, consumer prices (annual %)*, this indicator reflects inefficiencies in cash payment systems, relating to needs like stabilizing the economy, reestablishing public trust in the financial system and implementing monetary policy changes smoothly through intervening tools. Therefore, a higher number may point to CBDC design features of **an earlier Announcement Year, fast-moving Status, both retail and wholesale Type and a non-DLT Choice**, suggesting that CBDCs are promising solutions to inflation, which should be rolled out quickly, aiming at different markets and transactions, with safer, traditional designs.

For *Land area (sq. km)*, this indicator reflects the accessibility and differences in financial services offerings across regions, relating to needs like transaction efficiency improvements and infrastructure alignment for different geographical locations. Therefore, a larger number may point to CBDC design features of **a wholesale Type**, suggesting that CBDCs prioritize regional interbank transaction settlement.

For *Medium and high-tech manufacturing value added (% manufacturing value added)*, this indicator reflects the development of manufacturing sector and production of high-tech goods, relating to needs like improving transaction and settlement efficiency for large-amount payments, institutional players, import-export industries and cross-border entities. Therefore, a higher value may point to CBDC design features of **a wholesale Type**, suggesting that CBDCs emphasize the efficiency of interbank financial services.

For *Political Stability and Absence of Violence/Terrorism: Estimate*, this indicator reflects government effectiveness and social stability, relating to needs like improving or maintaining the present level of security and trust in governance. Therefore, a higher score may point to CBDC design features of **a later Announcement Year, slowly-moving Status, account Structure and non-DLT Choice**, suggesting that CBDCs require careful tests, and follow traditional structures which already proves to be effective, to reduce potential risks and disruptions.

For *Population ages 15-64 (% of total population)*, this indicator reflects the size of the working-age population or labor force, relating to factors like the potential for economic growth, people's engagement in digital technology, their purchasing power, salary distribution and social welfare systems. Therefore, a larger number may point to CBDC design features of **an earlier Announcement Year, token Structure and retail Type**, suggesting that CBDCs are urgent solutions, with cash-like structures and for individual end users.

## 4. Results

This section gives a description and theoretical explanation of the logistic regression outcomes, linking back with hypotheses on how macro development conditions relate to certain choices of CBDC design features, and further with discussions in existing CBDC literature.

For the main analysis below, it only displays important independent variables, including their coefficient estimates, standard error, p-value, calculated odds ratio and their corresponding influence direction (increase/decrease) on each dependent variable (see full output in **Appendix D**). An independent variable qualifies as long as the p-value of its coefficient estimate falls within a 0.2 threshold, because: 1) dependent variables here are categorical rather than continuous, and the dataset is small; 2) the aim of this research is to explore the relationship and explainability between variables rather than achieve prediction accuracy. Therefore, it is necessary to retain as many relevant variables as possible. Also, only the most important model fit measures – Pseudo $R^2$, Log-likelihood, LLR p-value, LL-null, AIC and BIC are included. Among them, AIC and BIC are used to compare models with the same set of independent variables across different dependent variables, to evaluate their performance differences. In other words, there is little information we can infer by looking at AIC and BIC of a single dependent variable, so this research does not include descriptions of them separately for each model here.

For *Type - Retail - Yes/No*, *Type - Wholesale - Yes/No* and *Type - Both/Wholesale/Retail* models, the number of observations for each is 43, after excluding two projects with an 'Undecided' Type choice from the 45 selected ones. Up to now, there are only three type choices explored for worldwide CBDC projects, namely 'Retail', 'Wholesale' and 'Both'. Therefore, 'Undecided' rather means not mentioned than hesitation, also because Type is typically among the earliest decisions made for CBDC initiatives. While for other design features, they may

receive different treatment. For example, if a country explores both an ‘Account’ and ‘Token’ Structure for its CBDC project, this research will leave its Structure choice ‘Undecided’, because the country is hesitating between two possible choices. Contrarily, if the country explores both a ‘Retail’ and ‘Wholesale’ CBDC, this research will categorize its Type choice either as ‘Both’, or as one ‘Retail’ and one ‘Wholesale’ if the country has two separate projects for them.

In short, countries are more likely to leave other CBDC design choices uncertain, reflecting their hesitation and justifying the inclusion of an ‘Undecided’ category. However, the only possibility for an ‘Undecided’ Type choice is that countries generally claim they are developing a CBDC, without specifying whether it is a retail or wholesale one. Then, ‘Undecided’ in Type feature gives no useful information for its analysis and two ‘Undecided’ instances are excluded. Moreover, the reason why applying logistic regression to CBDC Type feature in three ways is that comparisons between its classes (Retail vs. Wholesale vs. Both) is not enough – the ‘Both’ class indicates that choices on this feature is not a simple A **or** B one, but A **and** B is also possible. As a result, this research includes *Type - Retail - Yes/No* and *Type - Wholesale - Yes/No* to help better explore reasons behind choices for each Type class separately.

### 4.1. Output Description

**Table 3** Logistic Regression for Announcement Year - Before 2020/After 2020 (Binary)

| | | | |
|---|---|---|---|
| Dep. Variable: Announcement Year (Before 2020 - 1/After 2020 - 2) | | | |
| No. Observations: | 45 | | |
| Pseudo R-squ.: | 0.1760 | Log-Likelihood: | -24.954 |
| LLR p-value: | 0.2996 | LL-Null: | -30.286 |
| AIC: | 69.9086153249201 | BIC: | 87.97524022262328 |

| | | | | |
|---|---|---|---|---|
| Reference/Baseline: Before 2020 - 1 | | | | |
| Predicted: After 2020 - 2 | | | | |
| Variable (coefficient) | std err | P>\|z\| | Odds ratio | Direction (‘-’ means decrease) |
| Constant | | | | |
| 0.4980 | 0.352 | 0.158 | 1.6450 | 64.50% higher |
| GDP (constant 2015 US$) | | | | |

| | | | | |
|---|---|---|---|---|
| 0.8201 | 0.511 | 0.108 | 2.2710 | 127.10% |
| Land area (sq. km) | | | | |
| -0.7665 | 0.534 | 0.151 | 0.4650 | -53.50% |
| Political Stability and Absence of Violence/Terrorism: Estimate | | | | |
| 1.1378 | 0.524 | 0.030 | 3.1190 | 211.90% |

Considering model fit measures, the Pseudo $R^2$ suggests that the model explains about 17.60% of the variance in the CBDC Announcement Year choice. It indicates a relatively weak model fit compared to others. Comparing the log-likelihood of this model to the one of the null model, the one for this model is less negative, thus performing better in explanation but still has room for improvement. The LLR p-value is not statistically significant at 5% level, which means that the model with these independent variables does not significantly improve over a null one. But considering categorical dependent variables and the exploring aim of this research, it can still help examine how macro development conditions influence the Announcement Year choice. For coefficient estimates, the *baseline* odds of being 'After 2020' is naturally 64.50% higher compared to 'Before 2020', holding all other variables constant; a one-unit increase in *GDP* increases the odds of being 'After 2020' compared to 'Before 2020' by 127.10%; a one-unit increase in *Land area* decreases the odds of being 'After 2020' compared to 'Before 2020' by 53.50%; and a one-unit increase in *Political Stability and Absence of Violence/Terrorism* increases the odds of being 'After 2020' compared to 'Before 2020' by 211.90%.

**Table 4** Logistic Regression for Status - Launched/Pilot/PoC (Multinomial)

| | | | |
|---|---|---|---|
| Dep. Variable: Status (Launched - 1/Pilot - 2/PoC - 3) | | | |
| No. Observations: | 45 | | |
| Pseudo R-squ.: | 0.4746 | Log-Likelihood: | -21.499 |
| LLR p-value: | 0.002989 | LL-Null: | -40.921 |
| AIC: | 82.9976572706425 | BIC: | 119.13090706604889 |

Reference/Baseline: Launched - 1
Predicted: Pilot - 2

| Variable (coefficient) | std err | P>\|z\| | Odds ratio | Direction ('-' means decrease) |
|---|---|---|---|---|
| Employment to population ratio, 15+, total (%) (national estimate) | | | | |

| | | | | |
|---|---|---|---|---|
| -3.6732 | 1.952 | 0.060 | 0.0250 | -97.50% |
| Political Stability and Absence of Violence/Terrorism: Estimate | | | | |
| 3.3337 | 1.836 | 0.069 | 28.0270 | 2702.70% |

Considering model fit measures, the Pseudo $R^2$ suggests that the model explains about 47.46% of the variance in the choice of CBDC Status. It indicates a relatively strong model fit overall and among others. Comparing the log-likelihood of this model to the one of the null model, this model performs better in explanation, which indicates a good fit to the data. While for the LLR p-value, it is statistically significant at 5%, which means that the model with these independent variables significantly improves over the null one. For coefficient estimates, a one-unit increase in the *Employment to population ratio* decreases the likelihood of Status choice to be 'Pilot' rather than 'Launched' by 97.50%; and a one-unit increase in *Political stability and absence of violence/terrorism* increases the likelihood of Status choice to be 'Pilot' rather than 'Launched' by 2702.70%.

**Table 4 Cont.** Logistic Regression for Status - Launched/Pilot/PoC (Multinomial)

| Reference/Baseline: Launched - 1<br>Predicted: PoC - 3<br>Variable (coefficient) | std err | P>\|z\| | Odds ratio | Direction ('-' means decrease) |
|---|---|---|---|---|
| Inflation, consumer prices (annual %) | | | | |
| -62.9200 | 27.394 | 0.022 | 0.0000 | -100.00% |

While considering 'PoC' as the predicted class, a one-unit increase in *Inflation* decreases the likelihood of CBDC Status choice to be 'PoC' rather than 'Launched' by 100% (or in other words, choice of 'PoC' over 'Launched' is extremely close to 0%), but the standard error of this estimate is large, which means the variability of this prediction is large.

**Table 5** Logistic Regression for Structure - Account/Token/Undecided (Multinomial)

| Dep. Variable: Structure (Account - 1, Token - 2, Undecided - 3) | | | |
|---|---|---|---|
| No. Observations: | 45 | | |
| Pseudo R-squ.: | 0.1690 | LL-Null: | -46.585 |
| LLR p-value: | 0.6105 | Log-Likelihood: | -38.714 |

| AIC: | 117.42716000758915 | BIC: | 153.56040980299554 |
|---|---|---|---|

| Reference/Baseline: Account - 1<br>Predicted: Token - 2<br>Variable (coefficient) | std err | P>\|z\| | Odds ratio | Direction (‘-’ means decrease) |
|---|---|---|---|---|
| Constant<br>1.5875 | 0.843 | 0.060 | 4.8930 | 389.30% higher |

Considering the model fit measures, the Pseudo $R^2$ suggests that the model explains about 16.90% of the variance in Structure choice. It indicates a relatively weak model fit overall and among others. Comparing the log-likelihood of this model to the one of the null model, this model performs better in explanation but still shows room for improvements. LLR p-value is relatively far from being statistically significant at 5% level, which means that the model with these independent variables does not significantly improve over the null one. Therefore, this model may not be well-suited for predicting countries’ choices of CBDC Structure. However, considering the nature of this research, this model can still be considered for exploring how a country’s macro development conditions influence its choice of CBDC design features. For the coefficient estimate, the *baseline* odds of CBDC Structure choice is naturally 389.30% more likely to be ‘Token’ rather than ‘Account’.

**Table 5 Cont.** Logistic Regression for Structure - Account/Token/Undecided (Multinomial)

| Reference/Baseline: Account - 1<br>Predicted: Undecided - 3<br>Variable (coefficient) | std err | P>\|z\| | Odds ratio | Direction (‘-’ means decrease) |
|---|---|---|---|---|
| Inflation, consumer prices (annual %)<br>-8.4342 | 6.079 | 0.165 | 0.0002 | -99.98% |

While considering ‘Undecided’ as the predicted class, a one-unit increase in *Inflation* decreases odds of choosing ‘Undecided’ over ‘Account’ by approximately 99.98%, but standard error of this estimate is relatively large, which means the variability of this prediction is large.

**Table 6** Logistic Regression for Type - Retail - Yes/No (Binomial)

| | | | | |
|---|---|---|---|---|
| Dep. Variable: Type - Retail (Yes - 1, No - 0) | | | | |
| No. Observations: | 43 | | | |
| Pseudo R-squ.: | 0.3976 | | Log-Likelihood: | -14.049 |
| LLR p-value: | 0.02937 | | LL-Null: | -23.321 |
| AIC: | 48.09840268048634 | | BIC: | 65.71040383742196 |
| Reference/Baseline: No - 0 | | | | |
| Predicted: Yes - 1 | | | | |
| Variable (coefficient) | std err | P>\|z\| | Odds ratio | Direction (‘-’ means decrease) |
| Constant | | | | |
| 9.7935 | 5.619 | 0.081 | 17999.0000 | Very high |
| Inflation, consumer prices (annual %) | | | | |
| 39.8435 | 26.359 | 0.131 | Very high | Very high |
| Land area (sq. km) | | | | |
| -1.0173 | 0.689 | 0.140 | 0.3620 | -63.80% |
| Medium and high-tech manufacturing value added (% manufacturing value added) | | | | |
| -1.1235 | 0.668 | 0.093 | 0.3250 | -67.50% |

Considering model fit measures, the Pseudo $R^2$ suggests that the model explains about 39.76% of the variance in CBDC Type choice to be ‘Retail’ or not. It indicates a moderate model fit. Comparing the log-likelihood of this model to the one of the null model, this model performs better in explaining why a country is more likely to choose a Retail CBDC than not. The LLR p-value is statistically significant at 5% level, meaning that the model with these independent variables significantly improves over the null one. For coefficient estimates, the *baseline* odds of choosing a ‘Retail’ Type is almost definitely likely compared to not; a one-unit increase in *Inflation* increases the odds of choosing a ‘Retail’ Type compared to not by an extremely high magnitude, but also with a high standard error, which indicates a large variability in the prediction; a one-unit increase in *Land area* decreases the odds of choosing ‘Retail’ compared to not by approximately 63.80%; and a one-unit increase in *Medium and high-tech manufacturing value added* decreases the odds of choosing ‘Retail’ compared to not by about 67.50%.

**Table 7** Logistic Regression for Type - Wholesale - Yes/No (Binomial)

| | | | |
|---|---|---|---|
| Dep. Variable: Type - Wholesale (Yes - 1, No - 0) | | | |
| No. Observations: | 43 | | |
| Pseudo R-squ.: | 0.2556 | Log-Likelihood: | -22.111 |
| LLR p-value: | 0.08611 | LL-Null: | -29.701 |
| AIC: | 64.22108147986137 | BIC: | 81.83308263679699 |

| | | | | |
|---|---|---|---|---|
| Reference/Baseline: No - 0 | | | | |
| Predicted: Yes - 1 | | | | |
| Variable (coefficient) | std err | P>\|z\| | Odds ratio | Direction (‘-’ means decrease) |
| Inflation, consumer prices (annual %) | | | | |
| 0.7687 | 0.542 | 0.156 | 2.1600 | 116.00% |
| Land area (sq. km) | | | | |
| 1.2577 | 0.690 | 0.068 | 3.5200 | 252.00% |
| Medium and high-tech manufacturing value added (% manufacturing value added) | | | | |
| 0.9829 | 0.509 | 0.053 | 2.6700 | 167.00% |

Considering model fit measures, the Pseudo $R^2$ suggests that the model explains about 25.56% of the variance in CBDC Type choice to be ‘Wholesale’ or not. It indicates a moderate model fit. Comparing the log-likelihood of this model to the one of the null model, this model performs better in explanatory power. The LLR p-value is marginally significant at a 10% level, but not statistically significant at a 5% threshold. Therefore, this model still provides improvement over the null one. For coefficient estimates, a one-unit increase in *Inflation* increases the odds of choosing a ‘Wholesale’ Type compared to not by approximately 116.00%; a one-unit increase in *Land area* increases the odds of choosing a ‘Wholesale’ Type compared to not by about 252.00%; and a one-unit increase in *Medium and high-tech manufacturing value added* increases the odds of choosing a ‘Wholesale’ Type compared to not by 167.00%.

**Table 8** Logistic Regression for Type - Both/Wholesale/Retail (Multinomial)

| | | | |
|---|---|---|---|
| Dep. Variable: Type (Both - 1, Wholesale - 2, Retail - 3) | | | |
| No. Observations: | 43 | | |
| Pseudo R-squ.: | 0.3447 | Log-Likelihood: | -28.545 |
| LLR p-value: | 0.03709 | LL-Null: | -43.564 |
| AIC: | 97.09060696349557 | BIC: | 132.31460927736683 |

| Reference/Baseline: Both - 1<br>Predicted: Wholesale - 2<br>Variable (coefficient) | std err | P>\|z\| | Odds ratio | Direction ('-' means decrease) |
|---|---|---|---|---|
| Constant | | | | |
| -8.7770 | 5.699 | 0.124 | 0.00015 | 99.99% lower |
| Depth of credit information index (0=low to 8=high) | | | | |
| 1.1835 | 0.883 | 0.180 | 3.2670 | 226.70% |
| Inflation, consumer prices (annual %) | | | | |
| -42.4948 | 26.704 | 0.112 | 0.0000 | -100.00% |
| Population ages 15-64 (% of total population) | | | | |
| -1.3466 | 0.960 | 0.161 | 0.2600 | -74.00% |

Considering model fit measures, the Pseudo $R^2$ suggests that the model explains about 34.47% of the variance in CBDC Type choice further. It indicates a moderate-to-strong model fit. Comparing the log-likelihood of this model to the one of a null model, this model performs substantially better in explanatory power. The LLR p-value is statistically significant at a 5% level, suggesting that the model with these independent variables provides a significant improvement in predicting choices on CBDC Type. For coefficient estimates, the *baseline* odds of choosing CBDC Type to be 'Wholesale' compared to 'Both' is naturally about 99.99% lower; a one-unit increase in the *Depth of credit information index* increases the odds of choosing CBDC Type to be 'Wholesale' compared to 'Both' by 226.70%; a one-unit increase in *Inflation* decreases the odds of choosing CBDC Type to be 'Wholesale' over 'Both' by approximately 100.00%, but with a high standard error, which indicates a large variability in the prediction; and a one-unit increase in *Population ages 15-64* decreases the odds of choosing CBDC Type to be 'Wholesale' over 'Both' by approximately 74.00%.

**Table 8 Cont.** Logistic Regression for Type - Both/Wholesale/Retail (Multinomial)

| Reference/Baseline: Both - 1<br>Predicted: Retail - 3<br>Variable (coefficient) | std err | P>\|z\| | Odds ratio | Direction ('-' means decrease) |
|---|---|---|---|---|
| Constant | | | | |
| 0.9422 | 0.489 | 0.054 | 2.5660 | 156.60% higher |

| | | | | |
|---|---|---|---|---|
| Depth of credit information index (0=low to 8=high) | | | | |
| 0.8699 | 0.493 | 0.078 | 2.3870 | 138.70% |
| Inflation, consumer prices (annual %) | | | | |
| -0.8575 | 0.600 | 0.153 | 0.4240 | -57.60% |
| Land area (sq. km) | | | | |
| -1.4577 | 0.839 | 0.082 | 0.2330 | -76.72% |

While considering 'Retail' as the predicted class, for coefficient estimates, the *baseline* odds of choosing CBDC Type to be 'Retail' over 'Both' is naturally 156.60% higher; a one-unit increase in the *Depth of credit information index* increases the odds of choosing CBDC Type to be 'Retail' compared to 'Both' by 138.70%; a one-unit increase in *Inflation* decreases the odds of choosing CBDC Type to be 'Retail' over 'Both' by 57.60%; and a one-unit increase in *Land area* decreases the odds of choosing CBDC Type to be 'Retail' over 'Both' by 76.72%.

**Table 9** Logistic Regression for DLT Choice - DLT/Non-DLT/Undecided (Multinomial)

| | | | |
|---|---|---|---|
| Dep. Variable: DLT (DLT - 1, Non-DLT - 2, Undecided - 3) | | | |
| No. Observations: | 45 | | |
| Pseudo R-squ.: | 0.2590 | Log-Likelihood: | -31.961 |
| LLR p-value: | 0.2172 | LL-Null: | -43.131 |
| AIC: | 103.92119936461052 | BIC: | 140.0544491600169 |

Reference/Baseline: DLT - 1
Predicted: Non-DLT - 2

| Variable (coefficient) | std err | P>\|z\| | Odds ratio | Direction ('-' means decrease) |
|---|---|---|---|---|
| Constant | | | | |
| -3.5218 | 1.700 | 0.038 | 0.0300 | 97.00% lower |
| GDP (constant 2015 US$) | | | | |
| 2.5154 | 1.878 | 0.180 | 12.3700 | 1137.00% |
| GNI per capita (constant 2015 US$) | | | | |
| -3.2229 | 1.666 | 0.053 | 0.0400 | -96.00% |

Considering model fit measures, the Pseudo $R^2$ suggests that the model explains about 25.90% of the variance in the DLT Choice. It indicates a moderate fit. Comparing the log-likelihood of this model to the one of the null model, this model shows an improvement in explanatory power, suggesting that the independent variables contribute to the explanation of

DLT Choice. The LLR p-value is not statistically significant at 5% level, meaning that the model with these independent variables does not significantly improve over the null one. However, the independent variables can still provide useful insights. For coefficient estimates, the *baseline* odds of choosing 'Non-DLT' over 'DLT' is naturally 97.00% lower; a one-unit increase in *GDP* increases the odds of choosing 'Non-DLT' over 'DLT' by 1137.00%; and a one-unit increase in *GNI per capita* decreases the odds of choosing 'Non-DLT' over 'DLT' by about 96.00%.

**Table 9 Cont.** Logistic Regression for DLT Choice - DLT/Non-DLT/Undecided (Multinomial)

| Reference/Baseline: DLT - 1<br>Predicted: Undecided - 3<br>Variable (coefficient) | std err | P>\|z\| | Odds ratio | Direction ('-' means decrease) |
|---|---|---|---|---|
| Depth of credit information index (0=low to 8=high) | | | | |
| 0.6507 | 0.475 | 0.170 | 1.9170 | 91.70% |
| Political Stability and Absence of Violence/Terrorism: Estimate | | | | |
| 0.9345 | 0.573 | 0.103 | 2.5460 | 154.60% |

While considering 'Undecided' as the predicted class, for coefficient estimates, a one-unit increase in *Political Stability and Absence of Violence/Terrorism: Estimate* increases the odds of leaving DLT Choice 'Undecided' rather than choosing 'DLT' by 154.60%; and a one-unit increase in the *Depth of credit information index* increases the odds of leaving DLT Choice 'Undecided' rather than choosing 'DLT' by 91.70%.

### 4.2. Regression Explanation

For countries with higher *Inflation, consumer prices (annual %)*, they tend to choose CBDC designs to be: **a 'Launched' Status over 'PoC', a 'Both' Type over 'Retail' or 'Wholesale', and an 'Account' Structure over 'Undecided'**. Countries with higher inflation consider CBDC as a promising monetary tool to help stabilize the economy. If combined with an interest-bearing design, it helps central banks control inflation and implement monetary policy changes more smoothly. A 'Wholesale' design facilitates interbank transactions, helping banks

manage liquidity and reduce costs during this time. It allows central banks to intervene and ease inflation through institutional measures like banking reserves, or reduce currency depreciation and capital outflow by foreign reserve solutions which involve cross-border payments and settlements. While a 'Retail' design helps central banks reach every individual and influence their financial activities, distributing stimulus or subsidies directly. It serves as a digital, stable alternative to physical cash, helping low income populations protect assets against inflation, and enhancing financial inclusion. Thus, during high-inflation times, a 'Both' design aims at different markets, upgrades the traditional system, and restores public trust. Usually, central banks do not have enough time to develop new infrastructures at this point, so an 'Account' design works better – secure and familiar to the public and easier for government management and intervention. And an inflation-protected value storing system driven by an account-based CBDC, is more structured, stable and preferable during this time. Overall, higher inflation exposes problems in financial infrastructures, followed by a need to modernize and digitalize the system. Countries may want to push CBDC to a 'Launched' stage to expect its real influence.

Relating back to the hypothesis for *Inflation, consumer prices (annual %)*, we can see that a higher number does not show clear relation with CBDC design choices on Announcement Year and DLT as expected. But it indeed points to a fast-moving Status, especially a 'Launched' here, and a 'Both' Type. And unexpectedly, it is associated with an 'Account' Structure.

For countries with larger *Land area (sq. km)*, they tend to choose CBDC designs to be: **a 'Before 2020' Announcement Year over 'After 2020', a 'Both' or 'Wholesale' Type, but not a 'Retail' one**. Countries with larger land areas usually have dispersed populations, difficulties for traditional physical banking in connecting institutions, or insufficient financial infrastructures in remote areas. A 'Wholesale' design under this situation helps improve interbank transaction

and settlement efficiency; while a ‘Retail’ design supports daily transactions of individual end-users, especially those in remote areas, with poorer financial services offered to them compared to those in the central urban area. Therefore, a CBDC with ‘Both’ functions working in cooperation helps better improve the financial payment system in countries with large land areas. But a ‘Retail’ design alone does not solve the problem in interbank transaction efficiency, and it can be costly to roll out across vast land areas, because it requires extensive infrastructures to support a large number of individual accounts, integrate with existing systems and deal with cybersecurity risks and operational complexity. Overall, for the future development of countries with larger land areas, CBDC with benefits above, can be an urgent solution to the current situation, which points to a ‘Before 2020’ choice for them. It also helps reduce cash managing costs and security risks for physical banking across vast territory, bridging the regional gap between people’s access to financial services and technology, and improving financial inclusion.

Relating back to the hypothesis for *Land area (sq. km)*, we can see that a larger number indeed relates to a ‘Wholesale’ Type. Additionally, a ‘Both’ one is also preferred. And beyond hypothesis, it is associated with a ‘Before 2020’ Announcement Year.

For countries with higher *Depth of credit information index (0=low to 8=high)*, they tend to choose CBDC designs to be: **a ‘Wholesale’ or ‘Retail’ Type over ‘Both’ (larger preference for ‘Wholesale’) and an ‘Undecided’ DLT Choice over ‘DLT’**. Countries with deeper credit information already have well-established financial institutions and credit reporting systems, to provide individuals with wide-ranging financial services. Based on the security provided by deeper credit information, a ‘Retail’ design helps further improve financial inclusion by extending services to those unbanked who lack credit history; while a ‘Wholesale’ design facilitates interbank and cross-border settlements, improving information exchange and real-time

transactions between institutions and benefiting the efficiency of the whole system. However, a choice between these two designs depends further on countries' specific conditions (i.e. whether the retail or wholesale system needs urgent improvement) and a CBDC with both focuses is less necessary for countries already with deep credit information, to enable larger-coverage financial services. It is not an urgent but only supplementary solution. The 'Undecided' DLT Choice follows a similar logic. Those countries are usually more cautious and explore both a DLT and non-DLT design, delaying their choice first. They may even end up integrating a traditional non-DLT system with new DLT elements as long as it works for their specific cases.

Relating back to the hypothesis for *Depth of credit information index (0=low to 8=high)*, we can see that a higher index indeed relates to a 'Wholesale' Type. Additionally, a 'Retail' one is also slightly preferred. However, contrary to the hypothesis, it is not associated with a 'Non-DLT' Choice but an 'Undecided' one.

For countries with higher *Political Stability and Absence of Violence/Terrorism: Estimate*, they tend to choose CBDC designs to be: **an 'After 2020' Announcement Year over 'Before 2020', a 'Pilot' Status over 'Launched' and an 'Undecided' DLT Choice over 'DLT'**. Countries with higher political stability and less violence usually have more stable development and social conditions. Existing infrastructures are already sufficient – the banking system and private payment providers are enough to support people's financial transaction requirements. As a result, CBDC is not an urgent but a more supplementary solution to the existing system, which points to an 'After 2020' choice. Also, those countries tend to evaluate their CBDCs carefully before practical implementation. A 'Pilot' choice avoids pushing CBDC projects too quickly without thorough experiments, which can lead to unexpected risks such as disrupting established social stability, due to the failure to align with existing systems, security requirements and

regulations. An ‘Undecided’ DLT Choice follows a similar logic. For the two usual DLT choices, a non-DLT system may have security problems that a traditional, physical banking system also possesses, while a DLT system may have data security and cybersecurity problems. Since both have disadvantages, for countries with higher political stability, leaving DLT choice ‘Undecided’ before carefully assessing all potential problems on different DLT designs reduces uncertainty.

Relating back to the hypothesis for *Political Stability and Absence of Violence/Terrorism: Estimate*, we can see that a higher number does not show clear association with CBDC design choices on Structure as expected. But it indeed relates to a later Announcement Year and slow-moving Status (but only relatively), especially an ‘After 2020’ and ‘Pilot’ one. However, contrary to the hypothesis, it is not associated with a ‘Non-DLT’ Choice but an ‘Undecided’ one.

For countries with higher *GDP (constant 2015 US$)*, they tend to choose CBDC designs to be: **an ‘After 2020’ Announcement Year over ‘Before 2020’ and a ‘Non-DLT’ Choice over ‘DLT’**. Countries with higher GDP usually have well-developed banking systems and infrastructures which proves to contribute to stable economic growth and social environment, already gaining trust from people. They are cautious in planning for economic and financial changes, and prefer to upgrade or digitize payment systems based on existing ones, which points to a traditional ‘Non-DLT’ design. It aligns better with existing governance and regulations, has more scalability, less energy consumption and cybersecurity risks, which are more to the concerns of countries with higher GDP. Also, for those countries, CBDC is not a must for sustaining their growth or unlocking their economic potential. Therefore, capable of exploring different design frameworks, they may conduct different tests before finally deciding that it is necessary to have CBDCs. If there is already a balance reached between the public, market and

government, those countries may delay CBDC plans, which points to an ‘After 2020’ choice to avoid complicating the current situation with the introduction of CBDC.

Relating back to the hypothesis for *GDP (constant 2015 US$)*, we can see that a higher number does not show clear association with CBDC design choices on Status and Type as expected. But it indeed relates to a later Announcement Year, namely an ‘After 2020’ one. However, contrary to hypothesis, it is not associated with a ‘DLT’ Choice but a ‘Non-DLT’ one.

For countries with higher *Medium and high-tech manufacturing value added (% manufacturing value added)*, they tend to choose CBDC designs to be: **a ‘Wholesale’ Type over non-‘Wholesale’, and a non-‘Retail’ one over ‘Retail’**. Countries with more medium and high-tech manufacturing value added usually have more cross-border transactions in the manufacturing sector between businesses and financial institutions, which favors interbank settlement support from a ‘Wholesale’ design, rather than a ‘Retail’ one. A ‘Wholesale’ design reduces currency conversion costs, helps businesses access financing, and ensures necessary capital and smooth liquidity flow in countries’ key industries. Additionally, since high-tech manufactures may already have advanced infrastructures integrated into their business processes as built-in solutions for consumer transactions, a ‘Retail’ design may not help a lot.

Relating back to the hypothesis for *Medium and high-tech manufacturing value added (% manufacturing value added)*, we can see that a higher number indeed points to a ‘Wholesale’ Type choice. Additionally, a ‘Retail’ Type proves to be not preferred.

For countries with higher *Employment to population ratio, 15+, total (%) (national estimate)*, they tend to choose CBDC designs to be: **a ‘Launched’ Status over ‘Pilot’**. Countries with higher employment usually have a better social environment and stronger economy. There are more developed infrastructures and active workers, and a larger need for improving financial

transaction efficiency concerning salary, subsidy and social welfare. If employment is no longer a problem and people have higher living standards, the society tends to have more positive expectations on CBDCs, and overall, the public acceptance for digitized financial services tends to be higher. All these accelerate CBDC development and point to a ‘Launched’ choice.

Relating back to the hypothesis for *Employment to population ratio, 15+, total (%) (national estimate)*, we can see that a higher number shows no clear relation with CBDC design choices on Announcement Year, Structure and Type as expected. But it indeed points to a fast-moving Status, especially a ‘Launched’ one.

For countries with higher *GNI per capita (constant 2015 US$)*, they tend to choose CBDC designs to be: **a ‘DLT’ Choice over ‘Non-DLT’**. People in countries with higher GNI per capita usually value more about the efficiency and security of financial services, and have higher expectations for technological innovation, while a ‘DLT’ design performs better on these needs by enabling programmability. Also, those countries have better financial and technological infrastructures, established regulatory frameworks and more resources to support an advanced ‘DLT’ design, interoperable with existing systems.

Relating back to the hypothesis for *GNI per capita (constant 2015 US$)*, we can see that a higher number shows no clear relation with CBDC design choices on Announcement Year, Status, Structure and Type as expected. But it indeed points to a ‘DLT’ Choice.

For countries with larger *Population ages 15-64 (% of total population)*, they tend to choose CBDC designs to be: **a ‘Both’ Type over ‘Wholesale’**. Countries with larger working age populations usually have more stable economic growth and social environments, with more people requiring access to efficient digital payment systems and financial services. This points to ‘Both’ a retail design to facilitate consumption payments or money transfers, and a wholesale

design for interbank transactions or international settlements. Since a 'Retail' design improves financial inclusion, especially for unbanked individuals (employed does not necessarily imply access to banking services), only a 'Wholesale' design is not enough.

Relating back to the hypothesis for *Population ages 15-64 (% of total population)*, we can see that a higher number shows no clear relation with CBDC design choices on Announcement Year and Structure as expected. And contrary to hypothesis, it points to a 'Both' Type but not a 'Retail' one.

Apart from these nine independent variables with hypotheses, the results display significant coefficient estimates for 'Constant' class in some models, which indicates countries' natural tendency of choosing certain CBDC design categories, when holding all the other independent variables constant (see detailed explanation in **Appendix E**).

**4.3. Discussion**

Most basically and directly from result descriptions and explanations above, we can see that there are indeed patterns between countries' macro development conditions and their choices of CBDC design features: 1) different macro indicators are associated with different class choices inside each design feature; 2) some of those relations are intuitive to explain and correspond well to hypotheses, such as higher *Medium and high-tech manufacturing value added* with a 'Wholesale' Type; while others are unexpected, or less intuitive to explain at first, such as higher *GDP* with a 'Non-DLT' Choice; and 3) there are not only natural tendency for all countries to prefer certain CBDC feature choices, but the same WDI show different levels of influence in different design features or some of the WDIs have larger influence overall, namely relating to more design features. For instance, *Inflation*, though with larger standard errors in some of its estimated coefficients, is associated with six specific design feature classes.

Apart from these main insights on how countries' macro development conditions influence their CBDC design choices, results and explanations above also offer new and useful perspectives for us to reexamine CBDC related discussions in existing literature. Firstly, they help us evaluate propositions in them – some arguments in this research correspond with literature in general ideas and enrich them by providing further implications on design choices, connecting abstract propositions to specific designs with the support of certain macro indicators. Others, however, only show ambiguous connections, or their relation with literature requires further exploration (see detailed description in **Table 10**).

**Table 10** Evaluating propositions

| **Existing Literature** | **This Research** |
|---|---|
| **Improving financial inclusion**<br>1. One of the policy goals of CBDC projects, Soderberg et al. (2022).<br>2. One of the objectives for retail CBDCs, Kiff et al. (2020).<br>3. To promote financial inclusion, CBDCs should be designed for usage without requiring bank accounts. The unbanked only need a unique digital ID to use CBDCs, Ozili (2022). | **Agreement**<br>1. Similarly, it points to the benefit of financial inclusion in result explanations.<br>2. Especially, for CBDCs to improve financial inclusion, they should have designs like a 'Retail' Type and 'Token' Structure, driven by macro development conditions like larger *Land area*, higher *Inflation*, larger *Populations ages 15-64* and higher *Depth of credit information index.* |
| **Improving payment efficiency**<br>1. One of the policy goals of CBDC projects, Soderberg et al. (2022).<br>2. One of the objectives for retail CBDCs, Kiff et al. (2020). | **Agreement**<br>1. Similarly, it points to the benefit of payment efficiency in result explanations.<br>2. Especially, for CBDCs to improve payment efficiency, they should have designs like a 'Both' Type, 'Token' Structure and 'DLT' Choice, driven by a *natural* preference. |
| **Benefiting monetary system**<br>1. Retail CBDCs can help with transmission of monetary policy and monetary sovereignty, Kiff et al. (2020).<br>2. For academics and reformists, CBDCs 'make monetary policy more effective', Bindseil (2022).<br>3. One of the policy goals of CBDC projects is | **Ambiguous**<br>Monetary benefits connect with arguments like CBDCs as alternative inflation-protected solutions and monetary tools in result explanations, but nothing else more specific and explicit on designs. |

monetary sovereignty, Soderberg et al. (2022).

| **Benefiting market actions** | **Ambiguous** |
|---|---|
| 1. Retail CBDCs can enhance payment system competition (with private monopolistic service providers), Kiff et al. (2020).<br>2. For central banks working on CBDCs, they expect the 'availability and usability adds to competition', Bindseil (2022).<br>3. One of the policy goals of CBDC projects is competition, Soderberg et al. (2022). | Market benefits connect with other less-frequently mentioned design features excluded in this research for logistic regression analysis, such as Access, Fee, Platform, etc. |

Secondly, except for evaluating general beliefs in existing CBDC literature, results and explanations here also help evaluate challenges for CBDCs in the literature. Some arguments reflect and verify concerns raised, but from a more practical, design-related perspective, while others disagree with literature and provide solutions to these concerns through certain design choices discussed above (see detailed description in **Table 11**).

**Table 11** Evaluating challenges

| **Existing Literature** | **This Research** |
|---|---|
| **Concerns**<br>Legal and technological concerns, Kiff et al. (2020) and Soderberg et al. (2022). | **Translation into design choices**<br>Align with result explanations for a 'Pilot' Status choice under higher *Political Stability and Absence of Violence/Terrorism: Estimate*, 'Non-DLT' choice under higher *GDP* and a *natural* 'After 2020' Announcement Year choice. |
| Lack of precedents considering CBDC projects, Soderberg et al. (2022). | Align with the result explanation for a *natural* 'After 2020' Announcement Year choice. |
| Lack of resources for developing CBDCs, Soderberg et al. (2022). | Align with the result explanations for a 'Wholesale' Type choice under larger *Land area*. |
| **Oppositions**<br>Worries of 'structural bank disintermediation' and increased centralization power, Bindseil (2022). | **Solutions from certain designs**<br>Can be settled by considering CBDCs with design choices of a 'Both' Type that does not disintermediate commercial banks, and a 'DLT' feature that allows decentralization. |

Besides, for other types of worry like requirements for ‘skilled and knowledgeable human resources’ and ‘political support’ (Kiff et al., 2020), they do not seem to have clear relations with quantifiable macro indicators and categorical CBDC design features. Thirdly, except for evaluating these opinions in existing CBDC literature, results and explanations also relate to more specifically, real-life CBDC use cases or events, suggesting which design choices may support certain use cases, or sometimes the findings here themselves, are instead backed by conclusions drawn from relevant practical events (see detailed description in **Table 12**).

**Table 12** Evaluating real-life CBDC use cases or events

| **Existing Literature** | **This Research** |
|---|---|
| **Cross-border CBDCs**<br>Able to address existing banking problems like ‘high cost’, ‘low speed’, ‘limited access and transparency’, etc., World Bank Group (2021). | **Relation**<br>Aligns with the result explanation for a ‘Wholesale’ Type choice under higher *Medium and high-tech manufacturing value added*, but there can be other possible macro indicators or less-frequently mentioned CBDC design features supporting well-functioned cross-border CBDCs. |
| **CBDC sentiment and relevant events**<br>Covid-19 pandemic increases positive CBDC sentiment, while the invasion of Ukraine by Russia increases negative CBDC sentiment, Conlon et al. (2024). | **Relation**<br>Aligns with the result explanation for a *natural* ‘After 2020’ Announcement Year choice, and gives further implications on how a special event can exert an influence on countries’ CBDC design choices practically (not restricted to the five features here). |

Therefore, by connecting findings in this research to practical CBDC cases or relevant events directly, the insights we obtain are not only about their confirmation in ideas, but also their explanatory power on each other, and the direction for future studies to understand this area of CBDC literature.

Although this research contributes to valuable insights about CBDCs, it is important to recall one significant limitation that actually influences the results – a small dataset of only 45

CDBC projects. The small size makes it difficult for coefficient estimates to be statistically significant, complicates the model selection process, and requires relaxing the p-value threshold to be below 0.2 for analysis. However, we cannot solve this limitation simply by improving the data collection method. The only thing to do is to wait for more countries worldwide to release clearer descriptions on design choices for their CBDC projects, and repeat this analysis with updated, larger dataset and necessary corresponding adjustments. Then we can see whether the significance of coefficient estimates improves, or new relations and insights between macro development conditions, CBDC design choices and existing literature appear.

Moreover, results and explanations based on only nine WDIs and five CBDC design features can be expanded to include more factors, although this research already incorporates less common macro indicators such as *Land area*. And other perspectives beyond macro development conditions and CBDC designs can also be explored.

## 5. Conclusion

This research categorizes design features of worldwide CBDC projects, links them to macro indicators, and finds that countries' macro development conditions influence their choices of CBDC design frameworks.

One key pattern found is that countries with similar macro development conditions tend to choose the same CBDC designs. Thus, different countries can indeed initiate CBDCs with exact same designs, but still based on their own practical situations (if CBDC decisions accord with and are within the reach of their macro development conditions). Furthermore, each design implies certain expected outcomes, and they sometimes overlap. As a result, not only countries with similar macro development conditions, but also those with different ones, can have similar motivations. And since explaining the relationship between macro indicators and CBDC design

choices brings in more frequently-used macroeconomic theories, we can now better link the general, abstract opinions in literature on CBDCs to their potential, real outcomes in practice.

At the same time, conversely, countries with different macro development conditions tend to choose different CBDC designs, which explains the world's diverging focuses and trends on CBDC discussions. However, regardless of countries' CBDC design choices driven by similar or different development conditions, the world's interest in CBDCs is growing. Countries start with CBDC initiatives, or topics around CBDCs like decentralization, digitization or cybersecurity, but insights obtained from researching on CBDCs and testing different designs are far beyond these. Some countries may find halfway that CBDCs are not the best, necessary solution for their development. Instead, specific technology implied in certain designs become their new focus. While for others, probably at first, CBDC research is just to catch up with the global trend and improve competitiveness, or launching CBDCs is the initial plan but it receives objections from the public, so CBDC development is paused and further communication work is required.

However, it is difficult to study and interpret public opinions regarding their influence on CBDC initiatives, and more specifically, on the design features. The five most common ones included in this research for regression analysis are less closely related to public opinions on CBDCs, compared to other less common features, such as Fee, Security, Privacy, etc. But for these features, there is less information and more challenges in classifying different countries' detailed descriptions into as few categories as possible for quantitative analysis. Moreover, even if different countries have similar macro development conditions, design choices or motivations as discussed above, their public opinions can either align or differ significantly. The CFA Institute's global survey (Deane, S. & Fines, O., 2023) shows that emerging markets agree more on having CBDCs, using them and enhancing financial inclusion and stability with them, while

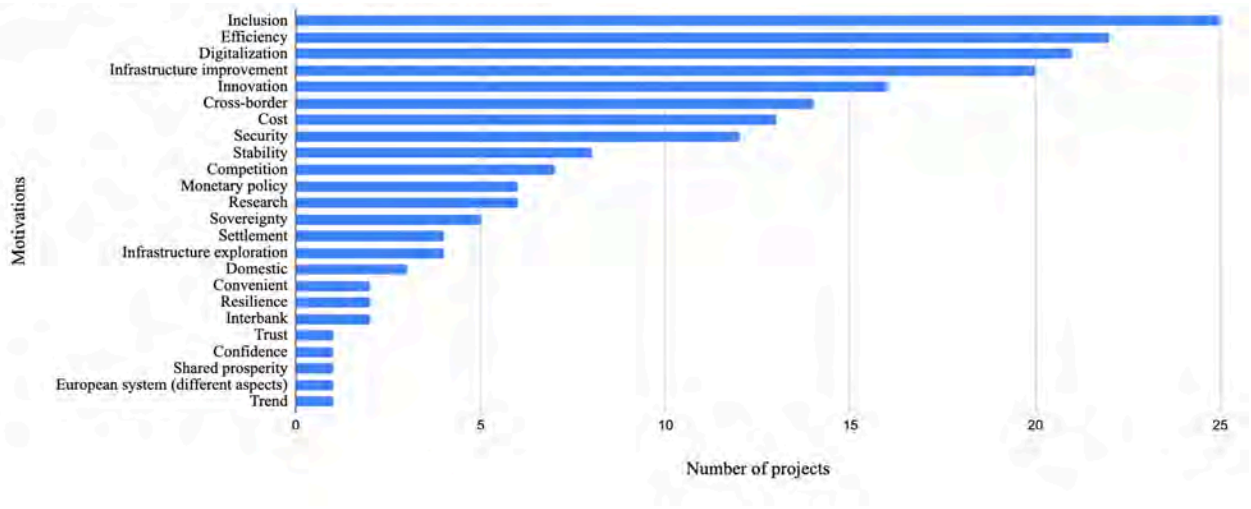
developed markets concern more about data privacy. However, when focusing only on the comparison within developed markets, Akana et al.'s study (2024) featuring U.S. respondents shows that about half of them feel 'warm' to CBDCs, and their top requirement for CBDCs is free-of-charge (2024). Contrarily, the report from Bank of Canada (2023) shows that Canadian respondents' top concern is anonymity and they do not trust central bank's ability to issue a secured CBDC, as well as the possibility that their feedback will be taken into account, which is a very different and negative view compared to the U.S. one.

In conclusion, by linking different countries' choices of CBDC design features with their macro development conditions, this research provides a new, more objective and practical perspective for understanding their motivations and decisions on CBDC initiatives, as well as the growing and diverging global interest in CBDC related issues. For analysis of a specific CBDC case, first, we can fit it into certain macro development condition categories based on this research, to evaluate whether it really connects with certain design choices. Meanwhile, we may want to incorporate public opinions to gain a deeper understanding of the case. However, this should involve either focusing on opinions unique to the initiating country, or finding other objective, quantifiable measures of their relations with design choices, and even new connections between CBDCs and public factors in general, such as people's trust in central authorities and financial literacy. Although countries have different preferences for CBDC designs due to their macro conditions, this difference in preference can be enlarged by different public opinions.

Looking at motivations mainly provides insights into government attitudes on CBDCs, while surveys offer useful information on public attitudes. However, investigating CBDC design features, gives a more aggregated view on both the government and public attitudes on CBDCs. But whether the influence truly comes from both sides and the proportion of influence from each

side depends on countries' specific situations. In general, we can compare the finalized CBDC design framework to both government motivations and public requirements, to assess whether a country considers opinions from both sides and decide whether the final framework needs further improvement. Overall, exploration on CBDC related topics gives us more knowledge than just CBDCs themselves. From this research, we learn that opinions and discussions around CBDCs, especially design choices related ones, indicate a country's future development potential and trajectory, as perceived by both the government and the public in relation to macro conditions.

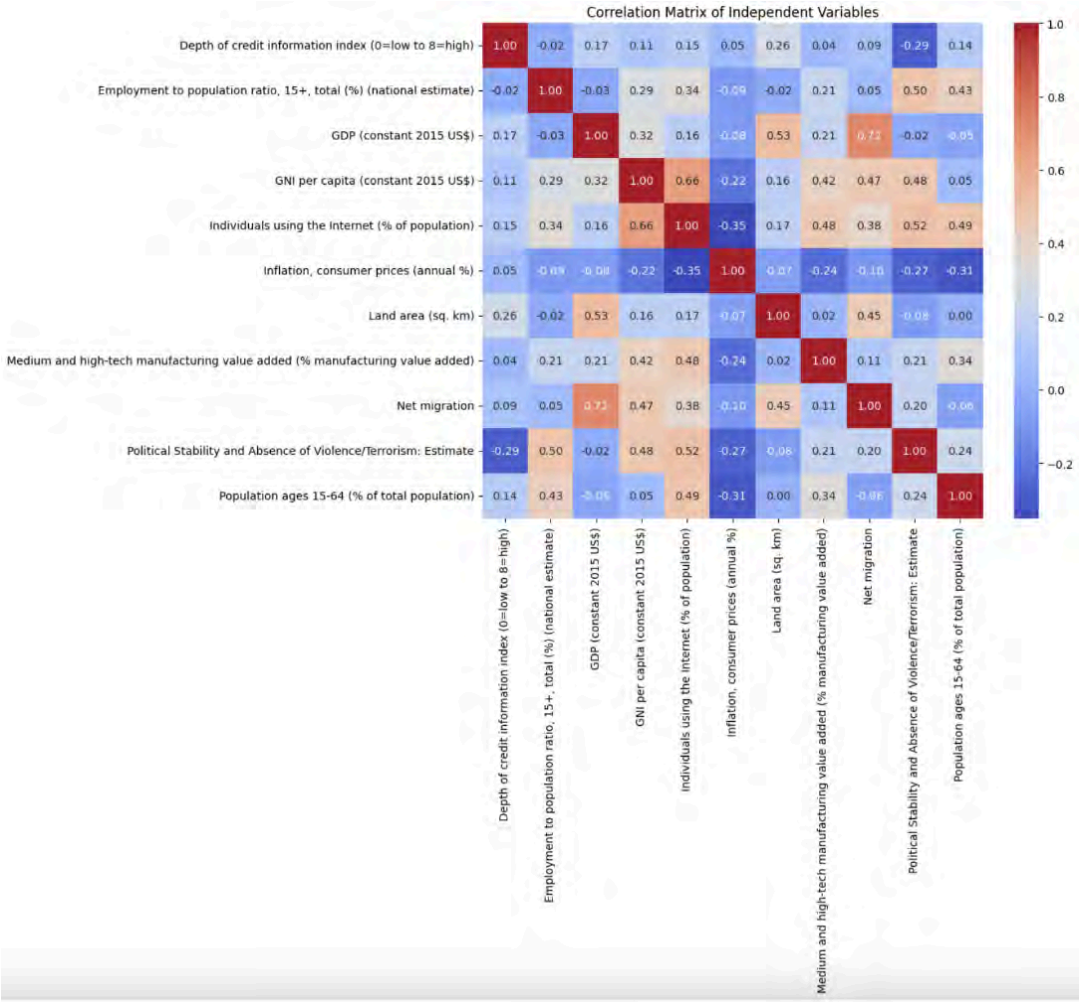
**Appendix A.** *Stated motivations by different CBDC projects (45 selected):*




**Appendix B.** *Variance Inflation Factor (VIF) for 15 independent variables:*

| | Variable | VIF |
|---|---|---|
| 5 | Government Effectiveness: Estimate | 9.786036 |
| 2 | Final consumption expenditure (% of GDP) | 7.123849 |
| 6 | Gross savings (% of GDP) | 5.180828 |
| 14 | Voice and Accountability: Estimate | 5.033482 |
| 7 | Individuals using the Internet (% of population) | 4.823210 |
| 12 | Political Stability and Absence of Violence/Te... | 4.060608 |
| 11 | Net migration | 3.559514 |
| 4 | GNI per capita (constant 2015 US$) | 3.337379 |
| 3 | GDP (constant 2015 US$) | 3.311566 |
| 10 | Medium and high-tech manufacturing value added... | 2.907511 |
| 13 | Population ages 15-64 (% of total population) | 2.583200 |
| 0 | Depth of credit information index (0=low to 8=... | 2.415285 |
| 1 | Employment to population ratio, 15+, total (%)... | 2.070280 |
| 9 | Land area (sq. km) | 1.601847 |
| 8 | Inflation, consumer prices (annual %) | 1.346334 |

**Appendix C.** *Correlation matrix and Variance Inflation Factor (VIF) for 11 independent variables:*




| | Variable | VIF |
|---|---|---|
| 4 | Individuals using the Internet (% of population) | 3.697443 |
| 8 | Net migration | 2.990061 |
| 2 | GDP (constant 2015 US$) | 2.889072 |
| 3 | GNI per capita (constant 2015 US$) | 2.749403 |
| 9 | Political Stability and Absence of Violence/Te... | 2.249129 |
| 10 | Population ages 15-64 (% of total population) | 2.192161 |
| 1 | Employment to population ratio, 15+, total (%)... | 1.656128 |
| 7 | Medium and high-tech manufacturing value added... | 1.587432 |
| 6 | Land area (sq. km) | 1.553433 |
| 0 | Depth of credit information index (0=low to 8=... | 1.379550 |
| 5 | Inflation, consumer prices (annual %) | 1.243733 |

**Appendix D.** *Logistic regression output for five dependent variables:*

```
Logistic Regression for Announcement Year (Before 2020 - 1/After 2020 -
2):
==========================================================================
Dep. Variable: Announcement Year (Before 2020 - 1/After 2020 - 2)
No. Observations:              45
Model:                      Logit   Df Residuals:                       35
Method:                       MLE   Df Model:                            9
Date:            Wed, 05 Mar 2025   Pseudo R-squ.:                  0.1760
Time:                    07:00:45   Log-Likelihood:                -24.954
converged:                   True   LL-Null:                       -30.286
Covariance Type:        nonrobust   LLR p-value:                    0.2996
==========================================================================
coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------
const
0.4980      0.352      1.413      0.158      -0.193       1.189
Depth of credit information index (0=low to 8=high)
0.3240      0.397      0.816      0.414      -0.454       1.102
Employment to population ratio, 15+, total (%) (national estimate)
-0.3308      0.423     -0.783      0.434      -1.159       0.497
GDP (constant 2015 US$)
0.8201      0.511      1.606      0.108      -0.181       1.821
GNI per capita (constant 2015 US$)
-0.4738      0.473     -1.002      0.316      -1.401       0.453
Inflation, consumer prices (annual %)
0.2589      0.519      0.499      0.618      -0.758       1.276
Land area (sq. km)
-0.7665      0.534     -1.436      0.151      -1.813       0.280
Medium and high-tech manufacturing value added (% manufacturing value
added)
0.0583      0.440      0.133      0.895      -0.804       0.921
Political Stability and Absence of Violence/Terrorism: Estimate
1.1378      0.524      2.171      0.030       0.111       2.165
Population ages 15-64 (% of total population)
-0.4901      0.441     -1.111      0.267      -1.355       0.374
==========================================================================
AIC: 69.9086153249201, BIC: 87.97524022262328

Logistic Regression for Status (Launched - 1, Pilot - 2, PoC - 3):
==========================================================================
Dep. Variable: Status (Launched - 1, Pilot - 2, PoC - 3)
No. Observations:              45
Model:                    MNLogit   Df Residuals:                       25
Method:                       MLE   Df Model:                           18
Date:            Wed, 05 Mar 2025   Pseudo R-squ.:                  0.4746
```

```
Time:                      07:00:45   Log-Likelihood:                -21.499
converged:                     True   LL-Null:                       -40.921
Covariance Type:        nonrobust   LLR p-value:                  0.002989
==============================================================================
Status (Launched - 1, Pilot - 2, PoC - 3)=2
coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const
8.2047     12.451      0.659      0.510     -16.199      32.609
Depth of credit information index (0=low to 8=high)
1.2039      0.954      1.261      0.207      -0.667       3.074
Employment to population ratio, 15+, total (%) (national estimate)
-3.6732      1.952     -1.882      0.060      -7.499       0.153
GDP (constant 2015 US$)
6.6093     33.706      0.196      0.845     -59.454      72.673
GNI per capita (constant 2015 US$)
-1.1335      1.453     -0.780      0.435      -3.982       1.715
Inflation, consumer prices (annual %)
-8.8584      7.513     -1.179      0.238     -23.583       5.866
Land area (sq. km)
8.3717     11.662      0.718      0.473     -14.486      31.229
Medium and high-tech manufacturing value added (% manufacturing value
added)
1.3951      1.704      0.819      0.413      -1.946       4.736
Political Stability and Absence of Violence/Terrorism: Estimate
3.3337      1.836      1.815      0.069      -0.265       6.933
Population ages 15-64 (% of total population)
-0.5434      1.048     -0.519      0.604      -2.597       1.510
------------------------------------------------------------------------------
Status (Launched - 1, Pilot - 2, PoC - 3)=3
coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const
-2.7231     13.394     -0.203      0.839     -28.975      23.529
Depth of credit information index (0=low to 8=high)
0.2203      0.816      0.270      0.787      -1.379       1.819
Employment to population ratio, 15+, total (%) (national estimate)
-0.9774      1.624     -0.602      0.547      -4.161       2.206
GDP (constant 2015 US$)
6.6214     33.722      0.196      0.844     -59.473      72.716
GNI per capita (constant 2015 US$)
0.1116      1.533      0.073      0.942      -2.892       3.115
Inflation, consumer prices (annual %)
-62.9200     27.394     -2.297      0.022    -116.612      -9.228
Land area (sq. km)
8.7611     11.682      0.750      0.453     -14.135      31.657
```

```
Medium and high-tech manufacturing value added (% manufacturing value
added)
-0.2038      1.732     -0.118      0.906      -3.599       3.191
Political Stability and Absence of Violence/Terrorism: Estimate
0.7114      1.949      0.365      0.715      -3.109       4.532
Population ages 15-64 (% of total population)
-0.4166      1.120     -0.372      0.710      -2.612       1.779
==============================================================================
AIC: 82.9976572706425, BIC: 119.13090706604889

Logistic Regression for Structure (Account - 1, Token - 2, Undecided - 3):
==============================================================================
Dep. Variable: Structure (Account - 1, Token - 2, Undecided - 3)
No. Observations:              45
Model:                     MNLogit   Df Residuals:                       25
Method:                        MLE   Df Model:                            18
Date:            Wed, 05 Mar 2025   Pseudo R-squ.:                  0.1690
Time:                    07:00:45   Log-Likelihood:                -38.714
converged:                   True   LL-Null:                       -46.585
Covariance Type:        nonrobust   LLR p-value:                    0.6105
==============================================================================
Structure (Account - 1, Token - 2, Undecided - 3)=2
coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const
1.5875      0.843      1.884      0.060      -0.064       3.239
Depth of credit information index (0=low to 8=high)
-2.0252      1.612     -1.257      0.209      -5.184       1.134
Employment to population ratio, 15+, total (%) (national estimate)
-0.4540      0.551     -0.824      0.410      -1.534       0.626
GDP (constant 2015 US$)
-0.2160      0.588     -0.367      0.713      -1.369       0.937
GNI per capita (constant 2015 US$)
-0.1236      0.641     -0.193      0.847      -1.380       1.133
Inflation, consumer prices (annual %)
0.1569      0.566      0.277      0.782      -0.953       1.267
Land area (sq. km)
0.1856      0.581      0.319      0.749      -0.953       1.324
Medium and high-tech manufacturing value added (% manufacturing value
added)
-0.0590      0.619     -0.095      0.924      -1.272       1.154
Political Stability and Absence of Violence/Terrorism: Estimate
0.4736      0.634      0.747      0.455      -0.768       1.715
Population ages 15-64 (% of total population)
-0.1594      0.608     -0.262      0.793      -1.352       1.033
------------------------------------------------------------------------------
Structure (Account - 1, Token - 2, Undecided - 3)=3
```

```
coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const
0.0635      1.378      0.046      0.963      -2.637       2.764
Depth of credit information index (0=low to 8=high)
-1.5996      1.621     -0.987      0.324      -4.777       1.578
Employment to population ratio, 15+, total (%) (national estimate)
-0.5769      0.654     -0.882      0.378      -1.859       0.705
GDP (constant 2015 US$)
-0.0138      0.543     -0.025      0.980      -1.079       1.051
GNI per capita (constant 2015 US$)
0.2747      0.663      0.414      0.679      -1.025       1.575
Inflation, consumer prices (annual %)
-8.4342      6.079     -1.387      0.165     -20.349       3.481
Land area (sq. km)
0.0097      0.599      0.016      0.987      -1.164       1.183
Medium and high-tech manufacturing value added (% manufacturing value
added)
-0.6880      0.664     -1.036      0.300      -1.990       0.614
Political Stability and Absence of Violence/Terrorism: Estimate
-0.2099      0.695     -0.302      0.763      -1.572       1.152
Population ages 15-64 (% of total population)
-0.2298      0.621     -0.370      0.711      -1.446       0.987
==============================================================================
AIC: 117.42716000758915, BIC: 153.56040980299554

Logistic Regression for Type - Retail (Yes - 1, No - 0):
==============================================================================
Dep. Variable: Type - Retail (Yes - 1, No - 0)
No. Observations:              43
Model:                      Logit   Df Residuals:                       33
Method:                       MLE   Df Model:                            9
Date:            Fri, 07 Mar 2025   Pseudo R-squ.:                  0.3976
Time:                    02:43:10   Log-Likelihood:                -14.049
converged:                   True   LL-Null:                       -23.321
Covariance Type:        nonrobust   LLR p-value:                   0.02937
==============================================================================
coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const
9.7935      5.619      1.743      0.081      -1.220      20.807
Depth of credit information index (0=low to 8=high)
-0.7012      0.814     -0.861      0.389      -2.297       0.895
Employment to population ratio, 15+, total (%) (national estimate)
0.0822      0.751      0.109      0.913      -1.390       1.555
GDP (constant 2015 US$)
0.4575      0.492      0.929      0.353      -0.507       1.423
```

```
GNI per capita (constant 2015 US$)
0.0475      0.771      0.062      0.951      -1.464       1.559
Inflation, consumer prices (annual %)
39.8435     26.359      1.512      0.131     -11.819      91.506
Land area (sq. km)
-1.0173      0.689     -1.477      0.140      -2.367       0.332
Medium and high-tech manufacturing value added (% manufacturing value
added)
-1.1235      0.668     -1.681      0.093      -2.433       0.186
Political Stability and Absence of Violence/Terrorism: Estimate
-0.2971      0.816     -0.364      0.716      -1.897       1.303
Population ages 15-64 (% of total population)
0.9666      0.841      1.150      0.250      -0.681       2.615
==============================================================================
AIC: 48.09840268048634, BIC: 65.71040383742196

Logistic Regression for Type - Wholesale (Yes - 1, No - 0):
==============================================================================
Dep. Variable:     Type - Wholesale (Yes - 1, No - 0)
No. Observations:                   43
Model:                        Logit   Df Residuals:                       33
Method:                         MLE   Df Model:                            9
Date:             Fri, 07 Mar 2025   Pseudo R-squ.:                  0.2556
Time:                     02:43:10   Log-Likelihood:                -22.111
converged:                    True   LL-Null:                       -29.701
Covariance Type:        nonrobust   LLR p-value:                   0.08611
==============================================================================
coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const
-0.1766      0.387     -0.456      0.648      -0.935       0.582
Depth of credit information index (0=low to 8=high)
-0.5269      0.419     -1.258      0.208      -1.348       0.294
Employment to population ratio, 15+, total (%) (national estimate)
0.0824      0.454      0.182      0.856      -0.807       0.972
GDP (constant 2015 US$)
-0.5749      0.538     -1.068      0.286      -1.630       0.480
GNI per capita (constant 2015 US$)
0.1893      0.486      0.390      0.697      -0.762       1.141
Inflation, consumer prices (annual %)
0.7687      0.542      1.418      0.156      -0.294       1.831
Land area (sq. km)
1.2577      0.690      1.822      0.068      -0.095       2.611
Medium and high-tech manufacturing value added (% manufacturing value
added)
0.9829      0.509      1.932      0.053      -0.014       1.980
```

```
Political Stability and Absence of Violence/Terrorism: Estimate
0.2337      0.549      0.426      0.670      -0.843       1.310
Population ages 15-64 (% of total population)
0.0978      0.459      0.213      0.831      -0.802       0.997
==============================================================================
AIC: 64.22108147986137, BIC: 81.83308263679699

Logistic Regression for Type (Both - 1, Wholesale - 2, Retail - 3):
==============================================================================
Dep. Variable: Type (Both - 1, Wholesale - 2, Retail - 3)   No.
Observations:                  43
Model:                    MNLogit   Df Residuals:                       23
Method:                       MLE   Df Model:                           18
Date:            Thu, 20 Mar 2025   Pseudo R-squ.:                 0.3447
Time:                    02:39:24   Log-Likelihood:                -28.545
converged:                   True   LL-Null:                       -43.564
Covariance Type:        nonrobust   LLR p-value:                   0.03709
==============================================================================
Type (Both - 1, Wholesale - 2, Retail - 3)=2
coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const
-8.7770      5.699     -1.540      0.124     -19.946       2.392
Depth of credit information index (0=low to 8=high)
1.1835      0.883      1.340      0.180      -0.547       2.914
Employment to population ratio, 15+, total (%) (national estimate)
0.0090      0.842      0.011      0.991      -1.641       1.659
GDP (constant 2015 US$)
-0.3060      0.602     -0.508      0.611      -1.487       0.875
GNI per capita (constant 2015 US$)
-0.1652      0.881     -0.187      0.851      -1.893       1.562
Inflation, consumer prices (annual %)
-42.4948     26.704     -1.591      0.112     -94.833       9.844
Land area (sq. km)
0.4499      0.770      0.585      0.559      -1.059       1.958
Medium and high-tech manufacturing value added (% manufacturing value
added)
0.9613      0.833      1.154      0.248      -0.671       2.594
Political Stability and Absence of Violence/Terrorism: Estimate
0.1344      0.993      0.135      0.892      -1.811       2.080
Population ages 15-64 (% of total population)
-1.3466      0.960     -1.403      0.161      -3.228       0.535
------------------------------------------------------------------------------
Type (Both - 1, Wholesale - 2, Retail - 3)=3
coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
```

```
const
0.9422      0.489      1.928      0.054      -0.015       1.900
Depth of credit information index (0=low to 8=high)
0.8699      0.493      1.765      0.078      -0.096       1.836
Employment to population ratio, 15+, total (%) (national estimate)
0.1427      0.548      0.260      0.794      -0.931       1.216
GDP (constant 2015 US$)
0.5743      0.680      0.845      0.398      -0.758       1.906
GNI per capita (constant 2015 US$)
-0.0892      0.605     -0.147      0.883      -1.276       1.097
Inflation, consumer prices (annual %)
-0.8575      0.600     -1.429      0.153      -2.033       0.318
Land area (sq. km)
-1.4577      0.839     -1.737      0.082      -3.103       0.187
Medium and high-tech manufacturing value added (% manufacturing value
added)
-0.3215      0.618     -0.520      0.603      -1.534       0.891
Political Stability and Absence of Violence/Terrorism: Estimate
-0.1028      0.723     -0.142      0.887      -1.521       1.315
Population ages 15-64 (% of total population)
-0.5033      0.617     -0.815      0.415      -1.713       0.707
==============================================================================
AIC: 97.09060696349557, BIC: 132.31460927736683

Logistic Regression for DLT (DLT - 1, Non-DLT - 2, Undecided - 3):
==============================================================================
Dep. Variable: DLT (DLT - 1, Non-DLT - 2, Undecided - 3)   No.
Observations:                    45
Model:                     MNLogit   Df Residuals:                       25
Method:                        MLE   Df Model:                           18
Date:            Thu, 20 Mar 2025   Pseudo R-squ.:                  0.2590
Time:                    02:38:26   Log-Likelihood:                -31.961
converged:                   True   LL-Null:                       -43.131
Covariance Type:        nonrobust   LLR p-value:                    0.2172
==============================================================================
DLT (DLT - 1, Non-DLT - 2, Undecided - 3)=2
coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const
-3.5218      1.700     -2.072      0.038      -6.853      -0.190
Depth of credit information index (0=low to 8=high)
1.3434      1.118      1.202      0.229      -0.847       3.534
Employment to population ratio, 15+, total (%) (national estimate)
1.0506      1.060      0.991      0.322      -1.027       3.128
GDP (constant 2015 US$)
2.5154      1.878      1.339      0.180      -1.166       6.196
```

GNI per capita (constant 2015 US$)
-3.2229 1.666 -1.935 0.053 -6.488 0.042
Inflation, consumer prices (annual %)
-0.7791 1.310 -0.595 0.552 -3.347 1.789
Land area (sq. km)
-1.9341 2.391 -0.809 0.419 -6.621 2.752
Medium and high-tech manufacturing value added (% manufacturing value added) \-0.9323 0.929 -1.004 0.315 -2.753 0.888
Political Stability and Absence of Violence/Terrorism: Estimate
1.5157 1.204 1.258 0.208 -0.845 3.876
Population ages 15-64 (% of total population)
-0.6016 0.957 -0.628 0.530 -2.478 1.275
---
DLT (DLT - 1, Non-DLT - 2, Undecided - 3)=3
coef std err z P>|z| [0.025 0.975]
---
const
-0.8421 0.785 -1.072 0.284 -2.381 0.697
Depth of credit information index (0=low to 8=high)
0.6507 0.475 1.371 0.170 -0.280 1.581
Employment to population ratio, 15+, total (%) (national estimate)
-0.3287 0.534 -0.615 0.538 -1.376 0.718
GDP (constant 2015 US$)
0.5174 0.444 1.166 0.244 -0.352 1.387
GNI per capita (constant 2015 US$)
-0.6391 0.528 -1.210 0.226 -1.674 0.396
Inflation, consumer prices (annual %)
-2.0518 4.068 -0.504 0.614 -10.026 5.922
Land area (sq. km)
-0.2488 0.447 -0.557 0.578 -1.125 0.627
Medium and high-tech manufacturing value added (% manufacturing value added)
-0.1746 0.418 -0.418 0.676 -0.993 0.644
Political Stability and Absence of Violence/Terrorism: Estimate
0.9345 0.573 1.632 0.103 -0.188 2.057
Population ages 15-64 (% of total population)
-0.0989 0.502 -0.197 0.844 -1.082 0.885
==========
AIC: 103.92119936461052, BIC: 140.0544491600169

**Appendix E.** *Explanation of 'Constant' class – natural tendency for certain designs:*

1) Countries *naturally* prefer an 'After 2020' Announcement Year compared to 'Before 2020'. Since there is growth or maturity of different digital technologies and financial infrastructures through time, as well as increasing discussions on CBDCs and exemplar CBDC cases these days, it suggests a need for researching CBDCs compared to the past. Meanwhile, Covid-19 exposes problems in traditional banking and cash payment systems, together with benefits and promising future of digital payment systems.

2) Countries *naturally* prefer a 'Token' Structure compared to an 'Account' one. Since CBDC aims more at improving transaction efficiency and digitizing payment systems but not strictly requiring track balances, and a token-based CBDC functions more like physical cash without intermediaries for track records and verification, it becomes a preferred choice. Also, a CBDC is usually expected to make the financial system more inclusive, which points to changing the traditional banking system based on accounts and providing financial services for the unbanked. And central banks might be interested in digital solutions like cryptos or want to compete over private digital payment providers, which points to a 'Token' design.

3) Countries *naturally* prefer a 'Retail' Type compared to not. A 'Retail' CBDC can access every individual end-users and assist their daily financial activities, which has a larger coverage and improves overall financial inclusion. Also, it helps upgrade the existing financial system, acting as a tool to help the government compete with private digital currency providers and smoothly implement monetary policy, which can have larger economic gains seen immediately compared to a non-retail design.

4) Countries *naturally* prefer a 'Both' Type compared to a 'Wholesale' one. If countries have enough resources to research and develop both retail and wholesale functions, they are more

likely to work on them together because they target different markets, modernize and digitize the whole financial system, improving the payment efficiency. Also, only developing a wholesale CBDC is a less common trend, possibly due to its limited focus on interbank transactions.

5) Countries *naturally* prefer a 'Retail' Type compared to a 'Both' one. The current world's average developing stage and knowledge of CBDC is still an exploring, starting one. Thus, beginning with a single functional design, such as a 'Retail' one, is easier for implementation and management, compared to a hybrid functional design aiming at both individual and institutional end-users. Also, only a 'Retail' design costs less than both, since it requires fewer updates in infrastructures and regulations, and is more likely to have immediate benefits.

6) Countries *naturally* prefer a 'DLT' Choice compared to a 'Non-DLT' one. A 'DLT' CBDC automates payment based on its programmable feature, and is easier to be integrated with international payment systems, which largely improves the transaction efficiency. If there are problems or concerns emerging over time with the existing financial system, such as transparency and security, or central banks want to develop their own digital currency with innovative technology, then a 'DLT' design helps more than a non-DLT one.

**References**

Akana, T., Cipriani, M., & Gorbachev, O. (2024). *Central bank digital currencies: Consumer attitudes and expectations in the United States*. Federal Reserve Bank of Philadelphia.

Atlantic Council. (2024). *CBDC tracker*. https://www.atlanticcouncil.org/cbdctracker/

Bank of Canada. (2023). *Digital Canadian dollar public consultation report*. https://www.bankofcanada.ca/

Bijlsma, M., van der Cruijsen, C., & Jonker, N. (2021). What triggers consumer adoption of CBDC? *Journal of Financial Services Research, 59*(3), 435–460. https://doi.org/10.1007/s10693-021-00341-z

Bilgen, C., & Dutto, M. (2023). Three-level CBDC design framework: A systematic literature review on design elements. *Journal of Payments Strategy & Systems, 17*(3), 229–247.

Bindseil, U. (2022). *The case for and against CBDC – Five years later*. European Central Bank Occasional Paper Series No. 296. https://www.ecb.europa.eu/

CBDC Tracker. (2024). *Central bank digital currency tracker*. https://cbdctracker.org/

Conlon, T., Cotter, J., & McGee, R. (2024). To CBDC or not to CBDC. That is the question. *Finance Research Letters, 56*, 104098. https://doi.org/10.1016/j.frl.2023.104098

Das, M., Gündüz, Y., & Tieman, A. F. (2023). *Implications of central bank digital currencies for monetary policy transmission*. International Monetary Fund.

Deane, S., & Fines, O. (2023). *CFA Institute global survey on central bank digital currencies*. CFA Institute.

Deutsche Bundesbank. (2021). *What do households in Germany think about the digital euro? First results from surveys and interviews*. https://www.bundesbank.de/

Kiff, J., Alwazir, J., Davidovic, S., Farias, P., Khan, A., Khiaonarong, T., Malaika, M., Monroe, H., Sugimoto, N., Tourpe, H., & Zhou, P. (2020). *A survey of research on retail central bank digital currency* (IMF Working Paper No. 20/104). International Monetary Fund. https://www.imf.org/

Kosse, A., & Mattei, I. (2023). *Making headway – Results of the 2022 BIS survey on central bank digital currencies and crypto*. Bank for International Settlements.

Makridis, C. A. (2024). *The rise of central bank digital currencies: Exploring adoption determinants and early macroeconomic and well-being impacts*. Hoover Institution, Stanford University.

Murphy, K., Black, D., & O'Connor, J. (2024). *Central bank digital currency data use and privacy protection*. Center for European Policy Studies.

Nocciola, L., & Pérez, A. (2024). Consumer demand for central bank digital currency as a means of payment. *Journal of Economic Behavior & Organization, 215*, 100–118. https://doi.org/10.1016/j.jebo.2023.10.004

Ozili, P. K. (2022). CBDC, fintech and cryptocurrency for financial inclusion and financial stability. *Financial Technology and Economics, 3*(4), 237–247. https://doi.org/10.1007/s10693-021-00034-2

Söderberg, G., Anayi, W., & Sadaba, F. (2022). *Behind the scenes of central bank digital currency: Emerging trends, insights, and policy lessons*. International Monetary Fund.

Tourpe, H., Codogno, L., & Sahdev, S. (2023). *A guide to central bank digital currency product development: 5P methodology and research and development*. International Monetary Fund.

World Bank Group. (2021). *Central bank digital currencies for cross-border payments – A review of current experiments and ideas*. https://documents.worldbank.org/