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Digital Currencies and Monetary Policy Effectiveness: What Does the Data Say?

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ABSTRACT

This study investigates the impact of digital currencies (including central bank digital currencies [CBDCs], cryptocurrencies, and Ethereum) on monetary policy effectiveness, specifically focusing on inflation-targeting success and financial stability. Using Autoregressive Distributed Lag (ARDL) modelling on monthly global data spanning January 2010 to December 2024, the empirical findings demonstrate that digital currencies significantly improve monetary policy outcomes. The results indicate that CBDCs and Ethereum transactions notably enhance inflation-targeting success, enabling central banks to better achieve targeted inflation through improved transaction efficiency and transparency. Ethereum also consistently demonstrates a stabilising impact on financial stability by reducing inflation volatility. Conversely, cryptocurrencies exhibit mixed impacts, suggesting potential speculative disruptions. The error-correction mechanisms highlight robust short-run adjustments towards equilibrium, supporting the reliability of the ARDL approach. These findings emphasize the need for policymakers to strategically integrate digital currencies into monetary policy frameworks, and recommend enhanced regulatory oversight, strategic adoption of Ethereum technology, and careful management of monetary growth and velocity of money to sustain economic stability.

Keywords: Central Banks, Digital Currencies, Monetary Policy, Money, Autoregressive Distributed Lag Modelling
JEL Classifications: E42, E52, E58, G21

1. INTRODUCTION

The advent of digital currencies has revolutionised the global financial landscape, challenging traditional monetary systems and central bank operations. Digital currencies have introduced new paradigms in currency issuance, payment systems, and financial intermediation (Adenutsi, 2024; Bank for International Settlements [BIS], 2021). These innovations have sparked global discussions among policymakers, economists, and researchers about their implications for monetary policy effectiveness. Effective monetary policy minimises unintended side effects in the form of asset bubbles, which are commonly associated with excessively low interest rates that fuel speculation, and income inequality that may arise when some policies disproportionately benefit certain groups at the expense of others. Central banks have traditionally relied on tools such as interest rates, open market operations, and reserve requirements to regulate liquidity, control inflation, and stabilise economies. However, the growing adoption of digital currencies raises questions about the effectiveness of these tools in an increasingly digitalised economy. The emergence of digital currencies has introduced complexities that could potentially undermine the effectiveness of these tools. Unlike fiat currencies, digital currencies operate on decentralised or centralised digital platforms, often bypassing traditional banking systems and regulatory oversight (BIS, 2021).

The increasing adoption of digital currencies by individuals, businesses, and even governments presents both opportunities and challenges for monetary policy. On the one hand, digital currencies can enhance financial inclusion, reduce transaction costs, and promote efficiency in payment systems. On the other hand, they may disrupt traditional monetary channels, diminish the control and surveillance power of central banks over money supply, and complicate the transmission of monetary policy (Adenutsi, 2025; Prasad, 2021). Key issues include the difficulty in tracking and regulating digital currency transactions, the potential for disintermediation of the banking system, and the impact on the velocity of money and inflation expectations (ECB, 2020).

Accordingly, the spirit behind this study is to contribute to providing the empirical answers to pertinent research questions: How do the transactions involving digital currencies (CBDCs, cryptocurrencies, and Ethereum) influence the effectiveness of monetary policy in achieving inflation-targeting success? In what ways do digital currency transactions affect the stability of the financial system, as indicated by changes in inflation volatility? To what extent do monetary policy transmission mechanisms, specifically through channels such as real interest rates, velocity of money, and exchange rates, respond to the growth of digital currency transactions? What adaptations should central banks consider to maintain or enhance monetary policy effectiveness in response to the disruptions associated with digital currency adoption?

The underlying objectives of this study are to empirically investigate the impact of CBDCs, cryptocurrencies, and Ethereum on inflation-targeting success, specifically assessing whether digital currencies improve or impair the capacity of central banks to maintain price stability; examine how increased adoption and transactional usage of digital currencies affect financial stability, particularly by assessing their influence on the volatility of inflation; evaluate the responsiveness of traditional monetary policy transmission mechanisms, specifically real interest rates, money velocity, and exchange rates, to the proliferation of digital currencies; and develop empirically grounded policy recommendations that assist central banks in adjusting their monetary policy frameworks to address the challenges and opportunities posed by the increasing adoption of digital currencies, ensuring continued monetary policy effectiveness and financial system stability.

This paper is significant for several reasons. First, it contributes to the growing body of literature on digital currencies and their implications for macroeconomic management. By exploring the intersection of digital currencies and monetary policy, the research provides valuable insights into the evolving financial landscape (Prasad, 2021). Second, the findings of this study will assist central banks and policymakers in understanding the challenges posed by digital currencies and devising strategies to mitigate their impact on monetary policy effectiveness. This is particularly critical in an era where digital currencies are becoming mainstream, and their adoption is expected to grow exponentially (BIS, 2021). Third, the study has broader implications for economic stability and growth. By identifying ways to adapt monetary policy frameworks, the research supports the development of resilient financial systems capable of withstanding disruptions from technological innovations. Finally, this study will serve as a reference for future research on digital currencies and monetary policy, encouraging further exploration of innovative solutions to address emerging challenges in the financial ecosystem.

The paper proceeds systematically with stylised facts, literature review, methodology, presentation of results, discussion of results, conclusions, and policy prescriptions.

2. STYLISED FACTS ON DIGITAL CURRENCIES, MONETARY GROWTH, AND MONETARY POLICY EFFECTIVENESS

Stylised facts provide a foundational understanding by summarising empirical regularities observed in data, serving as critical reference points for both theoretical and empirical research in economics and finance. Drawing insights from Figure A1 and descriptive statistics in Table A1, this essay synthesizes important observations regarding digital currencies, monetary growth, and monetary policy effectiveness (inflation targeting and financial stability).

Digital currencies, particularly CBDCs, cryptocurrencies, and Ethereum, exhibit distinct trends. Ethereum transactions show substantial variability with a notable maximum of 29.959 trillion USD and a mean of approximately 8.917 trillion USD, indicating substantial usage yet considerable volatility. CBDCs, conversely, exhibit more stability with a lower maximum of 0.816 trillion USD and a mean of 0.399 trillion USD. Cryptocurrencies other than Ethereum are moderately utilized with an average transaction volume of 1.258 trillion USD and lower variability, illustrating consistent but comparatively modest market engagement.

Monetary growth (M) demonstrates considerable volatility, oscillating widely between a maximum of 3.7124% and a minimum of −3.4599%, with an average growth rate of 0.2494%. This highlights pronounced fluctuations in money supply, suggesting potential challenges in controlling monetary aggregates, partly due to the evolving dynamics associated with digital currencies. These fluctuations underscore the difficulties central banks may face in managing inflation expectations and achieving monetary policy stability.

Monetary policy effectiveness, evaluated through inflation-targeting success, is measured by deviations from targeted inflation levels. The mean inflation rate recorded is approximately 4.863%, with variations between 0.978% and 8.478%, reflecting considerable volatility that central banks must manage. These variations illustrate the persistent challenges faced in achieving precise inflation targets. The inflation-targeting framework, as shown in the trends, is influenced by digital currency transactions, particularly Ethereum and CBDCs, due to their capacity to enhance transparency and transactional efficiency.

Regarding financial stability, assessed through inflation volatility (standard deviation), digital currencies significantly impact monetary stability. Ethereum transactions demonstrate potential for reducing inflation volatility, thus positively influencing financial stability. Conversely, the variability in cryptocurrency transaction volumes suggests speculative influences which potentially exacerbate short-term volatility. The relatively moderate stability of CBDC transactions indicates potential benefits in maintaining monetary and financial stability.

The velocity of money (V), averaging at 0.621, with limited fluctuation (0.539-0.682), underscores the relatively steady pace of monetary circulation within the economy despite digital innovations. This consistency suggests that digital currencies, while disruptive in some areas, have not substantially altered transaction frequencies at aggregate levels. Nonetheless, the slight variations observed can still influence inflation dynamics and monetary policy outcomes.

The real interest rate averages negatively at −2.63%, with considerable variability, suggesting that central banks engage in expansionary monetary policies possibly in response to global economic conditions or to stimulate economic activity amid digitalization pressures. Negative real interest rates emphasize ongoing efforts to support growth, potentially complicating monetary policy effectiveness, especially in the presence of digital currency fluctuations.

Finally, real GDP per capita (y), averaging approximately 9739 USD with relatively modest variability, indicates stable economic growth. However, the interaction between steady economic growth and fluctuating digital currency transactions presents mixed implications for monetary policy effectiveness. As digital currency adoption grows, monetary policy frameworks must adapt to ensure economic growth remains sustainable amid financial innovations.

In summary, these stylised facts underscore significant implications for monetary policy frameworks. The volatility inherent in digital currency transactions, particularly Ethereum, coupled with substantial monetary growth fluctuations, poses new challenges for central banks. Despite these challenges, the relatively stable velocity of money and steady economic growth provide a foundation upon which adaptive and innovative monetary policy approaches can be built. Understanding and leveraging these stylised facts will enable central banks to refine policies for enhanced inflation-targeting effectiveness and strengthened financial stability in an increasingly digital financial environment.

3. THE LITERATURE

3.1. Theories of Monetary Policy Effectiveness

The theoretical foundations of digital currencies and their impact on monetary policy are grounded in several key frameworks. Digital currencies introduce complexities in traditional monetary policy mechanisms, challenging the control that central banks have over monetary aggregates and financial stability (Adenutsi, 2025; Nakamoto, 2008). According to Adenutsi (2024), digital currencies embody varied theoretical viewpoints, including decentralisation, central bank control, and economic utility, necessitating clear distinctions to enhance academic and policy dialogues. To begin with, the Quantity Theory of Money provides a foundation for understanding how changes in money supply influence price levels and economic output and remains relevant to modern inflation targeting frameworks (Ball and Mankiw, 2002). Digital currencies, by altering the money supply and its velocity, challenge traditional assumptions of this theory. The decentralised nature of cryptocurrencies, for instance, introduces complexities in tracking and controlling money supply, potentially destabilising price levels (Adenutsi, 2024; Bordo and Levin, 2017).

Meanwhile, the Theory of Monetary Policy Transmission Mechanisms (Bernanke and Gertler, 1995) highlights the channels through which monetary policy impacts an economy, including interest rate, credit, and exchange rate channels. Digital currencies, by bypassing traditional banking systems, could weaken these channels, reducing the effectiveness of monetary policy tools. For example, stablecoins pegged to fiat currencies may compete with central bank-issued money, influencing interest rates and liquidity management (Adrian and Mancini-Griffoli, 2019).

Furthermore, the Theory of Currency Substitution explains how individuals may shift between currencies based on perceived stability and utility (Calvo and Végh, 1992). The rise of digital currencies as an alternative medium of exchange and store of value could lead to currency substitution, potentially undermining central bank control over domestic monetary policy. This phenomenon is particularly relevant in economies with high inflation or unstable fiat currencies, where digital currencies may offer a more attractive alternative (ECB, 2020).

Finally, the Theory of Financial Intermediation underscores the role of banks in facilitating monetary policy through credit creation and liquidity provision (Diamond and Dybvig, 1983). Digital currencies, by enabling peer-to-peer transactions and decentralised finance (DeFi) platforms, could disrupt traditional intermediation processes, challenging the ability of central banks to influence credit and money supply effectively (Adenutsi, 2024; BIS, 2021).

These theoretical perspectives provide a comprehensive framework for analysing the impact of digital currencies on monetary policy effectiveness. They highlight the need for central banks to adapt their monetary frameworks to address the challenges posed by digital currencies while leveraging their potential benefits.

3.2. Empirical Studies on Digital Currencies and Monetary Policy Effectiveness

Auer and Böhme (2021) examined CBDC designs and their implications for monetary policy transmission using cases from Sweden (e-krona) and China (digital yuan). The authors concluded that CBDCs can enhance monetary policy effectiveness by improving payment efficiency and providing a direct channel for policy implementation. However, risks to financial stability and privacy must be managed.

Ferrari et al. (2020) pursued quantitative analysis using macroeconomic models to simulate the impact of CBDCs on interest rate transmission by stimulating economic scenarios based on European Central Bank data (Eurozone). The study found that CBDCs strengthen monetary policy by enhancing interest rate pass-through and reducing reliance on traditional banking systems.

Mancini-Griffoli et al. (2018) conducted a comparative analysis of synthetic CBDCs versus traditional monetary instruments using cross-country analysis involving emerging and developed economies. The study found that synthetic CBDCs offer flexibility in monetary policy implementation but require robust regulatory frameworks to mitigate risks.

Bordo and Levin (2017) undertook a theoretical exploration of the role of CBDCs in achieving price stability and financial inclusion using historical monetary policy data from advanced economies (United States, and the Eurozone). The study concluded that CBDCs can improve monetary policy effectiveness by eliminating the zero-lower-bound constraint on interest rates and enhancing financial inclusion.

The reviewed studies underscore the transformative potential of digital currencies on monetary policy. While CBDCs appear to offer significant advantages in enhancing policy transmission and stability, their implementation must address challenges related to privacy, security, and financial stability.

3.3. An Integrated Theoretical Framework for Monetary Policy Effectiveness

Adenutsi (2025) introduces a hybrid theoretical framework that integrates the features of digital currencies with traditional monetary economics principles, extensively covering the implications for monetary policy transmission, financial stability, and regulation. This novel theoretical framework integrates digital currency economics into traditional monetary policy theories by emphasizing inflation-targeting success as the primary measure of monetary policy effectiveness. Drawing upon Adenutsi (2025), the framework introduces hybrid issuance mechanisms, stability protocols, and regulatory integration to model how digital currencies (cryptocurrencies, CBDCs, and Ethereum) influence inflation dynamics and inflation-targeting outcomes.

The framework identifies inflation-targeting outcome as the primary dependent variable, mathematically defined as the deviation of actual inflation (π) from target inflation (π^T), thus $\left|\pi_t - \pi_t^T\right|$. The dynamics of inflation (π_t) under digital currency integration can be expressed through the modified Quantity Theory of Money equation, incorporating digital currency parameters $\pi_t = \frac{\Delta M_t^d \cdot V_t^d}{Y_t}$; where π_t is the rate of inflation at time t; ΔM_t^d is the change in digital money supply, combining algorithmic issuance of cryptocurrencies and discretionary issuance of CBDCs; V_t^d denotes the velocity of digital money, representing the frequency of digital currency transactions; and Y_t is real GDP per capita, representing economic output per head.

The hybrid issuance mechanism proposed by Adenutsi (2025) incorporates both algorithmic issuance and central-bank discretionary adjustments, modelled mathematically as $\Delta M_t^d = \Delta M_t^c + \Delta M_t^{CBDC}$; where ΔM_t^c represents cryptocurrency supply governed algorithmically: $\Delta M_t^c = f(\alpha_t, P_t^c)$ ΔM_t^{CBDC} is the central bank-controlled digital currency issuance, and $\sigma M_t^{CBDC} = \mu_t, Y_t$ Here, μ_t is the central bank's discretionary monetary policy adjustment at time t.

The velocity of digital currency circulation incorporates real-time transaction dynamics, defined as: $V_t^d = \frac{P_t \cdot T_t}{M_t^d}$ where P and T represent the general price level and transaction volume, respectively.

To ensure stability, advanced stability protocols (algorithmic adjustments) are modelled through $\alpha_t = \gamma \cdot (\pi^T - \pi_t)\lambda \cdot (P_t^s - P_t)$ where π^T is the adjusted target inflation, P_t^s is the stablecoin price at any particular time t, while γ, and λ are algorithmic adjustment coefficients counteracting deviations from target inflation.

Finally, interoperability between decentralised and centralised financial systems is represented mathematically as the integration function I(·): $I(M_t^c, M_t^{CBDC}) = \omega \cdot M_t^c + (1-\omega) \cdot M_t^{CBDC}$. This function describes how decentralised (cryptocurrencies) and centralised (CBDCs) systems interact to produce a unified monetary system with enhanced inflation control. Overall, this theoretical framework provides mathematically robust models for predicting how digital currencies impact inflation and inflation-targeting outcomes, offering policymakers a rigorous toolset for navigating monetary policy in the digital currency era.

4. METHODOLOGY

4.1. Empirical Modelling Framework

This study employs the Autoregressive Distributed Lag (ARDL) econometric modelling approach to empirically examine how digital currencies, *viz*., central bank digital currencies (CBDCs), cryptocurrencies, and Ethereum, affect monetary policy effectiveness. The choice of ARDL methodology was necessitated by the mixed order of integration (I[0] and I[1]) of variables as confirmed by preliminary stationarity tests (see Table A2), precluding the use of conventional volatility models such as ARCH, GARCH, EGARCH, and TGARCH, which are ideal for monthly high-frequency monthly financial data but require strictly I(1) variables.

4.1.1. ARDL model specifications

The empirical ARDL models are specified to reflect two distinct measures of monetary policy effectiveness MP^ψ – inflation-targeting success (π_s^T) measured by the difference between actual and policy-targeted inflation rates, and financial stability (σ_π) measured by the volatility of inflation rates.

4.1.1.1. The empirical long-run model

The ARDL long-run model capturing the equilibrium relationship among the variables is expressed as Equation 1:

$$MP_t^\psi = \tau_0 + \tau_1 CBDC_t + \tau_2 Crypto_t + \tau_3 Ethereum_t$$
$$+\tau_4 M_t + \tau_5 r_t + \tau_6 V_t + \tau_7 XR_t + \sum_{\kappa=1}^{m} \theta_\kappa \ddot{Z}_t + \mu_t \quad (1)$$

Here, τ_0 is the constant term, τ_1, τ_2,…, τ_7 are the long-run coefficients to be estimated for each of the explanatory variables, excluding the exogenous control variables, θ_κ is the vector matrix of the parameters corresponding to the m exogenous control variables, and μ is the error term representing deviations from the long-run equilibrium, assumed to have zero mean and constant variance, so that $\mu_t \approx N(0,\sigma_\mu^2)$, where the subscript, and *t* denotes a specific time (any specific month). Digital technology penetration rate *(dt)* and macroeconomic performance *(y)* are the control variables embodied in matrix $\ddot{Z}$ while the definition and measurement of all other variables are presented in Table A1. If any of these estimated coefficients, $\hat{\tau}_1, \hat{\tau}_2, \hat{\tau}_3 < 0$ and statistically significant, then the corresponding component of digital currencies (CBDC, cryptocurrency, and Ethereum) improves monetary policy effectiveness in the long run; otherwise, digital currencies either exacerbate monetary policy ineffectiveness or have neutral or no effect in the long run.

4.1.1.2. The empirical short-run dynamic model

The short-run empirical ARDL model specification is generally expressed mathematically as Equation 2.

$$\Delta MP_t^{\psi} = \eta_0 + \sum_{i=1}^{p} \gamma_i \Delta MP_{t-i}^{\psi} + \sum_{j=0}^{q} \beta_j \Delta X_{t-j} + \varphi ECM_{t-1} + \varepsilon_t \qquad (2)$$

Where ΔMP_t^{ψ} denotes the first-differenced dependent variables (inflation-targeting outcome (π_s^T), or financial stability measured as inflation volatility, (σ_π)), X includes explanatory variables, including the qualified control variables. Essentially, X comprises CBDC transactions, cryptocurrency transactions, Ethereum transactions, monetary growth rate (M), real interest rate (r), velocity of digital money (V), real bilateral exchange rate (XR), and real GDP per capita (y); γ_i and β_j represent short-run dynamic coefficients of the dependent variable and the explanatory variables, respectively. The coefficient φ of the error-correction mechanism term, ECM_{t-1}, reflects the speed of adjustment to long-run equilibrium, and ε is the stochastic error term, assumed to be independently and identically distributed (IID) with zero mean and constant variance, i.e., $\varepsilon_t \approx IID\,(0, \sigma^2)$. The short-run and long-run ARDL specifications ensure that error terms are uncorrelated over time (no serial correlation), have constant variance (homoscedasticity), and maintain no correlation with explanatory variables, thus guaranteeing unbiased and efficient estimation results.

Given that a specific $\hat{\beta}_j$ corresponding to a digital currency component yields an empirical result such that $\hat{\beta}_j < 0$ and statistically significant, it suggests that increased digital currency transactions are associated with lower deviation of inflation from its target in the short run. This implies that digital currency enhances monetary policy effectiveness. If $\hat{\beta}_1 > 0$ and statistically, it suggests that higher digital currency usage is associated with greater deviation from target inflation, indicating that digital currency could be weakening the effectiveness of monetary policy. If $\hat{\beta}_1 = 0$ statistically, then it implies that digital currency has no impact on monetary policy effectiveness.

The justification of this empirical model is guided by the theoretical foundations that align with the theoretical framework of Adenutsi (2025), and theories such as the Quantity Theory of Money (Fisher, 1911) and Monetary Policy Transmission Mechanisms (Bernanke and Gertler, 1995), which emphasize the role of money supply, interest rates, and exchange rates in monetary policy effectiveness. The empirical relevance is anchored on highly cited previous related studies, notably Auer and Böhme (2021), and Ferrari et al. (2020), who used similar frameworks to evaluate the influence of digital currencies on monetary systems. The empirical model provides actionable insights for policymakers by quantifying the impact of digital currencies on traditional monetary tools, upon which effective monetary policy can be designed.

The relatively high frequency of the monthly financial and economic time series data has the potential of exhibiting volatility clustering, implying that periods of high volatility are likely to be followed by high volatility, and periods of low volatility are followed by low volatility. Accordingly, models such as Autoregressive Conditional Heteroskedasticity (ARCH), Generalised ARCH (GARCH), Exponential GARCH (EGARCH), and Threshold GARCH (TGARCH) are appropriate for analysing volatility in high-frequency financial data. Econometrically, however, these ARCH-family models are appropriately applicable only when each of the variables in contention is I(1), and the variables collectively pass the cointegration test[1]. As is the case with this study, under circumstances where the variables are a combination I(0) and I(1), no robust cointegration test can be performed, implying that VAR, VECM, ARCH-family modelling, and statistically inappropriate. Typically, the empirical time-series model specified as Equation 1 can be regressed by least squares (OLS, RLS, GLM), ARCH, VAR, or VECM if the fundamental pre-conditions of each variable being I(0) or I(1) or but not a combination; otherwise, autoregressive distributed lag (ARDL) approach remains the only option to capture the dynamics.

4.2. Estimation Procedures

Rigorous preliminary diagnostics (stationarity tests, variance inflation factor checks for multicollinearity [see Table A3], and bounds cointegration tests) preceded the ARDL estimations. ARDL model selections were made based on the Akaike Information Criterion (AIC), resulting in ARDL (4,0,2,1,3) for inflation-targeting success and ARDL (4,2,2,1,0) for financial stability. The diagnostic tests affirmed model robustness, confirming validity and suitability for policy analysis. The estimation process involved estimating a set of ARDL models and reporting the results from the estimated model in full compliance with all applicable underlying time-series econometric assumptions. The other estimated results were then reported for robustness.

As required, the order of integration for each of the variables comprising the model was investigated, with the result that the empirical model has I(0) and I(1) variables, restricting the estimations within ARDL framework. Variables such as Bitcoin adoption, Bitcoin transactions, and real lending rate, which were initially considered but turned out to be integrated at a higher order than (i.e., neither I[0] nor I[1]), were dropped from the estimations. Additionally, an initial stepwise linear estimation was executed to identify and drop redundant control variables, a procedure that led to the elimination of digital technology adoption index. For

1 Notwithstanding the fact that the model may conveniently pass the Engle-Granger residual-based test with a combination of I(0) and I(1) variables, the inclination of this paper to conduct the globally accepted robust Johansen cointegration test.

the main results, two estimations were systematically carried out to explore how digital currencies impact monetary policy effectiveness measured as either inflation targeting success or financial stability (see Table 1).

For robustness verification, I(0) variables were first-differenced so that each variable is treated as I(1). The Johansen cointegration test was then undertaken, and the results confirmed cointegration with at least five cointegration equations for both the inflation-targeting success model and the financial stability model (see Table A5). Following this, GARCH/TARCH and EGARCH models were estimated to validate, at least in part, the impact of digital currencies on monetary policy effectiveness. The results of these ARCH-model robustness estimations are reported in Table A6.1 and Table A6.2.

4.3. Data Issues

The paper relied on secondary data, including macroeconomic indicators such as inflation rates, interest rates, money supply, and exchange rates; and digital currency metrics such as CBDC adoption rates, cryptocurrency market capitalisation, and transaction volumes.

The data are sourced from the World Bank, International Monetary Fund (IMF), Bank for International Settlements (BIS); data on monetary policy tools and digital currency initiatives from the country-specific central bank; data on cryptocurrency adoption and transaction volumes (e.g., CoinMarketCap, Chainalysis) from cryptocurrency market platforms with supplementary data from academic and institutional reports (e.g., Auer and Böhme, 2021; Bordo and Levin, 2017). The analysis covers the period from January 2010 to December 2024 to capture the evolution of digital currencies and their interaction with monetary policy. For the specific measurement of each of these variables, refer to Table A1 and Table A4 in the Appendix.

5. PRESENTATION OF RESULTS

5.1. Long-Run Empirical Results

5.1.1. Long-run impact of digital currencies on inflation-targeting success

The negative coefficient (−1.0170, significant at 10%) implies that higher volumes of transactions reduce deviations from inflation targets (Table 1). This suggests that CBDC adoption enhances monetary policy effectiveness by improving inflation-targeting success, potentially due to increased efficiency and transparency in financial transactions, enabling better control over money supply and inflation.

Cryptocurrency (Crypto) has an insignificant coefficient in the long run, indicating no substantial direct long-run effect on inflation-targeting outcome. Ethereum, however, shows a significant negative coefficient (−1.2054, significant at 1%), implying that increased Ethereum transactions significantly enhance inflation-targeting success (Table 1). Ethereum's blockchain efficiency and smart contracts could play a beneficial role in stabilising inflation expectations.

The monetary growth rate is negatively but insignificantly associated with inflation-targeting success in the long run, indicating limited direct influence on inflation outcomes within the sample period studied. A significant negative coefficient (−0.3368, significant at 1%) indicates that an increase in real interest rates significantly contributes to improved inflation-targeting outcomes. Higher real interest rates effectively contain inflationary pressures in the long run. Positive and significant coefficient (1.6914, significant at 10%) reveals that increases in the velocity of money reduce the success of inflation targeting (Table 1). Rapid circulation of money tends to generate inflationary pressures, complicating inflation management. A positive and significant coefficient (0.3943, significant at 10%) suggests that depreciation in the real exchange rate negatively affects inflation-targeting success, potentially due to increased import prices contributing to higher inflation.

5.1.2. Long-run impact of digital currency and financial stability

The positive yet statistically insignificant coefficient implies no strong direct long-run effect of CBDC transactions on financial stability. A negative and significant coefficient (−0.4158, significant at 5%) indicates that increased Ethereum transaction volume contributes significantly to reducing inflation volatility, enhancing financial stability, possibly through smoother transaction mechanisms and more predictable market expectations (Table 1). Positive but statistically insignificant long-run impact, indicating no clear direct long-run relationship with financial stability.

Monetary growth is negative but insignificant coefficient, indicating limited long-run impact on financial stability. Negative and statistically significant coefficient (−0.0341, significant at 10%), highlighting that higher real interest rates enhance financial stability by reducing inflation volatility. Velocity of money bears a negative but statistically insignificant impact, suggesting a limited direct effect on financial stability in the long run. Equally, real exchange rate and real income per capita both show statistically insignificant coefficients, implying minimal long-run influence on financial stability.

5.2. Short-Run Empirical Dynamics

5.2.1 Short-run dynamics of digital currencies and inflation-targeting outcome

Lagged inflation-targeting has highly significant and positive coefficients across lags indicating a strong short-run persistence in inflation-targeting outcomes. A positive and significant coefficient (0.7435, significant at 1%) suggests that past cryptocurrency transaction volumes temporarily worsen inflation-targeting effectiveness. A negative and significant short-run coefficient (−0.5957, significant at 1%) indicates Ethereum transactions immediately improve inflation-targeting success, even in the short run. Significantly negative coefficients at current (−0.0588, significant at 1%) and lagged (−0.0234, significant at 10%; −0.0354, significant at 1%) levels indicate that monetary contraction significantly improves inflation-targeting outcomes in the short term (Table 2).

Strong negative short-run coefficient (−0.3368, significant at 1%) emphasizes immediate effectiveness of higher real interest rates in

Table 1: Results of long-run bounds tested empirical ARDL model

Inflation-targeting success (π_s^T)			Financial stability (σ_π)		
Dependent variable: Δ, π_s^T 2			Dependent variable: $\Delta\ \sigma_\pi$, 2		
Selected Model: ARDL (4, 0, 2, 1, 3)			Selected Model: ARDL (4, 2, 2, 1, 0)		
Variable	**Coefficient**	**Standard error**	**Variable**	**Coefficient**	**Standard error**
Constant	−0.1633	1.2409	Constant	0.1462	0.5443
$\Delta\ \pi_s^T$ ([−1])	−2.6307***	0.2237	Δ (σ_π [−1])	−1.8260***	0.1952
CBDC	−1.0170*	0.6105	CBDC (−1)	0.6821	0.7413
Crypto (−1)	−1.1243	0.7319	Crypto (−1)	0.4070	0.3172
Ethereum (−1)	−1.2054***	0.4068	Ethereum(−1)	−0.4158**	0.1784
M (−1)	−0.0574	0.0595	M	−0.0024	0.0063
Δ (π_s^T [−1], 2)	1.0202***	0.1801	Δ (σ_π[−1], 2)	0.6543***	0.1595
Δ (π_s^T [−2], 2)	0.5298***	0.1221	Δ (σ_π [−2], 2)	0.4653***	0.1193
Δ (π_s^T [−3], 2)	0.2411***	0.0595	Δ (σ_π [−3], 2)	0.2125***	0.0762
Δ (Crypto)	−0.0702	0.2898	Δ (CBDC)	−0.0094	0.2945
Δ (Crypto[−1])	0.7435**	0.2899	Δ (CBDC [−1])	−0.5724***	0.2909
Δ (Ethereum)	−0.5957**	0.2475	Δ (Crypto)	−0.0982	0.1258
Δ (M)	−0.0588***	0.0194	Δ (Crypto [−1])	−0.2504**	0.1255
Δ (M [−1])	−0.0234	0.0316	Δ (Ethereum)	−0.1467	0.1080
Δ (M [−2])	−0.0354**	0.0159	*r*	−0.0341*	0.0180
R	−0.3368***	0.0444	V	−0.6786	0.4294
V	1.6914*	1.0158	XR	0.1113	0.0908
XR	0.3943*	0.2124	*y*	−0.0164	0.0593
y	0.0289	0.1352			

***/**/* represents significant at 1%. 5% and 10% respectively. Δ denotes first difference; each I (1) variable is in its first difference

Table 2: Results of dynamic short-run empirical ARDL model

Inflation-targeting success estimates			Financial stability estimates		
Variable	**Coefficient**	**Standard error**	**Variable**	**Coefficient**	**Standard error**
Δ (π_s^T [−1], 2)	1.0202***	0.1735	Δ ($\sigma M_t^{CBDC} = \mu_t, Y_t$ D [−1], 2)	0.6543***	0.1487
Δ (π_s^T [−2], 2)	0.5298***	0.1188	Δ ($\sigma M_t^{CBDC} = \mu_t, Y_t$ [−2], 2)	0.4653***	0.1149
Δ (π_s^T [−3], 2)	0.2411***	0.0570	Δ ($\sigma M_t^{CBDC} = \mu_t, Y_t$ [−3], 2)	0.2125***	0.0735
Δ (Crypto)	−0.0702	0.1831	Δ (CBDC)	−0.0094	0.1881
Δ (Crypto [−1])	0.7435***	0.1818	Δ (CBDC [−1])	−0.5724***	0.1914
Δ (Ethereum)	−0.5957***	0.1393	Δ (Crypto)	−0.0982	0.0800
Δ (M)	−0.0588***	0.0120	Δ (Crypto [−1])	−0.2504***	0.0800
Δ (M [−1])	−0.0234*	0.0140	Δ (Ethereum)	−0.1467**	0.0610
Δ (M [−2])	−0.0354***	0.0102	*r*	−0.0341**	0.0171
r	−0.3368***	0.0425	V	−0.6786**	0.3354
V	1.6914*	0.9431	XR	0.1113	0.0861
XR	0.3943*	0.2074	*y*	−0.0164***	0.0017
y	0.0289***	0.0030	CointEq (−1)	−1.8260***	0.1782
CointEq (−1)	−2.6307***	0.2135			
R^2	*0.9022*		R^2	*0.6789*	
Adjusted R^2	*0.8943*		*Adjusted* R^2	*0.6548*	
Durbin-Watson stat	*2.3801*		*Durbin-Watson stat*	*2.1540*	
*F-Bounds Test (k=4): 24.5083***		*I (0): 2.56* *I (1): 3.49*	*F-Bounds Test (k=4): 16.9540***		*I (0): 2.56* *I (1): 3.49*

***/**/* represents significant at 1%. 5% and 10% respectively. Δ denotes first difference; each I (1) variable is in its first difference

reducing inflation deviation. Velocity of Money bears a positive and significant coefficient (1.6914, significant at 10%) in the short run aligns with the long-run interpretation, indicating that higher velocity temporarily exacerbates inflation-targeting challenges. With real exchange rate bearing a positive short-run coefficient (0.3943, significant at 10%) reinforces its immediate inflationary impact due to currency depreciation (Table 2).

5.2.2. Short-run impact of digital currency on financial stability

Lagged financial stability is positive and significant across lags, reflecting persistent inflation volatility in the short run. Significant negative coefficient (−0.5724, significant at 1%) indicates delayed effects of CBDCs in reducing inflation volatility, enhancing short-run financial stability. Negative and significant coefficient (−0.2504, significant at 1%) indicates lagged cryptocurrency transactions temporarily stabilise inflation volatility. Negative and significant coefficient (−0.1467, significant at 5%), indicating immediate contributions of Ethereum transactions in reducing short-run inflation volatility (Table 2).

Significant negative short-run coefficient (−0.0341, significant at 5%), reinforcing the immediate stabilisation effect of higher real interest rates. Significant negative short-run coefficient (−0.6786, significant at 5%), showing that higher money velocity initially contributes positively to reducing inflation volatility. Negative and highly significant short-run coefficient (−0.0164, significant at 1%) implies that increased economic growth consistently stabilises short-term inflation volatility.

Both models show significant negative ECM terms, (−2.6307 for inflation-targeting and −1.8260 for financial stability, significant at 1%), indicating robust and rapid adjustments toward long-run equilibrium after short-run disturbances (Table 2). These empirical findings robustly indicate that digital currencies, particularly CBDCs and Ethereum, significantly influence monetary policy effectiveness and financial stability. While Ethereum consistently enhances both inflation targeting and financial stability, CBDCs notably improve inflation targeting but have mixed impacts on financial stability. The strong adjustment dynamics suggest efficient monetary mechanisms exist to rapidly correct short-run disequilibrium.

The empirical insights have substantial implications for monetary policy frameworks, highlighting the strategic role digital currencies play in shaping contemporary macroeconomic stability. The results from the ARDL estimations have been validated by the estimates from the GARCH/TARCH, and EGRACH models reported in Tables A6.1 and A6.2.

6. DISCUSSION OF RESULTS AND POLICY RECOMMENDATIONS

The empirical findings obtained from the ARDL model offer important insights into how digital currencies, including CBDCs, cryptocurrencies, and Ethereum, impact monetary policy effectiveness, specifically in terms of inflation-targeting success and financial stability.

6.1 Inflation-Targeting Outcome

Empirical results indicate that increased transaction volumes in CBDCs significantly enhance the success of inflation targeting by reducing deviations from inflation targets. This aligns theoretically with the Quantity Theory of Money (Fisher, 1911), which posits that an effective control over the money supply leads to predictable inflation outcomes. CBDCs provide central banks with better tools for precise money supply management, allowing a more accurate attainment of inflation targets (Auer & Böhme, 2021; Ferrari, Mehl, and Stracca, 2020; Bernanke, Laubach, Mishkin, and Posen, 1999).

Interestingly, Ethereum transaction volumes also showed significant negative associations with deviations from inflation targets, indicating potential efficiency and transparency benefits arising from smart-contract-driven platforms, consistent with the insights provided by Nakamoto (2008) and Adrian and Mancini-Griffoli (2019). Conversely, the significant positive relationship between cryptocurrency volumes and inflation deviation, especially in the short-run lagged terms, suggests temporary disruptions due to speculative elements or instability inherent to crypto markets, supporting concerns raised by Bordo and Levin (2017).

Furthermore, the significantly negative impact of monetary growth rates (M) on inflation-targeting deviations supports the Quantity Theory of Money (Fisher, 1911; Friedman, 1968), highlighting that controlled monetary expansions are crucial for achieving inflation stability. The observed positive and significant relationship between velocity of money and inflation-targeting challenges further reinforces traditional monetary theory that rapid money circulation intensifies inflationary pressures (Fisher, 1911; Mishkin, 2019).

The significant positive relationship between the real exchange rate and deviations from targeted inflation aligns with the open-economy monetary policy framework by Mishkin (1995) and highlights that exchange rate depreciation pressures inflation upward through imported inflation, posing challenges to central banks.

6.2. Financial Stability

The empirical evidence also reveals critical dynamics related to financial stability. Ethereum transactions significantly reduce inflation volatility, suggesting a stabilising role, possibly through efficient digital finance platforms, aligning with arguments by Bordo and Levin (2017) and Mancini-Griffoli et al. (2018). In contrast, CBDC transaction volumes only exhibit significant stabilising effects in lagged terms, consistent with the perspective provided by Auer and Böhme (2021) who emphasized potential delayed benefits of CBDC implementation in reducing financial market uncertainties.

Real interest rate (r) demonstrated a significant negative relationship with inflation volatility, confirming the theoretical transmission mechanism where higher real interest rates stabilise inflation expectations and enhance financial stability (Bernanke and Gertler, 1995; Mishkin, 1995). The significant negative relationship between velocity of money (V) and financial instability further supports the assertion that more predictable and slower monetary circulation stabilises financial markets, consistent with Fisher's (1911) monetary velocity implications and contemporary empirical validation by Ferrari et al. (2020).

The significant negative impact of CBDCs (lagged values) on inflation volatility underscores their beneficial role in reducing short-run volatility, confirming Auer and Böhme's (2021) empirical evidence from Sweden and China. Meanwhile, cryptocurrencies exhibited mixed short-term effects, reflecting ongoing debates in the literature regarding their stability implications (Prasad, 2021; ECB, 2020).

Both models indicate highly significant negative error correction terms (−2.6307 for inflation-targeting and −1.8260 for financial stability), suggesting rapid convergence back to equilibrium after-shocks. This highlights the robustness of the ARDL methodology in capturing short-run disturbances and re-aligning swiftly to long-run equilibrium, aligning with Pesaran et al. (2001) methodological recommendations.

Overall, these empirical findings contribute to the growing literature on digital currencies and monetary policy by providing robust quantitative evidence that digital currencies can enhance monetary policy effectiveness, specifically inflation targeting and financial stability (Bordo and Levin, 2017; Ferrari et al., 2020; Mancini-Griffoli et al., 2018). They underscore the theoretical necessity for monetary frameworks to evolve, reflecting contemporary challenges and opportunities presented by financial digitalisation (BIS, 2021; Prasad, 2021).

6.3. Policy Recommendations

Central banks should accelerate the development and deployment of CBDCs as empirical evidence shows they significantly enhance inflation-targeting success. Enhanced transaction efficiency and transparency provided by CBDCs improve the ability of central banks to precisely manage inflation targets.

Central banks should explore strategic adoption and integration of Ethereum blockchain technology. Ethereum consistently demonstrates stabilising effects by reducing inflation volatility, thus contributing positively to financial stability. The adoption of smart contracts could further enhance operational transparency and trust in monetary policy execution.

Policymakers must develop robust regulatory frameworks to mitigate speculative risks associated with cryptocurrencies. Given the empirical evidence showing potential short-run disruptions caused by cryptocurrency transactions, effective regulation is essential to manage risks without stifling innovation.

Central banks should maintain careful and controlled monetary growth, as excessive monetary expansion has been found to undermine inflation-targeting success. Additionally, central banks need mechanisms to moderate the velocity of digital money, as high velocity is linked with inflationary pressures.

Empirical results recommend that central banks leverage interest rate adjustments effectively, as higher real interest rates significantly stabilise inflation expectations and reduce volatility. Monetary policy should thus emphasize transparent, responsive interest rate adjustments to anchor inflation and stabilise economic expectations. Again, central banks should formulate targeted exchange rate policies to mitigate the inflationary impacts arising from real exchange rate depreciation. Active management through interventions or stabilising measures could prevent imported inflation, thus enhancing monetary policy effectiveness.

Central banks must invest in capacity-building initiatives aimed at enhancing staff understanding and technical capability related to digital currency technologies. Institutional adaptation to digital financial ecosystems will support the informed deployment and integration of digital currencies into monetary policy frameworks. It is further recommended that monetary authorities should implement robust real-time analytics and monitoring systems to continually track the adoption, transaction patterns, and velocity of digital currencies. Accurate real-time data is essential to promptly address any destabilising effects, thereby ensuring effective monetary policy responses.

Central banks should foster public-private partnerships with blockchain and fintech firms to leverage technical expertise, ensuring that the integration of digital currencies aligns with broader monetary and financial stability objectives.

Policymakers should maintain clear and consistent communication regarding digital currency policies, usage guidelines, and potential risks. Transparent communication will enhance public confidence and understanding, aiding in the smoother adoption and integration of digital currencies within the monetary system.

7. CONCLUSION

This study comprehensively examined the effects of digital currencies (CBDCs, cryptocurrencies, and Ethereum) on monetary policy effectiveness, focusing specifically on inflation-targeting outcomes and financial stability. Using robust ARDL econometric modelling, this study empirically substantiated that digital currencies significantly impact monetary policy outcomes.

The findings validate previous theoretical frameworks, particularly Adenutsi's (2025) hybrid theoretical model, which integrates digital currency mechanisms into traditional monetary policy principles. Consistent with this framework and supported by the Quantity Theory of Money (Fisher, 1911) and Monetary Policy Transmission Mechanisms (Bernanke and Gertler, 1995), the study confirms that CBDCs and Ethereum transactions significantly enhance central banks' ability to achieve targeted inflation. These digital currencies improve monetary control by providing enhanced transparency and transaction efficiency, enabling more precise interventions in managing money supply dynamics.

Moreover, Ethereum exhibited a consistently stabilising impact on financial stability by significantly reducing inflation volatility. This effect corroborates the insights provided by Auer and Böhme (2021), and Ferrari et al. (2020), who highlight the importance of efficient digital transaction platforms in stabilizing market expectations and monetary dynamics. Conversely, cryptocurrencies displayed mixed effects, highlighting speculative disruptions consistent with concerns raised by Bordo and Levin (2017).

The rapid convergence back to equilibrium observed in both inflation-targeting and financial stability models underscores the robustness of the ARDL approach and highlights the strength and responsiveness of monetary mechanisms in correcting short-run disequilibria.

The originality of this study lies in its comprehensive empirical analysis spanning over a decade of monthly data, covering the crucial phases of digital currency evolution. It uniquely contributes to the body of literature by quantitatively demonstrating the nuanced impacts of different types of digital currencies on monetary policy effectiveness. These insights not only bridge theoretical gaps identified in prior studies but also offer critical guidance to policymakers. The contribution to knowledge extends beyond theoretical validation, providing empirically grounded strategies for the strategic integration of digital currencies into monetary frameworks, emphasizing enhanced regulatory oversight and the adoption of Ethereum-based platforms to optimise financial stability and inflation management.

Thus, this research distinctly advances scholarly discourse, setting a foundation for future studies and informing effective policy responses in an increasingly digitalised financial landscape.

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APPENDICES

Figure A1: Trends in digital currency transactions and key monetary policy indicators

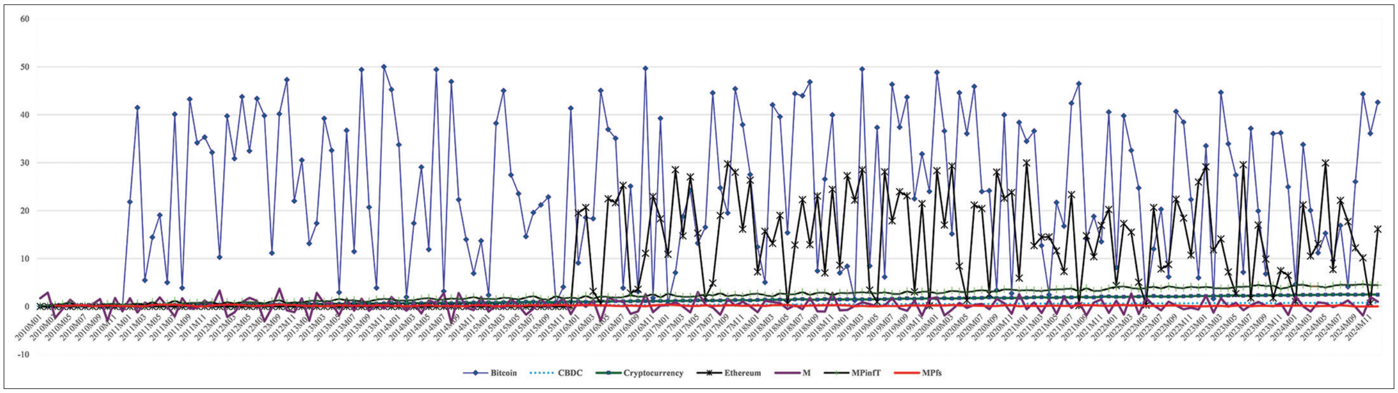

Table A1: Descriptive statistics summary of data

Statistic	CBDC	Crypto	Ethereum	*r*	V	XR	*y*	Inflation	M
Mean	0.3990	1.2577	8.9171	-2.6299	0.6206	1.0037	9739.027	4.8630	0.2494
Median	0.3925	1.2488	3.5129	-2.6374	0.6263	1.0027	9881.901	4.8140	0.2228
Maximum	0.8157	2.5464	29.959	0.1415	0.6817	1.2839	11606.22	8.4778	3.7124
Minimum	0.0068	0.0000	0.0000	-5.2150	0.5390	0.7210	7623.000	0.9777	-3.4599
Standard Deviation	0.2303	0.7361	10.1176	1.4524	0.0343	0.1259	1114.450	2.1476	1.4029
Observations	180	180	180	180	180	180	180	180	180

Table A2: Results of stationarity test

Variable	Level					First-differenced					Conclusion
	ADF	PP	KPSS	ERS	NG-P	ADF	PP	KPSS	ERS	NG-P	
$\pi - \pi^T$	−14.9536	−15.3205	0.1105	1.0910	1.0368	−10.7665	−88.2841	0.0957	93.0405	510.417	I (1)
Inflation	−14.9519	−15.2619	0.0883	1.3601	1.0891	−9.6816	−84.6534	0.1076	637.8121	730.865	I (1)
CBDC	−12.5083	−12.4839	0.0364	1.0266	1.0240	−9.9827	−118.557	0.2877	8.6677	1.1869	I (1)
Crypto	−12.8019	−12.7864	0.0561	1.1261	1.0846	−12.0092	−78.8255	0.1076	3.1642	1.3657	I (1)
Ethereum	−6.4586	−11.9035	0.2944	1.7109	1.7337	−10.5788	−73.2017	0.1139	17.439	0.9927	I (1)
r	−12.9933	−13.0010	0.1108	1.1602	1.0355	−9.8824	−74.2933	0.1196	137.9475	1.2411	I (1)
M	−9.3300	−68.9934	0.0665	7.2428	540.565	−9.3323	−83.1676	0.0415	15866.05	6592.7300	I (0)
y	−1.77833	−9.6052	0.4065	39.7056	37.4865	−13.1915	−61.0047	0.0665	15.1454	223.5000	I (0)
V	−12.0087	−12.4301	0.2830	1.0256	1.0313	−11.8489	−54.4007	0.0932	3.7926	733.2240	I (1)
XR	−14.7152	−14.7682	0.0487	1.0340	1.0427	−9.8552	−76.7962	0.0934	99.0669	340.9390	I (1)
α@5%	−3.4370	−3.4351	0.1460	5.6560	5.4800	−3.4371	−3.4353	0.1460	5.6558	5.4800	Not applicable

Table A3: Results of multicollinearity test (variance inflation factors)

Variable*	Inflation-targeting outcome (π_s^T)			Financial stability (σ_π)		
	Coefficient Variance	Uncentred VIF	Centred VIF	Coefficient Variance	Uncentred VIF	Centred VIF
CBDC	0.525397	1.139681	1.112263	0.072745	1.144637	1.118565
Crypto	0.092935	1.111606	1.063805	0.012761	1.111638	1.062903
Ethereum	0.082871	1.166842	1.121325	0.011376	1.164955	1.120599
M	0.000233	3.737067	3.737057	3.39E-05	3.959997	3.959920
r	0.002625	1.137547	1.132921	0.000366	1.151567	1.147402
V	1.449992	1.678096	1.676516	0.199339	1.666186	1.665235
XR	0.063903	1.101450	1.100685	0.008843	1.089599	1.089310
y	3.593316	4.669699	4.615672	0.535191	4.883188	4.838812
C	0.000610	1.146059	Not available	5.78E-05	1.157055	Not applicable

*In first differences

Table A4: Data measurement and sources

Variable	Measurement and Sources	
Monetary policy (MP^{ψ})	$\pi_s^T = \lvert\pi_{actual} - \pi_{target}\rvert$	This is the difference between the actual rate of inflation and the targeted rate, a measure of explicit outcome with price stability. It is the most appropriate measure of policy credibility amidst public expectations. Author computation based on raw data in IMF's *IFS* and IMF's official estimates
	σ_{π}	3-month period moving standard deviation of the rate of inflation is a measure of monetary policy effectiveness with respect to price maintaining purchasing power. Author computation based on *IFS*
Digital currency (DC)	Total transactions in CBDC	Monthly volume of central bank digital currencies in circulation in trillions of US dollars. Source: *BIS* compilations from Coinmarketcap, Coingecko, and BraveNewCoin
	Total transactions in cryptocurrency	Measures total monthly cryptocurrency transaction volumes in trillions of US dollars. Source: *BIS* compilations from Coinmarketcap, Coingecko, and BraveNewCoin
	Total transactions in Ethereum	Measures total monthly Ethereum transaction volumes in trillions of US dollars. Source: *BIS* compilations from Coinmarketcap, Coingecko, and BraveNewCoin
Monetary growth rate *(M)*	$\frac{M_t - M_{t-1}}{M_{t-1}} \times 100$	Monthly percentage variations in money supply, a key monetary variable as in Mishkin (2019) available in IMF's *IFS*
Real interest rate *(r)*	$r=i-\pi$	Inflation-adjusted nominal deposit interest rate, as a proxy for the real monthly cost of money. Author's computation based on *IFS*
Real exchange rate *(XR)*	$XR = E\frac{P_d}{P_f}$	Real bilateral exchange rate against the US dollar, which reflects currency competitiveness, accounting for price levels (Mishkin, 1995). Available in *IFS* and World Bank's *WEO*
Velocity of Money *(V)*	$V = \frac{GDP}{M}$	Indicates how quickly digital money circulates, impacting monetary policy transmission (Fisher, 1911). Author's computation based on *IFS* and *BIS*
Real GDP per capita *(y)*	Natural logarithm of real GDP	A measure of the world's economic performance in monetary terms of production, spending, and income, (*C*+*I* + *G*+*NX*)+*Subsides–Indirect Taxes* less capital allowance. Natural logarithmic transformation by the author based on data from *IFS* and *WEO*

Table A5: Results of johansen cointegration test

Inflation-targeting outcome (π_s^T) model				
Lags interval (in first differences): 1–4				
Unrestricted cointegration rank test (trace)				
Hypothesized No. of CE (s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical value**	**Probability****
None*	0.611057	755.4332	159.5297	0.0000
At most 1*	0.509103	591.1209	125.6154	0.0001
At most 2*	0.468591	467.3162	95.75366	0.0001
At most 3*	0.392982	357.3093	69.81889	0.0001
At most 4*	0.358918	270.4491	47.85613	0.0001
At most 5*	0.346913	193.0892	29.79707	0.0001
At most 6*	0.312620	118.9572	15.49471	0.0001
At most 7*	0.265669	53.73032	3.841466	0.0000
Trace test indicates 8 cointegrating eqn (s) at the 0.05 level, * denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) p-values				
Unrestricted cointegration rank test (maximum eigenvalue)				
Hypothesized No. of CE (s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical value**	**Probability****
None*	0.611057	164.3123	52.36261	0.0000
At most 1*	0.509103	123.8048	46.23142	0.0000
At most 2*	0.468591	110.0069	40.07757	0.0000
At most 3*	0.392982	86.86021	33.87687	0.0000
At most 4*	0.358918	77.35991	27.58434	0.0000
At most 5*	0.346913	74.13194	21.13162	0.0000
At most 6*	0.312620	65.22691	14.26460	0.0000
At most 7*	0.265669	53.73032	3.841466	0.0000
Max-eigenvalue test indicates 8 cointegrating eqn (s) at the 0.05 level, * denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) p-values				
Financial stability (σ_π) model				
Lags interval (in first differences): 1–4				
Unrestricted cointegration rank test (trace)				
Hypothesized No. of CE (s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical value**	**Probability****
None*	0.609380	668.5259	159.5297	0.0000
At most 1*	0.510734	505.9026	125.6154	0.0001
At most 2*	0.391077	382.2339	95.75366	0.0001
At most 3*	0.369858	296.4148	69.81889	0.0001
At most 4*	0.349033	216.5216	47.85613	0.0001
At most 5*	0.318797	142.2533	29.79707	0.0001
At most 6*	0.268680	75.83942	15.49471	0.0000
At most 7*	0.117921	21.70700	3.841466	0.0000
Trace test indicates 8 cointegrating eqn (s) at the 0.05 level, * denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) p-values				
Unrestricted cointegration rank test (maximum eigenvalue)				
Hypothesized No. of CE (s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical value**	**Probability****
None *	0.609380	162.6233	52.36261	0.0000
At most 1*	0.510734	123.6688	46.23142	0.0000
At most 2*	0.391077	85.81903	40.07757	0.0000
At most 3*	0.369858	79.89318	33.87687	0.0000
At most 4*	0.349033	74.26834	27.58434	0.0000
At most 5*	0.349033	66.41389	21.13162	0.0000
At most 6*	0.268680	54.13241	14.26460	0.0000
At most 7*	0.117921	21.70700	3.841466	0.0000

Max-eigenvalue test indicates 8 cointegrating eqn (s) at the 0.05 level, * denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) p-values

Table A6.1: Results of long-run variance modelling

Dependent variable: Inflation targeting outcome π_s^T					Dependent variable: Financial stability (σ_π)				
Method: GARCH/TARCH - Normal distribution (BFGS/Marquardt steps) GARCH=C (10)+C (11)*RESID(−1) ²+C (12)*GARCH(−1)					Method: GARCH/TARCH - Normal distribution (BFGS/Marquardt steps) GARCH=C (10)+C (11)*RESID(−1) ²+C (12)*GARCH(−1)				
Variable	**Coefficient**	**Standard error**	**z-statistic**	**Probability**	**Variable**	**Coefficient**	**Standard error**	**z-statistic**	**Probability**
CBDC	−0.7958	0.7079	−1.1241	0.2610	CBDC	0.3255	0.2061	1.5790	0.1143
Crypto	0.1759	0.3228	0.545	0.5857	Crypto	−0.1174	0.1259	−0.9335	0.3506
Ethereum	−0.5420*	0.3081	−1.7593	0.0785	Ethereum	0.0220	0.1059	0.2144	0.8302
M	−0.0052	0.0140	−0.3718	0.7100	M	−0.0103*	0.0060	−1.7169	0.0860
r	−0.4856***	0.0539	−9.0047	0.0000	*r*	−0.0631***	0.0173	−3.6560	0.0003
V	3.8779***	1.1995	3.2329	0.0012	V	−1.1466***	0.3489	−3.2861	0.0010
XR	0.6072**	0.2665	2.2784	0.0227	XR	0.0627	0.1170	0.5358	0.5921
y	−5.3281***	1.9324	−2.7573	0.0058	*y*	1.6132**	0.7300	2.2099	0.0271
C	0.0313*	0.0172	1.8218	0.0685	C	−0.0005	0.0075	−0.0599	0.9523
Variance Equation					**Variance Equation**				
C	0.0305**	0.0153	1.9915	0.0464	C	0.0041*	0.0021	1.9310	0.0535
RESID $(-1)^2$	0.2930*	0.1518	1.9310	0.0535	RESID $(-1)^2$	−0.1258***	0.0455	−2.7603	0.0058
GARCH (−1)	0.2245	0.2703	0.8307	0.4061	GARCH (−1)	0.5995**	0.2688	2.2300	0.0257
R^2	0.4693	Adjusted R^2		0.4444	R^2	0.081839	Adjusted R2		0.03812

Table A6.2: Results of short-run variance models

Dependent Variable: Inflation targeting outcome π_s^T					Dependent variable: Financial stability (σ_π)				
Method: EGARCH - Normal distribution (BFGS/Marquardt steps) LOG (GARCH)=C (10)+C (11)*ABS (RESID[1]/@ SQRT[GARCH(−1)])+C (12)*RESID(−1)/@SQRT (GARCH [−1])+C (13)*LOG (GARCH[−1])					Method: EGARCH - Normal distribution (BFGS/Marquardt steps) LOG (GARCH)=C (10)+C (11)*ABS (RESID[−1]/@ SQRT[GARCH(−1)])+C (12)*RESID(−1)/@SQRT (GARCH[−1])+C (13)*LOG (GARCH [−1])				
Variable	**Coefficient**	**Standard Error**	**z-statistic**	**Probability**	**Variable**	**Coefficient**	**Standard error**	**z-statistic**	**Probability**
CBDC	−0.5793	0.6688	−0.8662	0.3864	CBDC	0.2295	0.2424	0.9465	0.3439
Crypto	0.0309	0.3092	0.0999	0.9204	Crypto	−0.0764	0.1167	−0.6548	0.5126
Ethereum	−0.5783**	0.2855	−2.0258	0.0428	Ethereum	−0.0102	0.0970	−0.1050	0.9164
M	−0.0051	0.0138	−0.3721	0.7098	M	−0.0092*	0.0052	−1.7611	0.0782
r	−0.5022***	0.0525	−9.5637	0.0000	*r*	−0.0382**	0.0170	−2.2443	0.0248
V	3.1884***	1.0963	2.9083	0.0036	V	−1.0032***	0.3164	−3.1710	0.0015
XR	0.5903**	0.2512	2.3500	0.0188	XR	0.1119	0.0993	1.1266	0.2599
y	−4.573**	1.9281	−2.3717	0.0177	*y*	1.0358*	0.6012	1.7228	0.0849
C	0.0561***	0.0195	2.8824	0.0039	C	0.0062	0.0075	0.8159	0.4146
Variance equation					**Variance equation**				
C (10)	−1.8792**	0.8629	−2.1778	0.0294	C (10)	−3.2563**	1.6487	−1.9750	0.0483
C (11)	0.5219**	0.2086	2.5016	0.0124	C (11)	−0.6255***	0.1937	−3.2299	0.0012
C (12)	0.2228	0.1564	1.4245	0.1543	C (12)	−0.0666	0.1430	−0.4660	0.6412
C (13)	0.4827*	0.2857	1.6891	0.0912	C (13)	0.2327	0.3441	0.6761	0.4990
R^2	0.4570	Adjusted R^2		0.4314	R^2	0.0804	Adjusted R^2		0.0366