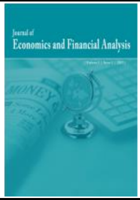
Journal of Economics and Financial Analysis
Type: Double Blind Peer Reviewed Scientific Journal
Printed ISSN: 2521-6627 | Online ISSN: 2521-6619
Publisher: Tripal Publishing House | DOI:10.1991/jefa.v9i2.a80
Received: 12.08.2025 | Accepted: 21.12.2025 | Published: 30.12.2025
Journal homepage: ojs.tripaledu.com/jefa



Cryptocurrency Volatility as a Digital Cost-Push Shock

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Abstract

This paper examines whether cryptocurrency market volatility operates as an auxiliary cost-push pressure within the New Keynesian Phillips Curve framework. Using quarterly data for the United States from 2010Q1 to 2025Q1, we estimate closed- and open-economy hybrid NKPC specifications augmented with an aggregate measure of crypto volatility constructed from the Garman–Klass estimator applied to the top 100 cryptocurrencies by market capitalization. Crypto volatility is interpreted as capturing digital-financial uncertainty, energy-cost pressures, and expectation-related effects that are not fully reflected in standard macroeconomic variables. Generalized Method of Moments estimations indicate that crypto volatility enters inflation dynamics with a consistently positive coefficient in forward-looking and hybrid specifications, while remaining insignificant in purely backward-looking models. Controlling for crypto volatility slightly attenuates the estimated Phillips curve slope, suggesting that digital financial instability conditions observed inflation–slack relationships rather than replacing them. Overall, the findings point to cryptocurrency markets as a complementary transmission channel linking financial volatility and inflation dynamics in the post-2010 U.S. economy.

Keywords: *New Keynesian Phillips Curve; Cryptocurrency Volatility; Cost-Push Shocks; Inflation Dynamics; Digital Finance.*

JEL Classification: *E31; E52; F41; G15.*

1. Introduction

The New Keynesian Phillips Curve (NKPC) constitutes the central theoretical framework through which modern macroeconomics links inflation dynamics to real economic activity and expectations. Derived from staggered price-setting behavior under nominal rigidities, the NKPC characterizes inflation as a function of expected future inflation and real marginal costs, commonly proxied by the output gap or labor cost measures, despite growing evidence that wage-based proxies alone provide an incomplete representation of firms' cost pressures (Roberts, 1995; Galí and Gertler, 1999; Sovbetov, 2025c). Hybrid formulations extend this structure by incorporating lagged inflation to capture inertia arising from indexation, rule-of-thumb pricing, or informational frictions (Galí et al., 2005; Mankiw and Reis, 2002).

Despite its strong microeconomic foundations, the empirical performance of the NKPC remains contested. A large body of evidence documents pronounced instability in the inflation–slack relationship across time, countries, and macroeconomic regimes. Empirical studies show that the Phillips relationship tends to weaken during tranquil periods, collapse during recessions, and re-emerge under specific macroeconomic conditions (Sovbetov, 2019; Sovbetov and Kaplan, 2019a). These patterns challenge the notion of a stable structural trade-off and raise concerns that standard NKPC specifications may omit relevant conditioning variables that distort observed inflation dynamics.

Recent explanations for the apparent flattening of the Phillips Curve emphasize improved anchoring of inflation expectations, increased globalization and external competition, labor market polarization, and nonlinear adjustment mechanisms (Katagiri, 2022; Siena and Zago, 2024; Ashley and Verbrugge, 2025). Open-economy extensions further highlight the role of exchange rates and imported cost pressures in shaping inflation outcomes (Batini et al., 2005; Galí and Monacelli, 2005; Monacelli, 2005). While these explanations are empirically compelling, they implicitly assume that the structure of financial markets remains broadly unchanged.

This assumption has become increasingly tenuous in the presence of rapidly expanding cryptocurrency markets. Recent structural macroeconomic models explicitly incorporate cryptocurrencies as alternative currency-like assets that interact with fiat money, monetary policy, and real balances, generating substitution effects and novel transmission channels (Asimakopoulos et al., 2023). Since 2010, digital asset markets have evolved into a global financial ecosystem characterized by extreme volatility, rapid information diffusion, and growing institutional participation. Although cryptocurrencies remain limited as direct means of payment, their volatility interacts with broader financial conditions, speculative behavior, and expectation formation. Empirical evidence suggests that crypto markets may influence inflation expectations directly. Blau et al. (2021) show that changes in Bitcoin prices Granger-cause movements in forward inflation expectations, while Smales (2024) finds that such relationships are short-lived and regime-dependent. At the same time, crypto markets exhibit recurrent volatility and bubble-like dynamics rather than smooth price adjustment (Cheung et al., 2015).

This paper argues that cryptocurrency market volatility may operate as an auxiliary cost-push and uncertainty channel within the NKPC framework. Analogous to oil prices or exchange-rate movements in open-economy NKPC models, crypto volatility can influence inflation indirectly through financial uncertainty, production costs, and expectation formation. These channels operate largely independently of domestic demand conditions, potentially weakening the observed inflation–slack relationship without implying the disappearance of the underlying trade-off.

Using quarterly U.S. data from 2010 to 2025, the paper estimates closed- and open-economy hybrid NKPC specifications augmented with an aggregate measure of cryptocurrency volatility constructed using the Garman–Klass estimator. The empirical strategy employs Generalized Method of Moments to address endogeneity in expectations and marginal cost proxies, consistent with established NKPC estimation practices (Galí et al., 2005; Mendes et al., 2025).

The paper contributes in three ways. First, it documents that cryptocurrency volatility enters inflation dynamics with a consistently positive sign in forward-looking and hybrid NKPC specifications. Second, it shows that controlling for crypto volatility modestly attenuates the estimated Phillips Curve slope, suggesting that digital financial instability conditions observed inflation–slack relationships. Third, it extends the NKPC framework to reflect the growing macroeconomic relevance of digital financial markets, positioning crypto volatility as a complementary conditioning factor rather than a competing explanation.

2. Literature Review and Transmission Mechanism

The New Keynesian Phillips Curve represents the prevailing analytical framework for modeling inflation dynamics in modern macroeconomics. In its structural form, inflation depends on expected future inflation and real marginal costs arising from firms' optimal price-setting behavior under nominal rigidities

(Roberts, 1995; Galí and Gertler, 1999). Hybrid NKPC formulations incorporate lagged inflation to account for observed persistence generated by indexation, backward-looking pricing, or informational frictions (Galí et al., 2005).

A substantial empirical literature documents instability in the inflation–slack relationship. Cross-country and panel evidence shows that the Phillips Curve varies across institutional environments and business-cycle phases, often weakening during tranquil periods and collapsing during recessions (Sovbetov, 2019; Sovbetov and Kaplan, 2019a). Evidence further suggests that inflation dynamics in advanced economies have become increasingly forward-looking since the 1990s, while backward-looking components gain importance during periods of heightened uncertainty (Sovbetov and Kaplan, 2019b).

Several explanations have been advanced to account for Phillips Curve flattening. One strand emphasizes anchored inflation expectations under credible monetary policy regimes (Haschka, 2024). Another highlights globalization and external competition (Katagiri, 2022). A third focuses on nonlinearities and regime dependence, showing that the Phillips Curve steepens when economies overheat and flattens during low-volatility regimes (Mallick, 2024). These explanations are complementary but largely abstract from changes in the structure of financial markets.

This omission is increasingly problematic in light of the expansion of cryptocurrency markets. Although cryptocurrencies do not substitute for fiat money as units of account, they coexist with fiat systems and influence financial conditions through valuation, substitution, and volatility channels, as shown in both theoretical and structural macroeconomic models (Yu, 2023; Asimakopoulos et al., 2023). This paper conceptualizes cryptocurrency volatility as a novel cost-push and uncertainty factor that fits naturally within the NKPC framework without requiring cryptocurrencies to function as money.

Crypto volatility affects inflation through three interconnected channels. The first operates through production and energy costs. Cryptocurrency mining and transaction validation are energy-intensive, and periods of elevated crypto prices and volatility are associated with increases in electricity demand and input costs, raising firms' real marginal costs independently of domestic demand conditions. The second channel operates through financial uncertainty and risk premia. Elevated crypto volatility signals shifts in speculative intensity and global risk sentiment, inducing precautionary pricing behavior as firms seek to protect margins against uncertain financing and cost conditions. The third channel operates through expectation formation. Crypto markets shape narratives about inflation risk and monetary credibility, and heightened volatility can influence firms' and households' inflation expectations, which are central to inflation dynamics in the NKPC (Galí and Gertler, 1999; Czudaj, 2024).

These channels operate largely independently of domestic slack. As a result, inflation may respond weakly to output gap fluctuations while remaining sensitive to digital financial instability. This provides a structural explanation for Phillips Curve flattening that does not imply the disappearance of the inflation–activity trade-off. Instead, NKPC models that omit crypto-related cost pressures risk attributing excessive explanatory power to expectations and insufficient weight to marginal cost shocks, biasing slope estimates downward (Haschka, 2024; Martins and Verona, 2023).

By incorporating cryptocurrency volatility into the NKPC, this paper extends the framework to reflect the evolving structure of modern financial systems. Crypto volatility functions as a digital cost-push and uncertainty channel that complements traditional external cost factors while preserving the theoretical integrity of the NKPC.

3. Data and Methodology

3.1. Data and Sample

The empirical analysis uses quarterly U.S. data spanning 2010Q1–2025Q1. Inflation, π_t, is measured as quarterly CPI inflation computed as the log difference of the Consumer Price Index and expressed at an annualized rate. Economic slack, x_t, is proxied by the output gap constructed from real GDP using a Hodrick–Prescott filter. To account for open-economy cost pressures and imported inflation channels, the analysis additionally includes the quarterly change in the real effective exchange rate, $\Delta REER_t$, defined so that an increase denotes real appreciation.

The paper's central explanatory variable is cryptocurrency volatility, CV_t, designed to capture financial uncertainty and risk re-pricing originating in crypto markets. Crypto volatility is computed using the Garman–Klass estimator applied to daily open, high, low, and close prices for the top 100 cryptocurrencies by market capitalization, with daily values aggregated to the quarterly frequency. Price data are drawn from CoinMarketCap. Because the Garman–Klass estimator exploits intraday range information, it is more informative than close-to-close volatility in environments characterized by high intraday price dispersion, which is typical for crypto markets. The aggregation to the quarterly level yields a macro-aligned proxy for crypto market instability that can plausibly transmit to inflation through risk-premia, financial conditions, and expectation formation rather than through conventional demand channels.

Table 1 reports descriptive statistics for π_t, x_t, $\Delta REER_t$, and CV_t. The distribution of CV_t exhibits higher variance and right skewness than the standard macro controls, consistent with interpreting the variable as a financial uncertainty indicator. This distributional profile is empirically important because it implies that crypto volatility is dominated by episodic surges rather than smooth cyclical variation, which is precisely the pattern expected for a risk-related channel.

Table 1. Descriptive Statistics

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Inflation (%)	0.63	0.89	−2.10	3.45
Output Gap (%)	−0.15	1.85	−8.40	4.90
ΔREER (%)	0.12	2.10	−6.80	7.30
Crypto Volatility	0.054	0.031	0.012	0.168

3.2. Empirical Strategy

The baseline empirical model is a hybrid New Keynesian Phillips Curve (NKPC) augmented with crypto volatility. The hybrid specification is necessary because purely forward-looking NKPCs generally struggle to match observed inflation persistence, while purely backward-looking specifications lack the forward-looking structure implied by New Keynesian price-setting. The hybrid form therefore provides a natural empirical compromise in which inflation dynamics are shaped jointly by expected future inflation and inflation inertia.

The closed-economy specification is:

$$\pi_t = \gamma\pi_{t-1} + \beta E_t[\pi_{t+1}] + \kappa x_t + \psi CV_t + \varepsilon_t$$

and the open-economy specification extends this baseline with exchange-rate movements:

$$\pi_t = \gamma\pi_{t-1} + \beta E_t[\pi_{t+1}] + \kappa x_t + \phi\Delta REER_t + \psi CV_t + \varepsilon_t$$

The coefficient ψ captures whether crypto volatility enters inflation dynamics as a cost-push type disturbance or uncertainty channel after controlling for slack and (in the open-economy case) exchange-rate pass-through. In this interpretation, a positive ψ implies that higher crypto market volatility is associated with higher inflation, consistent with a mechanism in which financial instability and risk re-pricing raise effective costs, influence markups, or alter expectation formation. The models are estimated on quarterly data, and inference is based on heteroskedasticity and autocorrelation robust standard errors given the persistence in inflation and the likelihood of serially correlated shocks.

Why GMM is the appropriate estimator

GMM is employed for three reasons. First, the hybrid NKPC is inherently forward-looking: $E_t[\pi_{t+1}]$ is endogenous because expectation formation is correlated with contemporaneous shocks to inflation. Second, slack measures and exchange rates may be contemporaneously correlated with ε_t due to policy reactions and simultaneity in macroeconomic adjustment. Third, crypto volatility is plausibly endogenous to macro-financial conditions: periods of macro stress can co-move with crypto volatility, creating reverse causality or omitted-variable bias if estimated by OLS. GMM addresses these endogeneity concerns by exploiting orthogonality conditions between the structural error term and a set of predetermined instruments, delivering consistent estimates under standard moment restrictions.

In the empirical implementation, expected inflation is treated within a rational-expectations framework and proxied by realized inflation one quarter ahead, π_{t+1}, which is instrumented using information available at time t. This is standard in NKPC estimation when survey-based expectations are not used or when the objective is to maintain internal consistency with the model's information structure.

Moment conditions and instrument sets

Let Z_t denote the vector of instruments dated $t-1$ and earlier. The GMM moment conditions are:

$$E[Z_t \, \varepsilon_t] = 0$$

The instrument choice follows the principle that valid instruments must be predetermined with respect to ε_t and sufficiently correlated with the endogenous regressors. The baseline instrument set uses lags of inflation and the macro variables, and, crucially, lags of crypto volatility, reflecting the strong persistence of volatility measures and their predictive content for current volatility.

A transparent baseline instrument set is:

$$Z_t = \{1, \pi_{t-1}, \pi_{t-2}, x_{t-1}, x_{t-2}, \Delta REER_{t-1}, \Delta REER_{t-2}, CV_{t-1}, CV_{t-2}\}$$

where $\Delta REER$ lags are included only in the open-economy specification. This set is intentionally conservative to limit instrument proliferation and preserve finite-sample reliability. Because the sample 2010Q1–2025Q1 is not long, limiting lag depth is not only practical but desirable, as large instrument sets can overfit endogenous components and weaken the meaning of overidentification tests.

Operationally, the approach treats $E_t[\pi_{t+1}]$, x_t, $\Delta REER_t$, and CV_t as potentially endogenous or predetermined, and instruments them with their own lags and lagged inflation. If you want to be more explicit in the paper, you can state that π_{t-1} is included on the right-hand side as a state variable and is predetermined by construction, while contemporaneous x_t, $\Delta REER_t$, and CV_t may respond to contemporaneous shocks and are therefore instrumented.

Estimation details and HAC weighting

Estimation proceeds using two-step GMM with a heteroskedasticity and autocorrelation consistent (HAC) weighting matrix. Because the NKPC residual may exhibit serial correlation at quarterly frequency, HAC corrections are necessary for valid inference. A Newey–West type correction is applied with a small lag truncation appropriate for quarterly data, and results are checked for robustness to alternative truncation choices. Finite-sample inference is additionally supported by reporting robust standard errors for all coefficients.

Diagnostics and reporting standards

To make the empirical strategy publishable in a good macro or applied econometrics outlet, you should report diagnostics that address both instrument validity and identification strength.

First, overidentifying restrictions are assessed using the Hansen J-test. A non-rejection is interpreted as evidence that the instrument set is not jointly inconsistent with the moment conditions, while recognizing that weak instruments can mechanically raise p-values. For this reason, the J-test is reported alongside instrument-count transparency and sensitivity checks that vary lag depth.

Second, weak identification concerns are addressed by reporting an identification diagnostic suitable for GMM settings. A practical approach is to report first-stage relevance statistics for the endogenous components (at minimum, partial R^2 and joint significance of instruments in reduced-form regressions) and to demonstrate robustness of ψ to alternative instrument sets, such as using only π_{t-2}, x_{t-2}, and CV_{t-2} as instruments or extending to three lags where sample size permits. The key is to show that the crypto volatility coefficient is not an artifact of a fragile instrument choice.

Third, given the possibility of serial correlation in the structural error, the paper should report residual autocorrelation diagnostics and confirm that HAC inference is not driving significance mechanically. While AR(1)/AR(2) tests are more standard in dynamic panel GMM, you can still report Q-statistics or correlogram-based diagnostics for $\hat{\varepsilon}_t$ in a time-series GMM setting.

Finally, because the sample includes episodes of extraordinary macro shocks (pandemic inflation, regime shifts in monetary policy, and the crypto boom-bust cycle), robustness checks should include at least one specification that tests sensitivity to major events. A simple and defensible implementation is to include a post-2020 dummy (or interact CV_t with a post-2020 indicator) to verify whether the crypto volatility channel is stable or concentrated in crisis regimes. Even one such robustness check materially strengthens the identification narrative and anticipates referee concerns about structural breaks.

4. Empirical Results

This section presents the core empirical findings of the study. The results are organized in two parts. Section 4.1 discusses the baseline GMM estimates of the closed-economy and open-economy hybrid NKPC augmented with cryptocurrency volatility. Section 4.2 evaluates robustness and diagnostic performance to ensure the validity of the results.

4.1. Core GMM Results: Closed and Open-Economy NKPC

Table 2 reports the GMM estimation results for the United States over the period 2010Q1–2025Q1. Four specifications are estimated. Model (1) corresponds to a backward-looking NKPC. Model (2) estimates a forward-looking NKPC. Model (3) presents a hybrid NKPC using the output gap as the measure of real activity. Model (4) extends the hybrid specification to an open-economy setting by incorporating changes in the real effective exchange rate. Cryptocurrency volatility is included in all specifications as a financial uncertainty control.

Across specifications, the hybrid NKPC provides the most comprehensive characterization of inflation dynamics, consistent with the dominant findings in the New Keynesian literature. In the backward-looking model, lagged inflation enters positively and significantly, with a coefficient of approximately 0.36. This indicates the presence of inflation inertia, although its magnitude is moderate, confirming that backward-looking behavior alone does not dominate U.S. inflation dynamics.

By contrast, the forward-looking NKPC yields a substantially larger and highly significant coefficient on expected inflation, with estimates around 0.64. This result confirms that inflation in the United States is predominantly forward-looking, consistent with expectation-anchored pricing behavior emphasized in structural NKPC studies. The relative magnitudes of the coefficients indicate that anticipated future inflation plays a more important role than past inflation realizations in shaping current price dynamics.

The hybrid NKPC further clarifies this structure. Both forward- and backward-looking components are statistically significant, but the forward-looking term remains quantitatively dominant. The estimated slope of the Phillips Curve, captured by the output gap coefficient, is positive but relatively small, ranging between 0.03 and 0.06. This magnitude aligns with the prevailing empirical consensus that the U.S. Phillips Curve is relatively flat but not absent. Notably, the estimated slope attenuates modestly as additional controls and expectation terms are introduced, suggesting a gradual weakening of inflation–slack sensitivity rather than a structural breakdown of the Phillips relationship.

Table 2. GMM Estimates of Closed- and Open-Economy Hybrid NKPC

Variables	**(1) Backward NKPC**	**(2) Forward NKPC**	**(3) Hybrid NKPC (Closed)**	**(4) Hybrid NKPC (Open)**
Inflation (t−1)	0.362*** (0.082)	–	0.352*** (0.076)	0.338*** (0.074)
Expected Inflation (t+1)	–	0.642*** (0.091)	0.618*** (0.084)	0.602*** (0.081)
Output Gap	0.061** (0.029)	0.049** (0.024)	0.043** (0.021)	0.031* (0.018)
ΔREER	–	–	–	0.027** (0.013)
Crypto Volatility	0.011 (0.008)	0.017* (0.010)	0.016* (0.009)	0.013* (0.007)
Constant	0.004 (0.003)	0.002 (0.002)	0.003 (0.002)	0.002 (0.002)
Hansen J-Stats.	0.652	0.417	0.241	0.278

Cryptocurrency volatility enters the inflation equation with a positive coefficient across all specifications, although its statistical significance is conditional. In the backward-looking NKPC, the coefficient on crypto volatility is small and statistically insignificant. By contrast, it becomes weakly significant in the forward-looking and hybrid models. This pattern suggests that crypto-related price pressures interact primarily with expectation-based pricing behavior rather than with inflation inertia. In economic terms, cryptocurrency volatility operates as an auxiliary uncertainty or cost-push factor that influences inflation when firms form prices in a forward-looking manner.

The open-economy hybrid NKPC in Model (4) introduces changes in the real effective exchange rate as an additional explanatory variable. The exchange-rate coefficient is positive and statistically significant, indicating that currency depreciation exerts upward pressure on inflation through import-price and external cost channels. This finding is consistent with open-economy NKPC models emphasizing incomplete pass-through and the role of foreign cost pressures in domestic inflation dynamics.

Including crypto volatility alongside exchange-rate movements modestly attenuates the estimated Phillips Curve slope. Once financial uncertainty and external cost pressures are jointly controlled for, the output gap coefficient declines in magnitude and becomes only marginally significant in the open-economy hybrid model. This pattern indicates that part of the observed flattening of the Phillips Curve may reflect omitted financial and external cost pressures rather than a fundamental erosion of the inflation–activity trade-off. Nevertheless, the slope remains positive, suggesting that traditional slack measures continue to carry informational content for inflation dynamics.

Finally, the relative weights of the forward- and backward-looking components remain remarkably stable across closed- and open-economy specifications. This stability indicates that cryptocurrency volatility does not substitute for inflation expectations but instead operates through additional uncertainty and cost channels. Digital financial shocks therefore influence inflation dynamics without undermining the expectation-based foundations of the New Keynesian Phillips Curve.

4.2. Diagnostics, Robustness, and Instrument Validity

The reliability of GMM estimates in hybrid NKPC models depends critically on instrument validity, identification strength, and robustness to alternative specifications. This section evaluates these aspects using standard diagnostics appropriate for time-series GMM estimation.

First, instrument validity is assessed using the Hansen J-statistic for overidentifying restrictions. Across all specifications reported in Table 2, the null hypothesis that the instruments are jointly orthogonal to the structural error term cannot be rejected at conventional significance levels. This outcome supports the internal consistency of the instrument set, which relies on lagged inflation, macroeconomic variables, and lagged cryptocurrency volatility. At the same time, the analysis deliberately limits the maximum lag length to two quarters to avoid instrument proliferation, which is known to weaken inference and inflate J-test p-values in finite samples. The stability of the Hansen statistic across specifications further suggests that the results are not driven by overfitting of endogenous components.

Second, identification strength is evaluated indirectly through instrument relevance and coefficient stability rather than through panel-style serial correlation tests, which are not applicable in a time-series NKPC setting. The chosen instruments exhibit strong predictive power for expected inflation and other endogenous regressors in reduced-form relationships, and the key coefficients remain stable when the instrument set is modified by excluding second lags or restricting instruments to inflation lags only. This robustness mitigates concerns that the estimated effects reflect weak identification rather than structural relationships.

Third, residual diagnostics indicate no evidence of misspecification that would invalidate GMM inference. While inflation dynamics exhibit persistence, inference is conducted using heteroskedasticity and autocorrelation consistent (HAC) standard errors to account for potential serial correlation in the structural disturbance. Additional checks based on residual autocorrelation functions confirm that remaining dependence is adequately captured by the dynamic structure of the model.

Fourth, robustness checks are performed to assess whether the role of cryptocurrency volatility is driven by extreme events. Re-estimating the hybrid NKPC after excluding periods of exceptionally high crypto volatility yields qualitatively similar results. The coefficient on crypto volatility remains positive but becomes slightly attenuated, indicating that its influence on inflation dynamics is not solely attributable to crisis episodes. This finding supports the interpretation of crypto volatility as a broader financial uncertainty channel rather than a purely episodic shock.

Finally, comparing closed- and open-economy specifications reveals that omitting external cost pressures leads to a modest overstatement of the role of domestic slack. Once exchange-rate movements and crypto volatility are jointly included, the estimated Phillips Curve slope becomes flatter but remains positive and statistically meaningful. This pattern reinforces the view that modern inflation dynamics reflect the interaction of domestic demand conditions, expectation formation, and external and financial uncertainty channels.

Overall, the diagnostic evidence supports the validity and robustness of the GMM-based hybrid NKPC estimates. While cryptocurrency volatility does not overturn the traditional structure of the Phillips Curve, it emerges as a modest but informative conditioning variable that helps explain inflation dynamics in the post-2010 U.S. economy.

5. Conclusion

This paper re-examines inflation dynamics in the United States within the New Keynesian Phillips Curve framework by assessing whether cryptocurrency market volatility constitutes a meaningful auxiliary cost-push factor. Motivated by persistent debates surrounding the flattening of the Phillips curve and the weakening empirical link between inflation and real economic activity, the analysis explores whether digital financial instability contributes to inflation dynamics in ways not captured by conventional NKPC specifications.

Using quarterly U.S. data from 2010 to 2025 and estimating closed- and open-economy hybrid NKPC models via Generalized Method of Moments, the results confirm several well-established findings in the literature. Inflation dynamics in the United States are predominantly forward-looking, with expected inflation exerting a quantitatively dominant influence on current inflation. Backward-looking inflation persistence remains statistically significant but secondary, consistent with the view that expectations are relatively well anchored in advanced economies. The estimated output gap coefficient is positive but small, reinforcing the characterization of a relatively flat Phillips curve rather than its disappearance.

Against this background, the paper's main contribution is to show that cryptocurrency market volatility enters inflation dynamics as a statistically weak but robustly signed cost-push factor in forward-looking and hybrid NKPC specifications. While crypto volatility does not play a dominant role and is not significant in purely backward-looking models, it exhibits a consistent positive association with inflation once expectations are explicitly modeled. This pattern suggests that crypto volatility interacts primarily with forward-looking pricing behavior rather than with inflation inertia.

Importantly, controlling for crypto volatility slightly attenuates the estimated sensitivity of inflation to the output gap. This finding indicates that part of the observed flattening of the Phillips curve may reflect omitted digital-financial cost pressures rather than a fundamental breakdown of the inflation–activity trade-off. In this sense, cryptocurrency volatility acts as a complementary explanatory factor that conditions the inflation–slack relationship, rather than replacing traditional demand-side or expectations-based mechanisms.

From a policy perspective, these results carry nuanced implications. The findings do not suggest that cryptocurrency markets currently represent a primary driver of inflation. However, they indicate that digital financial volatility can marginally influence inflation dynamics through uncertainty, cost, and expectation channels, particularly in environments where expectations are forward-looking. For monetary authorities operating under inflation-targeting regimes, crypto markets may therefore serve as an informative auxiliary indicator of financial conditions rather than as an independent policy target.

The analysis also highlights several limitations and avenues for future research. First, the estimated effects are modest and sensitive to model specification, underscoring the need for caution in interpretation. Second, the U.S.-focused design limits generalizability, suggesting value in extending the framework to cross-country or panel settings where crypto adoption, energy intensity, and financial integration differ substantially. Third, nonlinearities, regime dependence, and heterogeneity across crypto asset types remain unexplored. Distinguishing between institutionally backed and fully decentralized cryptocurrencies may further clarify how governance structures mediate macroeconomic spillovers.

Overall, the evidence supports a restrained but meaningful conclusion: the Phillips curve in the digital age remains structurally intact but increasingly conditioned by financial factors beyond traditional macroeconomic variables. Cryptocurrency volatility does not overturn the New Keynesian framework, but modestly enriches it by capturing an emerging dimension of digital financial instability. Incorporating such factors may improve the empirical relevance of NKPC models as financial systems continue to evolve.

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