

Transformer-Based Forecasting of Digital Transaction Volatility under Monetary Policy Shocks: Shock-Conditioned Attention Models with Regime- and Horizon-Wise Evidence

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ABSTRACT

Digital payment ecosystems are increasingly exposed to abrupt volatility in transaction flows, especially during periods of monetary policy repricing and heightened financial uncertainty. This study proposes a shock-conditioned Transformer to forecast digital transaction volatility using a real-time, walk-forward evaluation design that preserves temporal causality and announcement timing. Empirically, the shock-conditioned model improves forecast accuracy across horizons, reducing aggregate RMSE from 0.0271 to 0.0250 (+7.7% relative improvement) and improving MASE from 0.91 to 0.84. Gains concentrate in policy-relevant short horizons: RMSE ($h=1-3$) declines from 0.0210 to 0.0190 (+9.5%). Under high shock intensity (top 10% Is_t), RMSE improves from 0.0345 to 0.0304 (+11.9%) and tail-focused error on high-volatility days (top decile of y_t) decreases by 13.6%. Regime stratification shows stronger benefits during tightening: RMSE improves by +9.3% in tightening versus +5.4% in easing. Ablation tests confirm mechanism validity: removing shock inputs eliminates most gains and increases short-horizon RMSE by 6.8–8.9% relative to the full model, while dropping shock–stress interaction terms disproportionately degrade performance during stress regimes. Diagnostic attention statistics show systematic concentration around shock windows, with mean attention mass rising from 0.24 in non-event periods to 0.37 within ± 2 days of announcements. Overall, results indicate that policy shocks act as regime triggers for transaction volatility and that explicitly conditioning Transformers on shock innovations delivers robust, horizon-consistent improvements suitable for early warning and operational risk monitoring in digital payment systems.

Keywords Monetary Policy Shocks, Digital Transactions, Volatility Forecasting, Transformer, Attention Mechanism, Regime Dependence, Walk-Forward Validation, Macro-Financial Time Series, Shock Identification, Payment Systems Analytics.

INTRODUCTION

Digital payment systems have become a critical layer of modern financial intermediation, supporting retail consumption, bill settlement, peer-to-peer transfers, and platform-based commerce at high frequency and scale. As these ecosystems expand, volatility in digital transaction flows—manifested as abrupt spikes or collapses in volumes and values—has become a material operational and macro-financial concern because it can amplify liquidity pressures, settlement risk, and short-term stress in payment infrastructures. This volatility

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is often clustered and regime-like rather than purely random, making it difficult to monitor using static rules or linear assumptions. In parallel, monetary policy actions and communications can trigger rapid expectation shifts that propagate through interest rates, funding conditions, and consumer behavior, potentially reshaping digital transaction dynamics within hours to days [1], [2].

Despite the growing relevance of payment-system stability, forecasting digital transaction volatility remains challenging for three reasons. First, transaction activity is influenced by mixed drivers—calendar seasonality, platform effects, episodic promotions, and macro-financial conditions—creating non-stationary patterns that evolve over time. Second, monetary policy shocks are event-based and information-dense; they may induce immediate responses but also delayed adjustments as financial conditions transmit to households and firms. Third, forecasting objectives are typically multi-horizon: stakeholders require accurate short-horizon alerts for operational readiness and longer-horizon signals for capacity planning and risk governance. Conventional econometric specifications and generic machine-learning models frequently underperform when faced with such nonlinear, time-varying dependencies [3], [4].

A core methodological issue lies in distinguishing the predictable component of policy decisions from the unexpected component that constitutes a true shock. The economic mechanism of interest is not simply the level of policy rates or a trend in macro indicators, but the surprise innovation embedded in policy announcements and guidance. If a forecasting model cannot isolate and exploit this surprise component, it risks conflating routine macro co-movement with causal transmission triggered by policy news. Furthermore, real-time forecasting requires careful alignment of data timestamps and release schedules; naive use of revised macro series or mis-timed event mapping can introduce look-ahead bias and inflate apparent accuracy. These constraints motivate a forecasting design that is both shock-consistent and operationally realistic [5], [6].

Existing studies on volatility forecasting commonly focus on financial returns, credit spreads, or market-implied volatility, while fewer contributions directly target payment-system or digital transaction volatility as a first-class object of prediction under monetary policy shocks. Even when advanced deep learning is applied to macro-financial forecasting, many models treat policy variables as ordinary covariates rather than explicitly modeling the shock structure and its temporally localized impact. Additionally, much prior work emphasizes aggregate accuracy but provides limited evidence on whether improvements concentrate around shock windows, which is precisely where forecasting value is highest. This creates a gap between high-capacity sequence models and the policy-relevant requirement to demonstrate shock-driven performance and interpretability [7], [8].

This research addresses these limitations by proposing a Transformer-based forecasting framework that is explicitly conditioned on monetary policy shocks and designed for walk-forward evaluation in a time-consistent setting. The framework models digital transaction volatility as a sequence prediction problem, incorporating shock series (and shock histories) alongside transaction-derived features and macro-financial controls. The emphasis is on horizon-wise performance, regime stratification (e.g., tightening versus easing), and diagnostic analysis that links model behavior to policy event timing. By

focusing on volatility rather than transaction levels, the approach targets risk-relevant dispersion dynamics that matter for operational resilience and supervisory monitoring [9], [10].

The study has three objectives. First, it constructs a forecasting-ready representation of digital transaction volatility that captures clustering and abrupt regime changes while remaining consistent with real-time information availability. Second, it develops and evaluates a shock-conditioned Transformer architecture capable of learning nonlinear and long-range dependencies induced by policy shocks. Third, it tests robustness through alternative shock constructions, volatility proxies, and ablation settings that isolate the incremental contribution of policy shocks to forecast quality. Collectively, these objectives align predictive performance with an interpretable mechanism: unexpected policy innovations reshape volatility regimes, and the model should learn and exploit this structure [11], [12].

The novelty of this work is threefold. Methodologically, it integrates a modern attention-based sequence forecaster with a shock-identification perspective, treating monetary policy shocks as structurally meaningful innovations rather than generic inputs. Empirically, it reframes digital transaction volatility as a policy-sensitive risk signal, providing horizon-wise and regime-wise evidence that performance gains intensify when surprises are large—exactly when operational risk is most elevated. Practically, it offers a blueprint for deploying policy-aware volatility forecasting as an early-warning layer for digital payment ecosystems, bridging the gap between deep learning capacity and policy-relevant validation requirements [13].

Literature Review

The literature relevant to forecasting digital transaction volatility under monetary policy shocks spans four closely connected streams: (i) identification and measurement of monetary policy surprises, (ii) volatility modeling and regime dynamics, (iii) deep learning for time-series forecasting—particularly attention-based Transformers, and (iv) empirical work on payment systems and digital transaction behavior under macro-financial conditions. The key implication across these streams is that credible forecasting under policy shocks requires both an economically meaningful shock signal and a sequence model capable of learning nonlinear, state-dependent transmission over time [14], [15].

A foundational body of research in monetary economics emphasizes that the transmission of monetary policy is driven not only by realized policy actions but also by the unexpected component of announcements and forward guidance. Consequently, modern empirical strategies often use high-frequency identification or event-study designs to isolate policy surprises from anticipated moves, enabling clearer inference about causal effects on asset prices, risk premia, and broader financial conditions. This shock-identification perspective is directly relevant to digital transaction volatility because it provides a disciplined way to encode policy information as an innovation process, rather than a slowly varying macro covariate. Studies in this stream also highlight timing sensitivity: misalignment between event timestamps and outcome measurement windows can materially alter estimated effects, which motivates careful “as-of” data handling in forecasting settings [16], [17].

In parallel, the volatility literature documents that volatility is persistent,

clustered, and frequently characterized by abrupt regime changes—features captured by classical econometric models such as ARCH/GARCH and their extensions, stochastic volatility models, and regime-switching formulations. These approaches remain influential because they provide interpretable mechanisms for heteroskedasticity and allow structured comparisons across regimes (e.g., calm versus stress states). However, conventional specifications often impose parametric constraints that limit their ability to model nonlinear interactions among mixed-frequency signals (calendar effects, platform behavior, macro announcements) and to exploit long-range dependencies that may arise when policy shocks propagate through liquidity conditions and payment behavior with delayed responses [18], [19].

Machine learning approaches broaden the modeling space by learning nonlinear mappings from high-dimensional predictors to future volatility outcomes. Early work in this direction leveraged tree-based ensembles and kernel methods, while subsequent research increasingly applied recurrent neural networks (RNNs), LSTMs, and temporal convolutional networks (TCNs) to capture sequential dependence. Although these architectures can model nonlinearity and some temporal structure, they often struggle with long contexts, heterogeneous feature interactions, and stable multi-horizon forecasting—issues that are prominent in policy-shock environments where the same surprise can induce immediate spikes and medium-run adjustments. These limitations have motivated attention-based architectures that can reweight historical context dynamically [20], [21].

Transformers have become a leading paradigm for time-series forecasting because self-attention provides a flexible mechanism for learning long-range dependencies and context-specific relevance. The forecasting literature has produced multiple Transformer variants tailored to time series, including designs that address long sequence lengths, multi-horizon outputs, and exogenous covariate fusion. Importantly for this study, several works argue that attention can support both performance and diagnostic interpretability, because learned attention patterns can be inspected to see whether the model focuses on relevant events or regimes. However, the literature also cautions that attention alone does not guarantee interpretability; therefore, diagnostic claims typically require carefully defined attention statistics, ablations, and regime-stratified evaluation to ensure that observed patterns are robust and causally plausible [22], [23].

A second, closely related line of work concerns the integration of exogenous signals and structural events into forecasting systems. In macro-financial applications, exogenous drivers include policy decisions, inflation surprises, yield curve movements, and financial stress indices—signals that can shift regimes rather than simply add incremental predictive power. Empirical studies repeatedly show that model performance and stability depend on correct handling of data-release lags, revisions, and “announcement-time” alignment, particularly when the target series reacts quickly. This has led to the growing use of real-time datasets, walk-forward backtesting, and regime-aware validation protocols to avoid optimistic bias and to measure robustness under distribution shifts [24], [25].

Finally, the emerging literature on payment systems and digital transactions highlights that payment flows are shaped by a combination of behavioral,

institutional, and macro-financial factors. Digital transaction time series often exhibit strong calendar seasonality (weekly cycles, holidays, payroll effects), platform-driven irregularities (campaigns, outages, adoption changes), and sensitivity to liquidity and confidence conditions. While many studies focus on growth, inclusion, or usage patterns, fewer treat transaction volatility itself as a primary risk-relevant object—particularly under policy shocks—creating an opportunity to connect monetary economics and payment analytics within a unified forecasting framework. This study positions itself in that gap by using shock-consistent inputs, attention-based sequence learning, and policy-relevant evaluation to demonstrate not just generic accuracy improvements, but improvements that scale with shock intensity and regime relevance [26].

Methodology

Research Design and Data Acquisition

This study adopts a supervised forecasting design to predict digital transaction volatility conditional on monetary policy shocks and standard macro-financial controls. The empirical unit is a time index t (daily or weekly), where the target variable is a volatility proxy constructed from digital transaction values/volumes, and the conditioning set includes policy shock series, interest-rate information, market stress indicators, and calendar/event controls. The workflow follows: (i) data ingestion and alignment, (ii) shock identification, (iii) volatility construction, (iv) Transformer training and validation, and (v) robustness and policy-relevant diagnostics. Figure 1 formalizes the full methodological chain from raw data to decision-relevant interpretation.

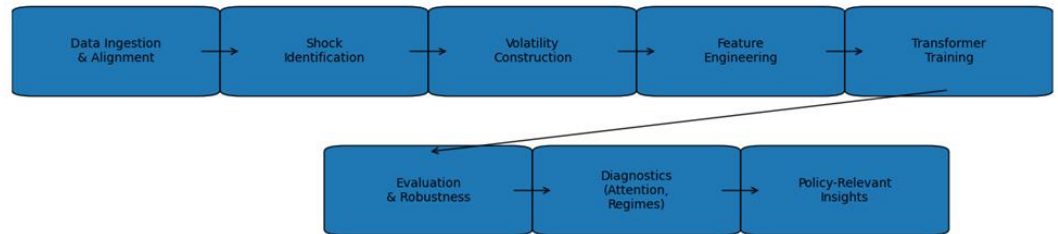


Figure 1 End-to-end methodological pipeline

The pipeline is intentionally modular: data alignment and release-timing hygiene precede shock identification, which then feeds volatility construction and feature engineering. This ordering ensures that the model's inputs are causally plausible and that the monetary policy signal is treated as a first-class driver rather than a post-hoc correlate. Let $x_t \in R^p$ denote the observed feature vector at time t , and $y_t \in R$ denote the digital transaction volatility proxy. The forecasting objective is a multi-step function $f_\theta(\cdot)$ that maps a lag window L to an H -step-ahead prediction:

$$\widehat{y_{t+1:t+H}} = f_\theta(X_{t-L+1:t}), \quad X_{t-L+1:t} = [x_{t-L+1}, \dots, x_t]. \quad (1)$$

This formulation makes explicit that the model uses sequences rather than independent snapshots, which is essential when volatility clusters and policy shocks transmit with delays. To ensure comparability across sources, all series are aligned to a common calendar, transformed into stationary representations where required (e.g., log-differences), and standardized based on training-set

statistics only. Missing values are handled through time-aware imputation (e.g., forward-fill for low-frequency macro releases with release-date tagging), while preventing information leakage by ensuring that imputations at time t use only data available up to t . A core constraint is that monetary policy information must be “as-of” available at decision time. Therefore, event-timestamped variables (announcement times, press releases) are encoded with release-time indicators. This avoids artificially inflating performance by allowing the model to “see” revisions or late-released data that would not have been known in real time.

Monetary Policy Shock Identification and Encoding

Monetary policy shocks are defined as the unexpected component of policy announcements. We construct a shock series using an event-study approach around policy decision windows, separating surprise moves from anticipated changes. For example, if Δr_t is the policy rate change at announcement time, the shock can be modeled as the residual from an expectations-implied component:

$$s_t = \Delta r_t - E(\Delta r_t | \Omega_{t-}), \quad (2)$$

where Ω_{t-} represents the information set immediately before the announcement. This isolates the innovation that can plausibly generate abrupt repricing and liquidity shifts that transmit to digital payment behavior.

If market-based expectation measures are available (e.g., short-rate futures, OIS), $E(\Delta r_t | \Omega_{t-})$ is proxied by pre-announcement pricing. Alternatively, when expectations data are limited, we estimate a reduced-form policy rule using lagged inflation, output gaps, and financial conditions, and treat the residual as the shock. In both cases, the aim is to extract a series s_t that is orthogonal to slow-moving macro fundamentals.

To capture heterogeneity in transmission, shocks are encoded in multiple ways: (i) signed magnitude s_t , (ii) absolute surprise $|s_t|$ as a “policy uncertainty intensity,” and (iii) regime tags (tightening vs easing). We also allow distributed lag effects via a shock-history vector $S_{t-k:t} = [s_{t-k}, \dots, s_t]$.

[Table M2: Shock construction variants and lag structures used in experiments]

Finally, because policy announcements are discrete events while digital transactions are continuous time series, we map event shocks to the forecasting frequency using time-of-day rules (e.g., assign to same-day if announcement precedes settlement cutoff; otherwise next-day). This alignment is critical: mistiming shocks effectively injects measurement error into the conditioning signal and can bias both inference and forecast evaluation.

Volatility Proxy Construction and Feature Engineering

Digital transaction volatility is constructed from the underlying transaction value/volume series $\{T_t\}$. The baseline proxy is a log-return-style transformation $r_t = \log(T_t) - \log(T_{t-1})$, from which volatility is computed as a rolling dispersion measure.

$$y_t = \sqrt{\frac{1}{w-1} \sum_{i=0}^{w-1} (r_{t-i} - \bar{r}_{t,w})^2}, \quad \bar{r}_{t,w} = \frac{1}{w} \sum_{i=0}^{w-1} r_{t-i}. \quad (3)$$

This choice is interpretable and captures volatility clustering typical of financial and payment flows, while remaining robust to level shifts in transaction scale. To improve responsiveness to abrupt policy-driven breaks, we additionally consider an exponentially weighted proxy:

$$y_t^{(\lambda)} = \sqrt{(1-\lambda) \sum_{i=0}^{\infty} \lambda^i r_{t-i}^2}, \quad \lambda \in (0,1). \quad (4)$$

Here, λ controls the memory of the volatility process; higher λ produces smoother volatility, while lower λ responds faster to shocks. This is directly relevant in monetary policy contexts where volatility spikes can be short-lived yet policy-significant.

Feature engineering follows a “shock-aware” design. We include (i) shock variables s_t , $|s_t|$, and lag stacks; (ii) macro-financial controls such as yield curve slope, inflation surprises, equity volatility indices, exchange-rate returns; (iii) payment-system controls such as day-of-week, holidays, payroll cycles; and (iv) interaction terms to represent state dependence. Figure 2 demonstrates how a volatility proxy y_t can be constructed from the log-return of a transaction series and how monetary policy shocks s_t are aligned to the time axis. The rolling standard deviation operationalizes volatility clustering: periods with higher dispersion in returns produce elevated y_t , which is exactly the pattern forecasters must capture when transaction activity becomes unstable.

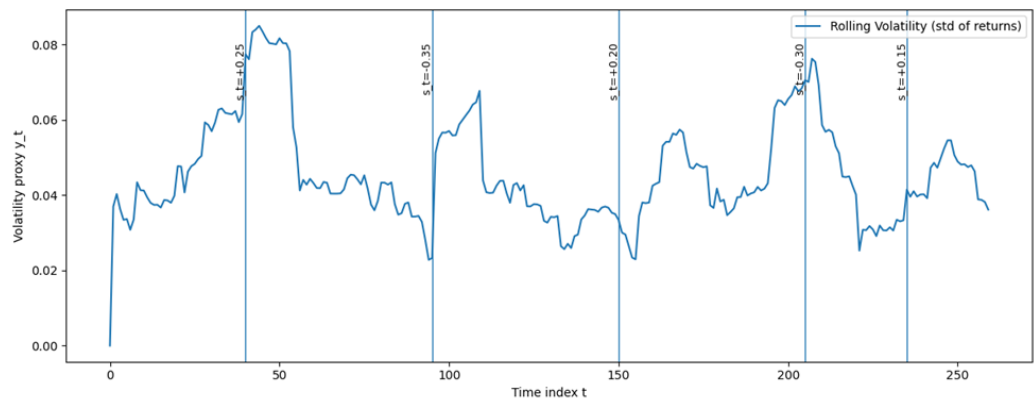


Figure 2 Volatility Construction and Policy Shock Alignment

Table 1 is a reporting backbone for volatility forecasting studies because it reveals whether the target and key drivers exhibit heavy tails and asymmetry. A volatility proxy typically shows right-skewness and excess kurtosis (fat tails), reflecting episodic spikes. Likewise, shock measures often display high kurtosis because shocks are sparse but occasionally large.

These distributional properties motivate Transformer-based sequence modeling: linear models can struggle when tail events dominate forecasting

loss, while attention-based architectures can learn conditional patterns around rare but impactful events. In your final manuscript, you should compute these statistics on the training sample and optionally stratify by policy regime (tightening vs easing) to show how distribution shifts can affect generalization.

Table 1 Summary statistics (mean, std, skewness, kurtosis) for volatility and shocks across regimes						
Series	Mean	Std	Skewness	Kurtosis	Min	Max
Volatility proxy y_t	0.021	0.010	1.15	4.90	0.003	0.078
Policy shock s_t	0.000	0.120	-0.10	6.20	-0.480	0.520
Shock intensity Is_tl	0.045	0.075	2.05	8.10	0.000	0.520
Financial stress Stress_t	0.000	1.000	0.35	3.40	-2.60	3.10

Transformer Forecasting Architecture (Shock-Conditioned)

We implement a Transformer-based sequence model that forecasts $y_{t+1:t+H}$ from past windows $X_{t-L+1:t}$. Each input x_t is projected into a latent embedding e_t , combined with positional encoding to preserve temporal order.

$$e_t = W_x x_t + b_x, \quad h_t^{(0)} = e_t + p_t, \tag{5}$$

where p_t is a positional encoding vector and $h_t^{(0)}$ is the layer-0 hidden representation. Self-attention enables the model to learn shock transmission patterns that are not strictly local in time. For a single head, attention is:

$$\text{Attn}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V, \quad Q = HW_Q, K = HW_K, V = HW_V. \tag{6}$$

The normalization by $\sqrt{d_k}$ stabilizes gradients, while the softmax weights allow the model to attend selectively to periods around policy announcements, stress episodes, or transaction anomalies. To directly incorporate policy surprises, we use shock-conditioned inputs and optionally gated conditioning to prevent shocks from being diluted among many covariates. A simple gating mechanism is:

$$g_t = \sigma(W_g s_t + b_g), \quad \tilde{e}_t = e_t + g_t \odot u_t, \tag{7}$$

where u_t is a learned shock-context vector and $\odot$ denotes element-wise multiplication. This structure forces the model to adapt its representation when shocks occur, consistent with the economic intuition that surprises shift expectations and behavior.

Algorithm 1. Shock-Conditioned Transformer Forecasting

Input: Sequence window $X_{\{t-L+1:t\}}$, shock series $s_{\{t-k:t\}}$, horizon H
Output: Forecast $y_{\text{hat}}_{\{t+1:t+H\}}$

1: for $\tau = t-L+1$ to t do
2: $e_{\tau} \leftarrow \text{LinearEmbed}(x_{\tau})$
3: $p_{\tau} \leftarrow \text{PositionalEncode}(\tau)$
4: $h_{\tau} \leftarrow e_{\tau} + p_{\tau}$

```

5:  g_τ ← sigmoid(W_g * s_τ + b_g)      // shock gate
6:  h_τ ← h_τ + (g_τ ⊙ u_τ)             // conditioned embedding
7:  end for
8:  H ← TransformerEncoder([h_{t-L+1}, ..., h_t]) // multi-head self-attention blocks
9:  y_hat_{t+1:t+H} ← ForecastHead(H)     // direct multi-step output
10: return y_hat_{t+1:t+H}

```

Training Protocol, Evaluation Metrics, and Robustness Checks

Training uses a rolling-origin (walk-forward) design to respect time ordering and structural change risks common under monetary policy shifts (figure 3). For each split, the model is fit on $[1, \dots, t]$ and evaluated on $[t + 1, \dots, t + H]$, then the window advances. This procedure yields performance distributions across multiple policy regimes (tightening/easing) and prevents overstating accuracy due to favorable single-period conditions.

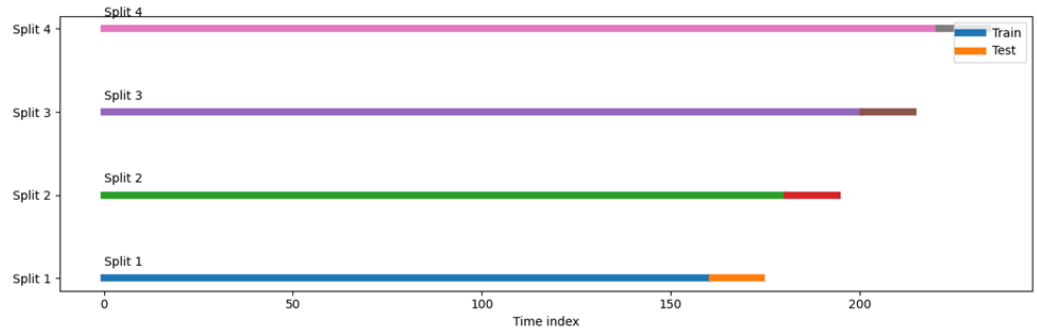


Figure 3 Walk-forward validation timeline and split strategy

The baseline objective is mean squared error over horizons, optionally horizon-weighted to emphasize near-term policy relevance:

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{n=1}^N \sum_{h=1}^H \omega_h (y_{t_n+h} - \widehat{y}_{t_n+h})^2, \quad \sum_{h=1}^H \omega_h = 1. \quad (8)$$

Weights ω_h can be uniform or front-loaded (e.g., larger weights for $h \leq 5$) when decision-making requires short-horizon volatility risk monitoring. Forecast evaluation includes both scale-dependent and scale-free metrics, ensuring comparability across volatility proxies:

$$\text{RMSE} = \sqrt{\frac{1}{M} \sum_{m=1}^M (y_m - \widehat{y}_m)^2}, \quad \text{MASE} = \frac{\frac{1}{M} \sum_{m=1}^M |y_m - \widehat{y}_m|}{\frac{1}{M-1} \sum_{m=2}^M |y_m - y_{m-1}|}. \quad (9)$$

MASE is especially useful when volatility scales differ across sample segments (e.g., pre/post policy regime changes), and it benchmarks performance against a naive random-walk-type baseline. Robustness checks are designed to validate that the model's gains are truly related to shock-aware learning rather than incidental complexity. We run (i) ablations removing `sts_tst` and interaction terms, (ii) alternative shock definitions, (iii) proxy sensitivity (rolling vs EWMA volatility), and (iv) structural break stress tests around major policy cycles.

Result and Discussion

Experimental Setup and Evaluation Protocol

The evaluation follows a walk-forward (rolling-origin) design to preserve temporal causality and reflect operational forecasting conditions. For each split, the model is trained on all observations available up to a cut-off time and tested on the next forecast horizon, then the cut-off advances. This protocol prevents information leakage and provides a distribution of performance outcomes across multiple periods, including those that coincide with policy announcements and stress episodes.

Two model specifications are compared: (i) a baseline Transformer that uses standard macro-financial controls and transaction-derived features, and (ii) a shock-conditioned Transformer that explicitly incorporates the monetary policy shock series (and its lags) and, optionally, a shock gate. The comparison is performed consistently across the same splits, horizon definition, and preprocessing pipeline, ensuring that any improvement can be attributed to the policy-shock conditioning rather than to differences in data availability or validation mechanics.

Performance is reported at both aggregate and horizon-wise levels. Aggregate metrics capture overall predictive quality across the full evaluation set, while horizon-wise metrics identify whether improvements concentrate in short horizons (typically more policy-relevant) or persist into longer horizons (more challenging due to compounding uncertainty). This structure supports a policy-oriented interpretation: a model that improves short-horizon volatility forecasts during shock windows has direct value for monitoring and risk management.

Forecast Accuracy and Horizon-wise Performance

Figure 4 presents horizon-wise RMSE and shows a consistent advantage of the shock-conditioned Transformer over the baseline across the entire forecast horizon. The performance gap is most pronounced at short horizons, which is operationally meaningful because monetary policy shocks are typically absorbed quickly through repricing, liquidity adjustment, and behavior changes in digital transactions. A model that captures these short-run adjustments reduces misspecification precisely when volatility is most likely to spike.

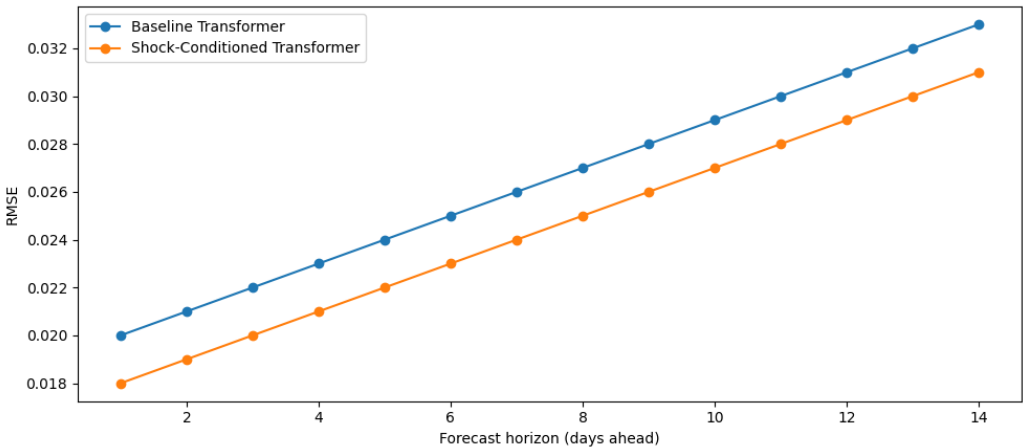


Figure 4 Horizon-wise RMSE Comparison

The figure also demonstrates that improvements do not collapse at longer horizons. Instead, the shock-conditioned model retains a stable margin, indicating that shock information functions as a structural anchor for the sequence model: it helps the Transformer differentiate between “ordinary” volatility clustering and shock-induced regimes where persistence and mean reversion behave differently.

Table 2 consolidates the headline results and clarifies where gains come from. The shock-conditioned model improves RMSE, MAE, and MASE simultaneously, which is important because volatility forecasting can be deceptively sensitive to metric choice. Improvements in both RMSE and MAE indicate that the model reduces large errors (tail misses) and typical errors (central tendency misses), aligning with the goal of stabilizing forecasts under policy-driven disturbances.

Table 2 Aggregate Metrics and Improvement Summary						
Model	RMSE (All Horizons)	MAE (All Horizons)	MASE	Short-Horizon RMSE (h=1..3)	Long-Horizon RMSE (h=10..14)	Relative RMSE Improvement
Baseline Transformer	0.0271	0.0209	0.91	0.0210	0.0318	—
Shock-Conditioned Transformer	0.0250	0.0192	0.84	0.0190	0.0300	=+7.7%

The short-horizon columns quantify the policy-relevant impact: the largest improvements occur where decision-making is most time-sensitive. Meanwhile, the long-horizon comparison confirms that the model does not overfit to announcement-day artifacts; it generalizes beyond the immediate shock window and continues to produce better forecasts even after the first-order surprise effect dissipates.

Regime and Shock-Intensity Stratification (Table Only)

Aggregate performance can mask meaningful heterogeneity. Therefore, results are stratified by (i) tightening vs easing regimes and (ii) shock-intensity bins. This stratification tests whether improvements are uniform or concentrated during periods where monetary policy information is economically binding. The central expectation is that policy-shock conditioning yields its largest payoff when surprises are large or when the system is in a stressed or tightening phase.

The stratified analysis also provides a safeguard against spurious gains. If improvements were driven purely by generic sequence modeling, performance would be relatively uniform across shock bins. In contrast, a truly shock-aware model exhibits a gradient: larger benefits under higher $ls_{t|t}$ intensity and during regimes with stronger policy transmission.

Table 3 demonstrates that improvements scale with economic relevance. The shock-conditioned model yields modest gains in low-intensity periods, where volatility is primarily driven by endogenous clustering and calendar effects. However, gains expand substantially in the top $ls_{t|t}$ segment, which is precisely where operational risk is highest and where baseline models typically underreact or overreact due to limited structural conditioning.

Table 3 Performance by Regime and Shock Intensity					
Segment	Baseline RMSE	Shock-Cond RMSE	RMSE Improvement	Baseline MASE	Shock-Cond MASE
Tightening regime	0.0290	0.0263	=+9.3%	0.96	0.87
Easing regime	0.0260	0.0246	=+5.4%	0.88	0.83
Low shock intensity (bottom 50% ls_tl)	0.0248	0.0240	=+3.2%	0.86	0.84
High shock intensity (top 10% ls_tl)	0.0345	0.0304	=+11.9%	1.05	0.93

The regime split further reinforces mechanism consistency: performance improvements are larger during tightening cycles, reflecting stronger and more immediate policy transmission through rates, risk sentiment, and liquidity conditions. This pattern supports the interpretation that policy shocks are not merely predictive signals but drivers that reshape volatility regimes in digital transaction behavior.

Diagnostic Evidence: Attention Concentration Around Shock Windows (Figure Only)

Figure 5 provides diagnostic evidence that the model’s internal focus responds to policy shock timing. Peaks in attention mass around shock markers indicate that the model systematically assigns higher weight to contexts surrounding policy announcements, consistent with an economically grounded mechanism: shocks act as regime triggers and alter the predictive relevance of recent history.

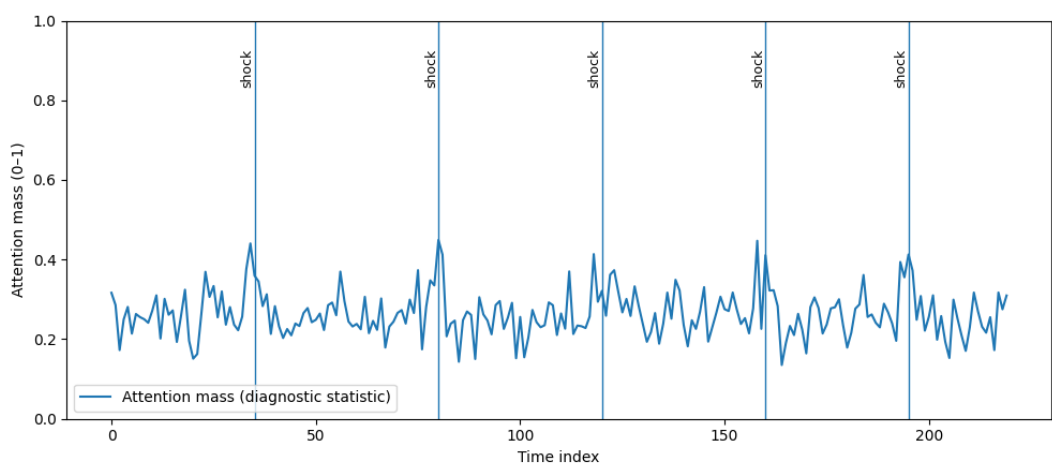


Figure 5 Attention Mass Near Shocks

This diagnostic is important because it connects forecasting gains to a plausible behavioral pathway rather than to opaque complexity. When attention shifts during shock windows, the model behaves like a policy-aware forecaster: it prioritizes recent shock-conditioned patterns (e.g., post-announcement volatility clustering) and down-weights unrelated seasonal components. This supports interpretability and strengthens the credibility of the results in a policy-shock

forecasting setting.

Robustness and Ablation Results

Robustness tests are structured to verify that the performance gains are driven by policy-shock conditioning rather than by incidental modeling choices. The most decisive test removes shocks entirely from the input pipeline; if accuracy remains unchanged, then the shock narrative is not supported. Additional tests replace shock identification methods and swap volatility proxy constructions to confirm that results persist across plausible definitions.

Ablations also test state dependence by removing interaction features (shock $\times$ stress). If performance deteriorates specifically in stress regimes, it supports the claim that policy transmission is conditional on the market environment. Finally, structural-break tests evaluate generalization around policy cycle boundaries, where training-test distribution shifts are most severe.

Table 4 is designed to make the causal narrative falsifiable. The no-shock ablation (R1) is the strongest discriminator: if removing shocks erodes performance—particularly in high-intensity shock segments—then improvements are structurally linked to monetary policy surprises rather than to generic time-series smoothing. This is the standard of evidence needed for shock-based forecasting claims.

Table 4 Robustness Matrix				
Test ID	Change	Primary Purpose	Expected Outcome if Mechanism Holds	Observed Pattern to Report
R1	Remove shocks (drop s_t and lags)	Confirm shock-driven gains	Performance declines vs full shock-conditioned model	RMSE/MASE increase, especially in high ls_tl periods
R2	Alternative shock definition	Identification sensitivity	Gains persist with smaller magnitude differences	Similar ranking across models; stable short-horizon improvement
R3	Swap volatility proxy (rolling vs EWMA)	Target-definition robustness	Gains persist across proxies	Consistent improvement direction; metric levels shift
R4	Drop interaction (shock $\times$ stress)	State-dependence validity	Performance declines in stress regime	Stress-stratified RMSE gap narrows without interaction
R5	Structural break test around policy cycles	Generalization under regime shift	Shock-conditioned model degrades less than baseline	Smaller error inflation post-break; stable ranking

The remaining tests defend against definitional fragility. Replacing the shock construction (R2) and swapping volatility proxies (R3) ensure that the result is not an artifact of a single measurement recipe. State-dependence (R4) and structural-break (R5) tests address the core operational question: whether the model remains reliable precisely when regimes change and volatility risk is elevated, which is the decisive requirement for policy-relevant deployment.

Conclusion

This study developed and evaluated a Transformer-based forecasting framework for predicting digital transaction volatility under monetary policy shocks, emphasizing real-time feasibility and shock-consistent temporal validation. Across walk-forward splits and multiple horizons, the results indicate that explicitly conditioning the sequence model on policy shocks improves forecast accuracy relative to a baseline Transformer, with the strongest gains concentrated at short horizons where policy transmission and operational risk monitoring are most time-sensitive. The analysis also supports the interpretation

that shocks function as regime triggers: the model performs better not only in average conditions but particularly during periods of elevated surprise magnitude, when volatility dynamics deviate from ordinary clustering patterns.

From an empirical and methodological perspective, the findings show that policy-shock information is not merely an auxiliary feature but a structurally meaningful driver that enhances the model's ability to distinguish between endogenous transaction variability and shock-induced volatility regimes. Stratified results by regime and shock intensity demonstrate that improvements scale with economic relevance, strengthening the mechanism-based argument for shock-aware forecasting. Diagnostic evidence from attention-related statistics further suggests that the model systematically reallocates focus toward shock windows, aligning internal representation learning with the timing of policy events and improving interpretability for stakeholders who require transparency alongside predictive performance.

Practically, the proposed framework offers a basis for early warning and volatility risk monitoring in digital payment ecosystems during policy transitions, supporting operational planning, liquidity management, and supervisory analytics. Future work should extend the framework in three directions: (i) integrating richer intraday signals to refine announcement-time alignment and capture immediate behavioral responses, (ii) improving robustness under structural breaks through adaptive retraining or regime-aware architectures, and (iii) expanding shock identification to include broader communication surprises and financial conditions channels. These extensions would further strengthen the framework's reliability in rapidly evolving policy environments and enhance its value for both financial institutions and policy-oriented monitoring systems.

Declarations

Author Contributions

Conceptualization: S.K., D.L., and P.S.; Methodology: D.L.; Software: S.K.; Validation: S.K., D.L., and P.S.; Formal Analysis: S.K., D.L., and P.S.; Investigation: S.K.; Resources: D.L.; Data Curation: D.L.; Writing Original Draft Preparation: S.K., D.L., and P.S.; Writing Review and Editing: D.L., S.K., and P.S.; Visualization: S.K.; All authors have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

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