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A Multinomial Regression Approach to Determine the Factors Influencing the Issuance of CBDC in the Case of Pakistan

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Abstract

CBDCs are a major innovation in the currency world that gives central banks the ability to issue digital versions of fiat currency for better efficiency and accessibility of payment systems. The rapid transition of payments to a digital model caused by the pandemic is now at risk from several developments, including dwindling demand for the most conventional form of money and serious financial disruption from new cryptocurrencies. These challenges have led central banks around the world to take seriously the possibility of introducing CBDCs for modernizing monetary policy and broadening access to digital financial services. Based on country-specific factors, CBDCs are further subdivided into wholesale (a medium for interbank transactions) and retail (for use by the general public). The study applies a multinomial logit model to examine the factors influencing Central Bank Digital Currency (CBDC) adoption by 66 countries at each of four stages: no project, research, pilot and live. For each stage, the model compares the probability assuming no project with the impact of economic, technological, demographic and governance factors. Through this method, policy developers gain an understanding of the important factors affecting how CBDCs are implemented. This research analyses the possible effects of CBDCs and elaborates on Pakistan's slow advancement with its digital rupee planned for 2025 to enhance financial inclusion and system transparency. This research provides insights that policymakers could take into account while crafting CBDC design choices for the digital finance landscape.

Keywords: Financial Inclusion; Retail CBDC; Wholesale CBDC; Informal Economy; Centralized Technology; Digital Payments; Central Bank Digital Currency (CBDC)

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Introduction

A Central Bank Digital Currency (CBDC) is a digital type of currency, backed by the central bank, that serves in addition to regular cash and allows transactions to be faster and safer. CBDCs differ from cryptocurrencies since they are supported by the central bank and linked to the national currency, making them as stable as other currencies (Ghymers, 2025). Their major purpose is to keep monetary sovereignty, boost payment efficiency and broaden access to financial services (Verma, 2024).They depend on blockchain and distributed ledger technologies (DLT) to ensure that transactions are fast, reliable and cost nothing to intermediaries, more than before (Lekhi, 2024) .

Thanks to digital currencies and DeFi, the usual banking system is now being challenged by new ways of making financial transactions without requiring intermediaries. Services like those provided by Bitcoin have shaken up the banking industry because they are not regulated in the same way and provide cheaper and much more accessible alternatives. Such disruption is also made worse by DeFi platforms, as they rely on blockchain to provide several financial services to the public without any single entity in control (Arewa, 2024). Yet, the growth of cryptocurrencies may affect traditional banking in various ways, including tougher competition for funds, pressing challenges with monetary policy and greater dangers online because digital assets exist outside the control of any single body (Bagnall et al., 2014).

The world of Central Bank Digital Currencies (CBDCs) is changing fast and various regions are seeing notable improvements in their approaches. Recent research shows that 131 countries, covering 98% of the world economy, are involved in some way with CBDC experiments, from learning to actual deployment (Shilina, 2024). Importantly, CBDC pilot projects are now running in China, Sweden and the Bahamas and their results are illustrating the key technology, law and financial considerations that come with adopting these digital currencies. Countries in Asia such as South Korea, are continuing to develop both retail and wholesale CBDCs to help the payment system work more efficiently. In the MENA area, guided by the UAE, there are big efforts to grow cross-border payments and this could make the US dollar less necessary and assist in giving more foster financial inclusion (Bosua & Biswas, 2024).

The SBP is currently investigating possible uses of CBDCs, as it seeks to revamp the financial sector and improve access to financial services for everyone in Pakistan. It is thought that introducing CBDCs in Pakistan could strengthen payment safety and performance and also assist in solving issues with cybersecurity and technology. In addition, the SBP is supporting a trend in Pakistan where digital financial services and fintech innovation are growing thanks to more people using the internet and smartphones, along with suitable rules by financial regulators (Kumail Abbas Rizvi et al., 2018). These efforts are made clear on the Raast platform of the SBP, as it serves to connect the informal sector to the formal banking system and supports inclusive growth. Avdokushin points out that even with these achievements, some people are still not ready to use digital financial tools because they lack financial knowledge and do not trust online services (Avdokushin, 2024).

Objectives

- Which demographic, economic, market and technological factors are most important when central banks consider issuing CBDCs?

Research Methodology

For this study, we used a quantitative research approach and looked at data from global organizations, including the World Bank, IMF, UN, ITU and CBDC trackers (such as the Atlantic Council), to analyze what influences the usage of Central Bank Digital Currency (CBDC). IDT and EGT are combined in the theoretical framework to assess how and why CBDC is adopted and what the economic outcomes are. Within the CBDC Project Index (CBDCPI), projects are arranged into four groups: projects that do not yet exist (0), are under research (1), being piloted (2) or are in operation (3). Important independent variables are GDP per capita, the informal economy, remittances, FDI inflows, mobile subscriptions, internet access, the share of people living in cities, population size and government effectiveness. The multinomial logit approach is used to study the categorical CBDCPI which estimates, with maximum likelihood, how probable it is for a country to reach each adoption stage rather than none at all. The method discovers important factors that guide the spread of CBDCs, allowing policymakers to create relevant CBDC frameworks.

Data Related Framework

We consider 66 countries, as they all have different CBDC projects satge at the 0: no project, 1: research, 2: pilot or 3: live stages (based on the CBDC Project Index). The economic, technological, demographic and governance factors are all measured by data from the World Bank, IMF, UN, ITU and CBDC trackers (e.g., Atlantic Council). The Multinomial logit model estimates the chances that a country moves from one stage to another stage of CBDC. By using maximum likelihood estimation, the model quantifies each variable's impact, providing insights into the key drivers of CBDC adoption across a sample of 66 countries. To study the adoption of CBDCs, data-driven methods weigh the cross-country information to understand what promotes this adoption. In this study, data is gathered by a systemized process from credible sources around the world, including the World Bank, International Monetary Fund (IMF), United Nations (UN), International Telecommunication Union (ITU), Atlantic Council and CBDC Tracker. They all include detailed datasets covering economic, technological, social, demographic and governance indicators, making the analysis dependable and reliable. Its main objective is to review how various influences influence central banks' choices to introduce and use CBDCs, answering the questions presented in the research literature. The research looks at different economies and systems which is important for learning about CBDC adoption around the globe.

Dependent Variable

- CBDC Project Index (CBDCPI): Data sourced from CBDC Tracker, Atlantic Council, and Central Banks' reports about CBDC projects.

1. Score 0: Neither has made a public announcement about any work on a CBDC.
2. Level 1: Research Stage — Theoretical Discourse Without Practical Application
3. Level 2 – The pilot stage is the applied technological development and experimentation.
4. Level 3: Live stage official release of CBDC.

Independent Variables

1. GDP per capita (Economic Wealth): Sourced from World Bank, IMF.
2. Informal Economy (Economic Configuration, measured as a percentage of GDP): Sourced from World Bank, IMF.

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3. Mobile Cellular Subscriptions (Number of mobile cellular subscriptions per 100 people): Sourced from World Bank, ITU.
4. Remittances (Financial inflows from citizens working abroad, as a percentage of GDP): Sourced from World Bank, IMF.
5. Urbanization Rate (Percentage of the population living in urban areas): Sourced from World Bank, UN.
6. Population Size (Total number of people living in the country): Sourced from World Bank, UN.
7. Government Effectiveness (Quality of public services and policy formulation): Sourced from World Bank Governance Indicators.
8. FDI Inflow (Foreign direct investment received by the country, as a percentage of GDP): Sourced from World Bank, UNCTAD.
9. Internet Access (Availability of Internet services in the country): Sourced from World Bank, ITU.
10. Electricity Access (Percentage of the population with access to electricity): Sourced from World Bank, IEA. Data analysis

Empirical Framework

The multinomial logit model expresses the log-odds of being in a particular outcome category versus the base category as a linear function of the predictors.The general form of the model is represented as:

$$\ln\left(\frac{(p(y=j)}{(p(y=0)}\right) = \beta j0 + \beta j1 \times zgdpc + \beta j2 \times zinfoecon + \beta j3 \times zrem + \beta j4 \times zfdi + \beta j5 zmobsub$$

where:

- P(Y=j) is the probability of being in group j (such as group 1, 2, or 4),
- P(Y=0) is the probability of being in the base group (Base group 0)
- βj0 = constant (intercept) for group j.
- βjn = Coefficients for the Predictors (where n=1,2,3,4,5)
- zgdpc, zinfoecon, zrem, zfdi, zmobsub

Theoretical Framework

Endogenous Growth Theory

Theoretical Relevance to Pakistan's CBDC Adoption: Endogenous Growth Theory (posits that economic growth is driven by internal factors such as technological innovation, human capital, and knowledge accumulation, positioning CBDCs as tools to enhance financial efficiency and inclusion in Pakistan. Technological drivers, including the information economy, mobile subscriptions, and internet access, represent investments in digital infrastructure that can reduce transaction costs and scale financial services, fostering growth. Socioeconomic drivers, such as GDP per capita and remittances, reflect Pakistan's economic capacity and potential for financial inclusion, particularly in a cash-heavy economy with significant remittance inflows.

Innovation Diffusion Theory (IDT)

Theoretical Relevance to Pakistan's CBDC Adoption: Innovation Diffusion Theory (IDT) provides a framework for understanding how Pakistan, a developing economy aiming to launch a digital rupee by 2025, adopts Central Bank Digital Currencies (CBDCs) as a financial innovation. IDT posits that adoption depends on five attributes: relative advantage (e.g., improved financial inclusion, reduced transaction costs compared to cash-based systems), compatibility (alignment with existing technological and financial infrastructure), complexity (ease of implementation), trialability (ability to test CBDCs through pilots), and observability (learning from successful global CBDC implementations, such as China's digital yuan). For Pakistan, technological drivers like the information economy, mobile subscriptions, and internet access are critical for ensuring compatibility, as the country has a robust mobile penetration and growing digital payment systems (e.g., Easypaisa). Socioeconomic drivers, such as GDP per capita and remittances, shape the perceived relative advantage by highlighting the need for efficient financial systems in a cash-heavy economy. Market drivers, like foreign direct investment (FDI), influence whether CBDCs are prioritized over existing financial structures. Demographic drivers, including urban population and population size, support scalability in urban centers like Karachi and Lahore, though rural areas may pose challenges. IDT suggests that Pakistan's central bank will adopt CBDCs if they align with its technological infrastructure and offer clear benefits, with observability of global pilots reducing perceived risks.

Data Analysis

Multinomial Logit Model

The multinomial logit model (MNL) is a regression model used for nominal (unordered) categorical outcomes, making it suitable when the dependent variable's categories do not necessarily follow a strict ordinal progression or when the assumptions of the ordered probit model are violated. In the context of your study, the MNL treats the four CBDCPI categories (no project, research, pilot, live) as distinct, nominal outcomes rather than assuming a strict ordering. This approach offers several advantages in addressing the issues with your data,The multinomial logit model expresses the log-odds of being in a particular outcome category versus the base category as a linear function of the predictors.**Specific Regression Equations** Based on the multinomial logit results, the model estimates separate equations for each CBDC adoption group (1, 2, 4), each relative to the base group (group 0). The specific regression equations for each group are as follows:

For Group 1 (e.g., no CBDC plans):

$$\ln\left(\frac{(p(y=1)}{(p(y=0)}\right) = \beta 10 + \beta 11 \times zgdpc + \beta 12 \times zinfoecon + \beta 13 \times zrem + \beta 14 \times zfdi + \beta 15 zmobsub$$

For Group 2 (e.g., planning/research):

$$\ln\left(\frac{(p(y=2)}{(p(y=0)}\right) = \beta 20 + \beta 21 \times zgdpc + \beta 22 \times zinfoecon + \beta 23 \times zrem + \beta 24 \times zfdi + \beta 25 zmobsub$$

For Group 4 (e.g., pilot/issued):

$$\ln\left(\frac{(p(y=4)}{(p(y=0)}\right) = \beta 40 + \beta 41 \times zgdpc + \beta 42 \times zinfoecon + \beta 43 \times zrem + \beta 44 \times zfdi + \beta 45 zmobsub$$

Probability Equations

The probabilities of being in each group are derived from the log-odds using the softmax function. Assuming the base group is Y=0, the probability of being in group j is calculated as follows:

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$$P(Y=j) = \frac{\exp(\beta j0 + \beta j1 \times zgdpc + \beta j2 \times zinfoecon\beta j3 \times zrem\beta j4 \times zfdi + \beta j5zmobsub)}{1 + \sum k = 1,2,4\exp(\beta k0 + \beta k1 \times zgdpc + \beta k2 \times zinfoecon + \beta k3 \times zrem + \beta k4 \times zfdi + \beta k5zmobsub)}$$

For the base group

$$P(Y=0) = \frac{1}{1 + \sum k = 1,2,4\exp(\beta k0 + \beta k1 \times zgdpc + \beta k2 \times zinfoecon + \beta k3 \times zrem + \beta k4 \times zfdi + \beta k5zmobsub)}$$

Results and Discussion

The multinomial logit model results reveal that economic and technological factors significantly influence the categorical outcome variable "group," with distinct effects across groups 1, 2, and 4, likely representing different economic or technological development stages. GDP per capita (z_gdp_c) and mobile subscriptions (z_mob_sub) consistently promote membership in group 4, suggesting that higher economic prosperity and digital connectivity are key drivers of this outcome, potentially indicative of advanced economies or digitally integrated societies. Conversely, foreign direct investment (z_fdi) and remittances (z_rem) exhibit strong negative effects on groups 1 and 2, implying that these factors may deter certain outcomes, possibly due to economic dependency or structural shifts induced by external financial flows. The information economy (z_info_econ) shows a dual role, reducing the likelihood of groups 1 and 2 but increasing it for group 4, highlighting its context-specific impact. The marginal effects further underscore FDI's substantial influence on group membership probabilities, particularly increasing the likelihood of group 1 by 41.3% and decreasing group 2 by 46.0%, while other variables show more modest probability effects, suggesting their influence is stronger in relative odds than absolute probabilities. The model's robust fit (pseudo R-squared = 0.341, chi-square = 541.355, p = 0.000) and minimal multicollinearity (mean VIF = 2.34) enhance confidence in these findings, indicating that the predictors effectively capture variations in group membership.

group	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
0	0	.	.	.	.	.	
0	0	.	.	.	.	.	
0	0	.	.	.	.	.	
0	0	.	.	.	.	.	
0	0	.	.	.	.	.	
0	0	.	.	.	.	.	
z_gdp_c	1.261	.476	2.65	.008	.327	2.194	***
z_info_econ	-1.241	.255	-4.86	0	-1.742	-.741	***
z_rem	-.445	.166	-2.68	.007	-.771	-.12	***
z_fdi	-3.763	.399	-9.42	0	-4.546	-2.98	***
z_mob_sub	.498	.149	3.35	.001	.206	.79	***
Constant	.438	.22	1.98	.047	.005	.87	**
z_gdp_c	.465	.486	0.96	.338	-.487	1.417	
z_info_econ	-2.127	.3	-7.09	0	-2.715	-1.539	***

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Delta-Method

z_rem	-1.301	.323	-4.03	0	-1.934	-.668	***
z_fdi	-3.863	.436	-8.86	0	-4.718	-3.008	***
z_mob_sub	1.266	.189	6.69	0	.896	1.637	***
Constant	-.765	.273	-2.80	.005	-1.3	-.23	***
z_gdp_c	2.262	.522	4.33	0	1.239	3.285	***
z_info_econ	1.234	.272	4.53	0	.7	1.768	***
z_rem	-.042	.164	-0.25	.8	-.364	.28	
z_fdi	-.068	.154	-0.44	.658	-.37	.234	
z_mob_sub	.65	.212	3.07	.002	.235	1.066	***
Constant	-1.939	.327	-5.93	0	-2.58	-1.298	***

Delta-method

Mean dependent var	1.957	SD dependent var	0.896
Pseudo r-squared	0.341	Number of obs	649
Chi-square	541.355	Prob > chi2	0.000
Akaike crit. (AIC)	1083.084	Bayesian crit. (BIC)	1163.642

*** *p<.01*, ** *p<.05*, * *p<.1*

Multinomial Logit Results

The multinomial logit model assesses the influence of standardized explanatory variables—GDP per capita (z_gdp_c), information economy (z_info_econ), remittances (z_rem), foreign direct investment (z_fdi), and mobile subscriptions (z_mob_sub)—on the log-odds of belonging to groups 1, 2, or 4 relative to a reference group (assumed to be another category, e.g., group 3). For group 1, significant predictors include z_gdp_c (β = 1.261, p = 0.008), z_info_econ (β = -1.241, p = 0.000), z_rem (β = -0.445, p = 0.007), z_fdi (β = -3.763, p = 0.000), and z_mob_sub (β = 0.498, p = 0.001), indicating that higher GDP and mobile subscriptions increase the likelihood of group 1 membership, while a stronger information economy, remittances, and FDI decrease it. For group 2, z_info_econ (β = -2.127, p = 0.000), z_rem (β = -1.301, p = 0.000), z_fdi (β = -3.863, p = 0.000), and z_mob_sub (β = 1.266, p = 0.000) are significant, with similar patterns to group 1 except for z_gdp_c, which is non-significant (β = 0.465, p = 0.338). Group 4 shows significant positive effects from z_gdp_c (β = 2.262, p = 0.000), z_info_econ (β = 1.234, p = 0.000), and z_mob_sub (β = 0.650, p = 0.002), but z_rem (β = -0.042, p = 0.800) and z_fdi (β = -0.068, p = 0.658) are non-significant. The model's pseudo R-squared (0.341) and chi-square (541.355, p = 0.000) indicate a good fit with 649 observations, suggesting that economic and technological factors differentially influence group membership, with group 4 likely representing a more prosperous or digitally advanced category.

Marginal Effects

Average marginal effects Number of obs = 501
Model VCE: Robust
dy/dx wrt: z_gdp_c z_info_econ z_rem z_fdi z_mob_sub
1._predict: Pr(group==1), predict(pr outcome(1))
2._predict: Pr(group==2), predict(pr outcome(2))
3._predict: Pr(group==4), predict(pr outcome(4))

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	dy/dx	std.err	z	p>z	[95%	conf interval].
z_gdp_c _predict						
1	-0.201	0.264	-0.760	0.446	-0.718	0.316
2	0.094	0.192	0.490	0.623	-0.282	0.470
3	0.107	0.086	1.240	0.215	-0.062	0.276
z_info_econ _predict						
1	0.128	0.122	1.050	0.295	-0.111	0.367
2	-0.219	0.114	-1.910	0.056	-0.443	0.005
3	0.091	0.053	1.730	0.084	-0.012	0.194
z_rem _predict						
1	0.065	0.058	1.130	0.257	-0.048	0.178
2	-0.072	0.057	-1.270	0.203	-0.183	0.039
3	0.007	0.032	0.210	0.834	-0.056	0.070
z_fdi _predict						
1	0.413	0.174	2.370	0.018	0.071	0.754
2	-0.460	0.198	-2.320	0.020	-0.849	-0.071
3	0.047	0.036	1.340	0.182	-0.022	0.117
z_mob_sub _predict						
1	-0.078	0.058	-1.350	0.176	-0.191	0.035
2	0.042	0.046	0.910	0.363	-0.048	0.131
3	0.037	0.028	1.310	0.189	-0.018	0.091

The marginal effects table, based on 501 observations, quantifies the change in the probability of belonging to groups 1, 2, or 4 for a one-unit increase in each standardized explanatory variable, using the delta method with robust standard errors. For z_gdp_c, the marginal effects are non-significant across all groups: group 1 (dy/dx = -0.201, p = 0.446), group 2 (dy/dx = 0.094, p = 0.623), and group 4 (dy/dx = 0.107, p = 0.215). Despite the significant positive logit coefficient for group 4 (β = 2.262), the non-significant marginal effect suggests that GDP per capita's impact on the probability of group 4 membership is modest, possibly due to nonlinear effects or the distribution of the outcome variable. For z_info_econ, the marginal effects are marginally significant for group 2 (dy/dx = -0.219, p = 0.056), indicating a 21.9% decrease in the probability of group 2 membership per unit increase, and group 4 (dy/dx = 0.091, p = 0.084), suggesting a 9.1% increase in probability, aligning with the logit model's negative and positive coefficients, respectively. The non-significant effect for group 1 (dy/dx = 0.128, p = 0.295) contrasts with its significant logit coefficient, indicating a limited practical impact. For z_rem, all marginal effects are non-significant (group 1: dy/dx = 0.065, p = 0.257; group 2: dy/dx = -0.072, p = 0.203; group 4: dy/dx = 0.007, p = 0.834), suggesting that remittances have a minimal effect on probabilities despite significant logit coefficients for groups 1 and 2, possibly due to small effect sizes or contextual factors. For z_fdi, significant effects are observed for group 1 (dy/dx = 0.413, p = 0.018), increasing the probability by 41.3%, and group 2 (dy/dx = -0.460, p = 0.020), decreasing the probability by 46.0%, consistent with the strong negative logit coefficients. The non-significant effect for group 4 (dy/dx = 0.047, p = 0.182) aligns with its non-significant logit coefficient. For z_mob_sub, all marginal effects are non-significant (group 1: dy/dx = -0.078, p = 0.176; group 2: dy/dx = 0.042, p = 0.363; group 4: dy/dx = 0.037, p = 0.189), indicating that mobile subscriptions have a modest impact on probabilities despite significant logit coefficients. These findings highlight FDI's substantial influence on group membership probabilities, particularly for groups 1 and 2, while other variables' effects are less pronounced in probability terms, suggesting that their influence operates more through relative odds than absolute probabilities.

Summary

The multinomial logit model examined the effects of standardized variables—GDP per capita (z_gdp_c), information economy (z_info_econ), remittances (z_rem), foreign direct investment (z_fdi), and mobile subscriptions (z_mob_sub)—on the categorical outcome "group," likely representing economic or technological development categories. For group 1, z_gdp_c (β = 1.261, p = 0.008), z_info_econ (β = -1.241, p = 0.000), z_rem (β = -0.445, p = 0.007), z_fdi (β = -3.763, p = 0.000), and z_mob_sub (β = 0.498, p = 0.001) are significant. Group 2 shows similar patterns, with significant z_info_econ (β = -2.127, p = 0.000), z_rem (β = -1.301, p = 0.000), z_fdi (β = -3.863, p = 0.000), and z_mob_sub (β = 1.266, p = 0.000), but z_gdp_c is non-significant. For group 4, z_gdp_c (β = 2.262, p = 0.000), z_info_econ (β = 1.234, p = 0.000), and z_mob_sub (β = 0.650, p = 0.002) are significant. Marginal effects highlight FDI's impact, increasing group 1 probability by 41.3% (p = 0.018) and decreasing group 2 by 46.0% (p = 0.020). The correlation matrix shows a strong negative correlation between z_gdp_c and z_info_econ (r = -0.6937), and VIF analysis (mean VIF = 2.34) confirms minimal multicollinearity. The model's fit (pseudo R-squared = 0.341, chi-square = 541.355, p = 0.000, N = 649) supports these findings.

Limitations of the Study

This study, while providing valuable insights into the factors influencing the categorical outcome variable "group" using a multinomial logit model, is subject to several limitations that warrant consideration. First, the lack of clarity regarding the specific definitions of the "group" categories (groups 1, 2, 4, and the assumed reference group) limits the interpretability of the findings. Without explicit definitions—such as whether these groups represent economic development stages, levels of digital adoption, or other categories—it is challenging to fully contextualize the results, particularly for policy implications in Pakistan, where economic and technological disparities are pronounced. Second, the non-significant marginal effects for several variables (e.g., z_gdp_c, z_rem, z_mob_sub across groups) despite significant logit coefficients suggest limited practical significance in terms of probability changes. This discrepancy may reflect nonlinear relationships or the influence of unmeasured factors, which could be particularly relevant in Pakistan's heterogeneous economic landscape, where GDP per capita and remittance impacts vary across urban and rural regions.

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