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Overnight Interbank Rate Volatility Across Liquidity States: Key Drivers and Policy Implications

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Overnight Interbank Rate Volatility Across Liquidity States: Key Drivers and Policy Implications[1][2]

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Central Bank of the Republic of Azerbaijan

Abstract

Effective monetary policy requires maintaining the short-term interbank rate close to the policy rate while limiting its volatility, ensuring smooth transmission, and reducing banks' liquidity and interest rate risks. This paper seeks to identify and explain the drivers of volatility in short-term interbank rates, while examining the impact of the reserve averaging framework on banking sector liquidity. Drawing on evidence from an emerging market, this study demonstrates that deviations of cumulative reserves from their trend exert a significant influence on interbank rate volatility. Specifically, the results identify distinct states in the money market: a high-responsiveness state and a low-responsiveness state, depending on prevailing liquidity conditions. The findings imply that central banks should closely monitor cumulative reserve positions and proactively guide liquidity toward its trend path.

Keywords: overnight interbank rate, required reserves, markov-switching model, liquidity state.

JEL Classification: C22, E53, E58, G21.

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[2]The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the Central Bank of the Republic of Azerbaijan.

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1 Introduction

Effective implementation of monetary policy in money markets depends critically on steering the short-term interbank rate close to the policy rate while keeping its volatility low. Low volatility facilitates smooth transmission of interest rate changes and minimizes liquidity and interest rate risks for banks, which can otherwise be costly.

Central banks, therefore, prioritize maintaining low volatility in short-term interest rates, especially where reserve requirements can be fulfilled on an average basis over the maintenance period. This study contributes to the literature by examining how in a market with front-loading bank behavior, an averaging-based reserve requirement system influences the banking sector's liquidity and generates volatility in interbank rates. In addition, it explores policy options for central banks, including the use of specific indicators to guide open market operations and manage short-term liquidity. Using data from the Central Bank of the Republic of Azerbaijan, it analyzes an emerging financial market and finds conclusions that are broadly consistent with prior studies on advanced markets.

Empirical and theoretical research on major advanced and emerging economies consistently shows that volatility remains low early in the maintenance period due to the flexibility afforded by averaging, which allows reserve shocks to be spread across the remaining days. However, volatility rises sharply toward the end of the period, particularly on settlement days, when averaging options disappear, uncertainty becomes concentrated, and banks must make forceful adjustments to meet their requirements (Bartolini et al., 2002; Durré & Nardelli, 2008; Eagle, 1995; Spindt & Hoffmeister, 1988).

This study analyzes the impact of the maintenance period on interbank interest rates, using the cumulative reserve position gap, which is defined as aggregate reserves accumulated relative to its trend, as a key indicator. Our results show that significant deviations from the trend strongly influence interbank rate behavior in the money market, raising the probability of observing high volatility. These findings are consistent with the study of Hilton and Hrung (2010).

The study recommends that central banks closely monitor the accumulated reserves to mitigate risks and proactively steer aggregate reserves toward the trend through liquidity provision or absorption. Otherwise, pronounced volatility, especially in the final days of the maintenance period, when no further standard open market operations are scheduled before settlement, may lead to high volatility in interbank rates. To address this, central banks could consider more reactive responses to evolving liquidity conditions late in the period, including fine-tuning operations.

The remainder of the paper is organized as follows: Section 2 presents literature on the topic; Section 3 introduces the operational framework of the Central Bank of the Republic of Azerbaijan and the data used within the paper; Section 4 presents the methodology and the results; Section 5 concludes and provides policy implications based on the findings.

2 Literature Review

Interbank interest rate volatility plays a pivotal role in the transmission of monetary policy, financial stability, and the efficiency of short-term funding markets. Research on money markets in both advanced and emerging economies identifies a set of interconnected drivers rooted in reserve requirements, bank liquidity management, central bank operations, and institutional design. The study synthesizes the principal mechanisms through which these factors generate and modulate volatility, drawing on theoretical models and empirical patterns documented across diverse monetary regimes.

The primary micro-level driver is the inherent uncertainty surrounding banks' daily reserve positions. Poole's (1968) stochastic model of commercial bank reserve management demonstrates that unpredictable reserve drains, such as deposit outflows or payment shocks, prompt banks to optimize excess reserve holdings or borrowing at the central bank's penalty rate. Because the expected cost of a reserve shortfall exceeds the opportunity cost of idle funds, banks rationally maintain positive excess reserves even when these yield zero return. This behavior fundamentally shapes the demand for reserves, the money multiplier, and the central bank's leverage over short-term interest rates, establishing the foundation for all subsequent analyses of interbank volatility.

The most robust and pervasive driver identified in the literature is the institutional structure of reserve maintenance periods combined with averaging mechanisms. Regulatory constraints, accounting conventions, and asynchronous trading in continuous markets generate systematic day-of-the-week and calendar effects, with volatility rising markedly toward the end of each maintenance period (Spindt & Hoffmeister, 1988). Stochastic equilibrium models formalize this pattern: early in the period, new information about reserve shocks is diffused across remaining days through averaging, dampening daily impacts. On the settlement day, however, all accumulated uncertainty must be absorbed immediately as averaging options vanish, producing sharply higher volatility through rational expectations alone (Eagle, 1995). Empirical tests reject the hypothesis that reserves on different days are perfect substitutes, confirming predictable, non-random-walk behavior directly attributable to averaging rules (Hamilton, 1996).

These maintenance-period dynamics are remarkably consistent across contexts. Theoretical models integrating profit-maximizing banks with daily open-market operations show that uncertainty accumulation heightens volatility near settlement, while credible central bank commitments attenuate the biweekly cycle (Bartolini et al., 2002). In practice, minimum reserve requirements induce intertemporal substitution, banks accumulate excess reserves on low-rate days and economize on high-rate days, generating systematic volatility that intensifies toward period ends (Bruna, 2007). Design features of reserve requirements prove critical: longer averaging periods amplify last-day volatility; partial (daily) averaging restricts flexibility and exacerbates rate pressures; mismatches in remuneration or penalty rates further magnify end-period spikes (Della Valle et al., 2022; Vandenbussche et al., 2009). Even in the euro area, operational refinements reduced average EONIA[4] volatility yet increased sensitivity to shocks precisely when averaging constraints bind at period ends (Durré & Nardelli, 2008).

Central bank operational frameworks and policy credibility constitute a second-order yet powerful driver. In structural liquidity-surplus environments, liabilities-side instruments (deposit facilities and sterilization tools) combined with averaging provisions moderate banks' interest-rate sensitivity, stabilize reserve demand, and contain volatility despite abundant aggregate liquidity (Antal et al., 2001). Conversely, the daily liquidity effect of reserve shocks is often weak or confined to settlement days because averaging rules and the small size of typical operations relative to normal fluctuations

[4] EURO Overnight Index Average

obscure policy impacts (Thornton, 2001). Adaptations in reserve-supply management following secular declines in required balances initially elevated volatility before subsequent stabilization, underscoring that effective institutional arrangements matter more than reserve levels (Demiralp & Farley, 2005).

Credible policy commitments exert a particularly pronounced dampening effect. Stronger target announcements and transparent procedures reduce precautionary demand and weaken biweekly volatility patterns, as banks anticipate central bank actions more reliably (Bartolini et al., 2002). Event-study evidence across the United States, euro area, and Japan shows that announcement effects dominate quantity adjustments under normal conditions, with low interest elasticity of reserve demand allowing rate control without large reserve changes, although maintenance-period structures retain influence during crises or under weaker credibility regimes (Friedman & Kuttner, 2010). Standing facilities, intraday credit, and precise liquidity forecasting further limit large swings when paired with well-calibrated reserve requirements (Bruna, 2007; Verga & Vasilcovschi, 2019).

Aggregate and distributional liquidity conditions interact with the above drivers. In currency-board systems characterized by excess aggregate reserves, overnight rates may decline toward period end as banks front-load accumulation when rates are higher, yet responsiveness to liquidity shocks still weakens late in the maintenance period (Jurgilas, 2006). In emerging markets, uneven distribution of liquidity across banks rather than aggregate shortages, drives additional volatility when averaging is limited (Vandenbussche et al., 2009). During financial crises, reserve requirements exert amplified influence on spreads between overnight rates and policy rates by shaping liquidity management behavior (Fiszeder & Pietryka, 2018).

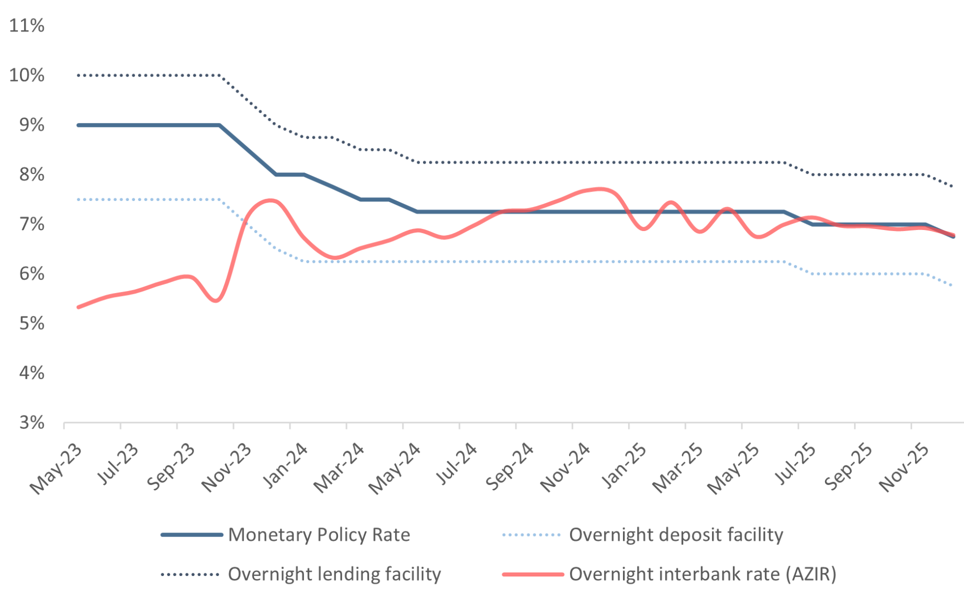
Collectively, the literature reveals a systematic volatility pattern: interbank rates exhibit low volatility early in maintenance periods owing to averaging flexibility but experience sharp increases toward settlement as uncertainty concentrates and banks make forceful adjustments to meet requirements. This pattern persists across advanced and emerging economies, yet is moderated by central bank credibility, operational refinements, and careful design of reserve requirements (averaging length, remuneration, penalties). Higher requirements elevate both rate levels and, under certain conditions, volatility via increased reserve demand; lower or zero requirements typically reduce average rates and volatility, provided supporting instruments and credible commitments are in place (Della Valle et al., 2022).

These findings carry direct implications for monetary policy design: volatility is not an exogenous feature of interbank markets but an endogenous outcome of institutional rules and behavioral responses.

3 The Operational Framework of the Central Bank of the Republic of Azerbaijan

The Central Bank of the Republic of Azerbaijan (CBAR) operates a symmetric interest rate corridor framework centered on the monetary policy rate (MPR), also referred to as the refinancing rate. The upper and lower bounds of the corridor are set at the standing overnight lending facility rate and the overnight deposit facility rate, respectively, each 1 percentage point away from the MPR (i.e., +1 pp for lending and –1 pp for deposits).

Figure 1: CBAR Interest Rate Corridor and AZIR



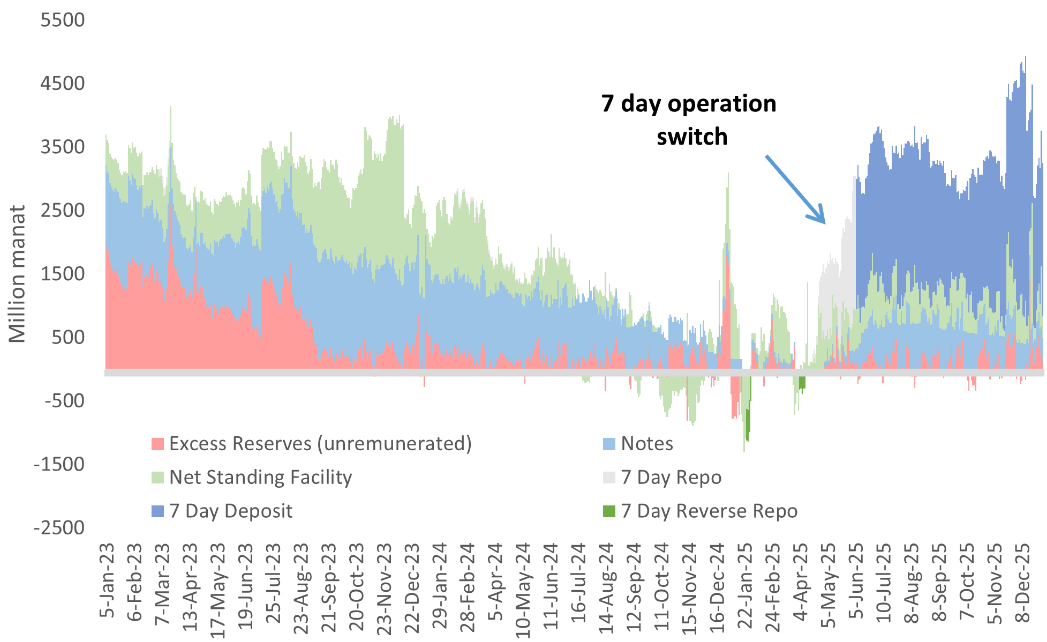
Source: Central Bank of the Republic of Azerbaijan.

The supportive operational target of the CBAR is the overnight unsecured interbank rate, known as the Azerbaijan Interbank Rate (AZIR). The CBAR began the official calculation and publication of AZIR in May 2023. AZIR entered and stabilized within the CBAR's interest rate corridor in late 2023, following the exit from the quotas [5] on banks' overnight deposits placed with the standing deposit facility (see Figure 1). The quota regime had been introduced to facilitate the gradual implementation of the corridor system.

The CBAR actively employs open market operations (OMOs) to steer AZIR toward the MPR. Since mid-2024, AZIR has remained close to the MPR.

OMOs encompass 7-day sterilization (or injection) operations as well as longer-term central bank notes with maturities of 1, 3, 6, and 9 months. As illustrated in Figure 2, the CBAR previously relied more on note placements for liquidity absorption until early 2025. Subsequently, 7-day operations have become the primary tool for managing liquidity, designated as the main liquidity operation (MLO). These MLOs are typically conducted twice weekly, on Tuesdays and Fridays, following deliberations and decisions by the CBAR's Open Market Operations Committee on the preceding day.

Figure 2: CBAR Open Market Operations



Source: Central Bank of the Republic of Azerbaijan.

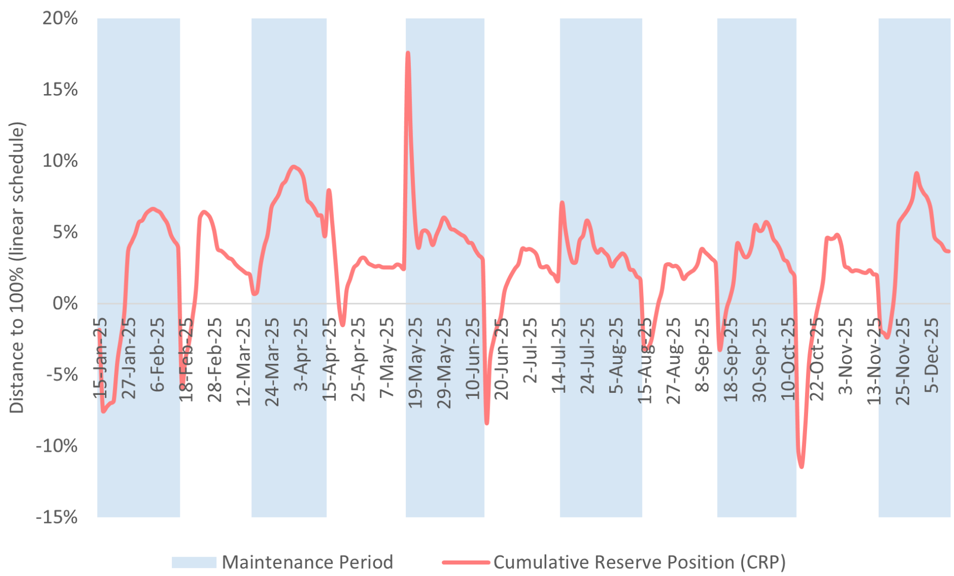
With the increased emphasis on 7-day sterilization operations, the CBAR transitioned its main sterilization operation from 7-day repo agreements to 7-day deposit auctions in mid-2025. Considering this operational reform, the empirical analysis in

[5]The quotas worked as a fixed limit for each bank on overnight deposits at the CBAR, enabling banks to gradually adapt to the new framework.

this study focuses exclusively on the post-switch period.

A pivotal element of the CBAR's monetary policy framework is the required reserve system. In 2023, the CBAR increased and differentiated required reserve ratios in several phases (February, August, and November) to absorb excess liquidity prevalent in the banking sector and to stimulate activity in the interbank market. The reserve maintenance period spans one month, running from the 15th of each month to the 14th of the following month. Banks are permitted to hold reserves on an averaging basis to meet compliance requirements.

Figure 3: Cumulative Reserve Position During Maintenance Period



Source: Central Bank of the Republic of Azerbaijan and authors' calculations.

Figure 3 depicts the cumulative reserve position of the banking sector across eleven maintenance periods in 2025. The time series exhibits a persistent pattern: the cumulative reserve position typically rises early in the period, peaks around the middle, and gradually declines toward a level of 2–3% by the period's end. This observed front-loading behavior, where banks accumulate reserves early, implies that de facto free reserves or excess reserves available for interbank lending increase substantially toward the end of each maintenance period. We hypothesize that this pattern is a critical consideration for the CBAR in calibrating its OMOs, as it influences liquidity conditions and interbank rate dynamics. Introducing the cumulative reserve position factor into empirical analysis represents one of the main contributions to both empirical literature and policymakers. This hypothesis will be evaluated and further developed in subsequent sections.

Below, Table 1 summarizes the primary variables utilized in the paper. All data in the paper are sourced from the CBAR. High-frequency daily data is used covering the period between 17th of June to 12th of December, which corresponds to 6 maintenance periods.[6] Historical series on MPR, AZIR, OMOs, and standing facilities are publicly available on the CBAR's website. From these core series, additional variables are constructed, which will be discussed in subsequent sections.

Table 1: Summary Statistics

Variable (millions AZN)	N	Mean	SD	Min	Median	Max	Mode
AZIR rate(%)	124	6.983	0.101	6.65	6.95	7.23	7.10
AZIR volume	124	179	110.03	64.5	129.25	461	95
Notes	124	610.4	90.6	400.3	612.4	734.2	419.9
7 day sterilization (deposits)	124	2200	509.5	1250	2200	3856.5	2223.5
7 day injection (reverse-deposits)	124	0	0	0	0	0	0
Standing facility lending	124	0.323	3.592	0	0	40	0
Standing facility sterilization	124	492.021	213.808	87.1	482.4	1098	342.3

Notes: N counts non-missing observations. All statistics computed excluding missing values.
Source: Central Bank of the Republic of Azerbaijan.

4 Methodology and Results

The estimation is conducted in two stages. The first stage aims to capture the varying responsiveness of AZIR to liquidity fluctuations observed in the data. This is achieved by employing a Markov-switching model, which divides our sample into periods based on the responsiveness of AZIR, called high and low states. The second stage expands on the analysis by explaining the drivers of the high state periods, which is when AZIR exhibits dramatically increased sensitivity to changes in liquidity conditions.

4.1 Stage I: Identifying Volatility States

In the first stage, daily observations are analyzed within a standard Hidden Markov Model (HMM) to assess the responsiveness of AZIR, allowing for state changes be-

[6]The actual start and end of the data may differ from the defined maintenance periods, as those days coincided with non-working days.

tween periods of high and low responsiveness. Specifically, a Markov- switching (MS) (Hamilton, 1989) regression framework is employed. By estimating an MS regression in which AZIR is generated under latent regimes, distinct regression relationships are obtained for each state. Moreover, the model produces posterior probabilities for each state, which serve as crucial inputs for the second-stage estimations.

4.1.1 Short-Term Effective Rate

In the two-state Markov Switching regression, the primary explanatory variable is the central bank's short-term effective rate, which captures the influence of monetary policy on changes in the AZIR condition on the latent regime. The short-term effective rate, called the CBAR rate, is defined as the weighted average interest rate across the CBAR's key monetary policy instruments, including overnight standing facility (lending and deposit) and weekly (7-day) open market operations. It is calculated as:

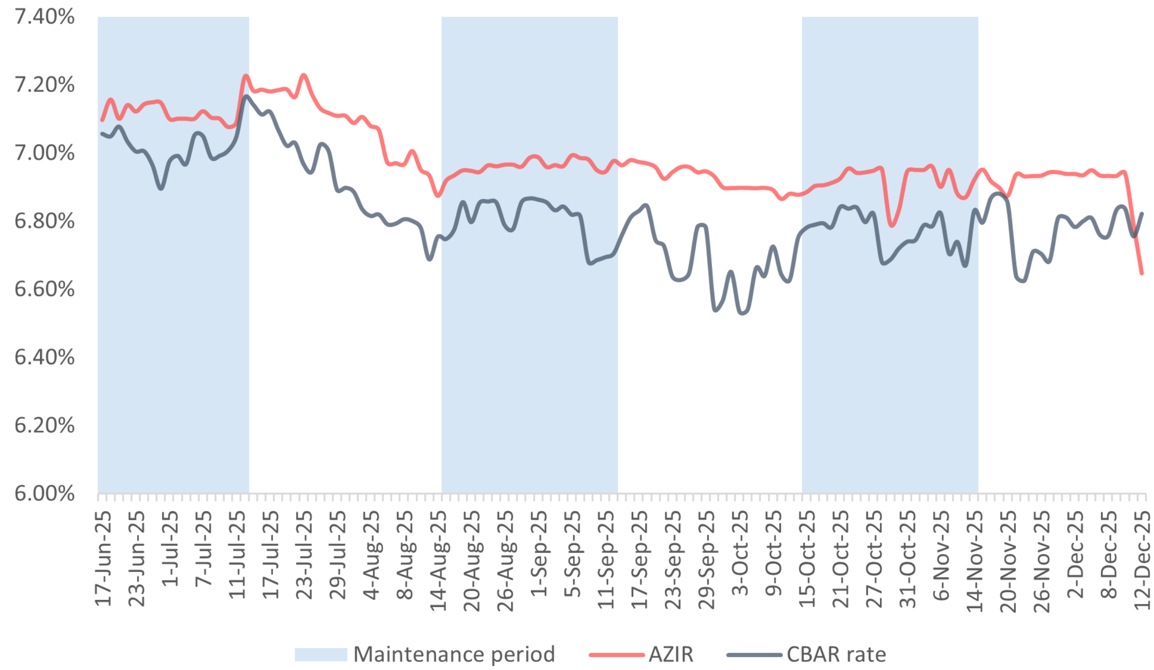
$$\textbf{CBAR rate} = \frac{ON_{\text{inj}} \cdot i^u + ON_{\text{ster}} \cdot i^l + W_{\text{inj}} \cdot i^{wi} + W_{\text{ster}} \cdot i^{ws}}{ON_{\text{inj}} + ON_{\text{ster}} + W_{\text{inj}} + W_{\text{ster}}} \tag{1}$$

where

- the overnight standing facility (ON) comprises lending (injection) volume ON_{inj} and sterilization (absorption) volume ON_{ster};
- weekly open market operations (OMO) comprise liquidity injection volume W_{inj} and liquidity sterilization (absorption) volume W_{ster};
- the overnight standing facility rates are the lending (upper) rate i^u and sterilization (lower) rate i^l;
- the weekly OMO rates are the injection rate i^{wi} and sterilization rate i^{ws}.

The primary rationale for employing this constructed indicator is twofold. First, given the relatively short estimation sample, the CBAR rate enables the integration of interest rates and transaction volumes from the CBAR sterilization and liquidity injection operations into a single, comprehensive measure. Banks are assumed to determine rates in the unsecured overnight market (AZIR), not solely based on posted interest rates on CBAR instruments (7-day operations and the overnight standing facility), but also in consideration of the aggregate volumes absorbed or injected through these tools. In other words, banks benchmark interbank rates against the overall effective return available from central bank facilities. Furthermore, the constructed CBAR rate demonstrates a strong positive association with AZIR, as can be seen from Figure 4. The Spearman rank correlation coefficient between AZIR and CBAR rate is 0.72, indicating a moderately strong monotonic relationship.

Figure 4: AZIR and Central Bank's Short-Term Effective Rate



Source: Central Bank of the Republic of Azerbaijan and authors' calculations.

4.1.2 Markov-Switching Model

A central assumption of Markov-Switching model is that the latent regime process follows a first-order Markov chain. To ensure stable estimates and avoid weakly identified or poorly separated states, the number of latent states is fixed at two: "high-responsiveness" state and "low-responsiveness" state. For robustness, the sensitivity test was conducted (table 2) looking into the alternative 3 and 4-state Markov-switching models. Even though AIC favored the model with 4 states, the results of BIC, as well as the interpretation of the transition matrix [7], provided evidence for two state model

[7]The transition matrix showed that State 4 exhibits zero persistence ($p_{44} = 0.00$) and immediately switches to other states, indicating a non-recurrent state. Therefore, models with 4 states did not

as the best fit.

Table 2: Sensitivity Test Results of Markov Switching Model

States	Log-likelihood	AIC	BIC
2	870.997	-1719.993	-1688.707
3	886.065	-1732.130	-1675.246
4	903.581	-1745.162	-1656.992

The estimated transition probabilities are as follows:

$$p_{ij} = \Pr(S_t = j \mid S_{t-1} = i), \qquad i, j \in \{1, 2\}. \tag{2}$$

where the states are defined as follows:

- The latent state s_t indexes the regime at time t.
- States are interpreted based on the estimated volatility and the coefficients of the explanatory variables, such that $\sigma^2_{\text{low}} < \sigma^2_{\text{high}}$ and $|\beta_{\text{low}}| < |\beta_{\text{high}}|$.

The model assumes time-homogeneous transitions. By excluding covariates from the transition matrix, the specification imposes that transition probabilities remain constant over time. To accommodate state-specific heterogeneity, state-dependent variance is incorporated into the error structure. These variances will be another indicator in defining the state type. Thus, the transition matrix is:

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}, \quad \sum_{j=1}^{2} p_{ij} = 1 \text{ for } i = 1, 2, \quad p_{ij} \geq 0. \tag{3}$$

Lastly, to make the variables stationary and obtain reliable results, we take the first differences of each variable. Our regression model within MS:

$$\begin{aligned} &\Delta AZIR_t = \beta_{0,S_t} + \beta_{1,S_t}\,\Delta\text{CBAR rate}_t + \beta_{2,S_t}\,\Delta\text{CBAR rate}_{t-1} + \varepsilon_{t,S_t}, \\ &\text{where } \varepsilon_{t,S_t} \sim \mathcal{N}(0, \sigma^2_{S_t}) \end{aligned} \tag{4}$$

provide additional information, and considering results from Akaike Information C riterion (AIC) and Bayesian Information Criterion (BIC), the two-state model was preferred.

The Markov Switching model is estimated to use the depmixS4 package in R (Visser & Speekenbrink, 2010). The package is specifically designed for fitting hidden Markov models and accommodates all the model assumptions outlined above, including time-homogeneous transitions, state-specific variances, and the absence of covariates in the transition probabilities. In each state, AZIR is modeled as a function of the contemporaneous CBAR rate and its first lag. To mitigate the risk of convergence to local optima, a common concern in expectation-maximization (EM) estimation of HMMs, multiple random starting values are used. The EM algorithm is run from each starting point, and the solution with the highest log-likelihood is selected. To further promote numerical stability and convergence, the maximum number of iterations is set to 500, and the convergence tolerance is configured to a value close to zero.

The estimation results of the two-state Markov-switching model are presented in Table 3. In both states, the contemporaneous coefficient on the CBAR rate is insignificant, whereas the coefficient of the first lag is positive and statistically significant. This pattern is consistent with the timing of liquidity operations in the CBAR's framework. A substantial portion of the daily variation in the CBAR rate arises from changes in the volume of overnight deposits at the standing facility, which are determined only after the interbank market closes for the day. Consequently, when banks make lending or borrowing decisions in the unsecured overnight market, they rely primarily on the previous day's overnight deposit balance as a reference point—particularly for transactions executed early in the trading session.

The magnitude of the lagged effect differs markedly across liquidity states. In state 2, a one percentage point change in the CBAR rate is associated with a 0.07 percentage point change in the following day's AZIR. In state 1, the corresponding effect is substantially larger, at 0.45 percentage points. Both coefficients are statistically significant at least at the 5% level.

Given the markedly stronger responsiveness and the higher state-specific variance, state 1 is designated the "high-responsiveness state" (or "high state"), in which the interbank market exhibits vigorous adjustment to changes in the effective central bank rate.

Table 3: Markov-Switching Regression Output

State 1

Variable	Coef.	Std. Err.	z-Stat	p-Value
Constant	-0.000115	0.000101	-1.142	0.2536
ΔCBAR rate$_t$	0.001092	0.019690	0.055	0.9558
ΔCBAR rate$_{t-1}$	0.446316	0.176729	2.525	0.0116**
Sigma	0.000590	0.000076	7.731	0.0000***

State 2

Variable	Coef.	Std. Err.	z-Stat	p-Value
Constant	-0.000003	0.000015	-0.183	0.8552
ΔCBAR rate$_t$	0.017334	0.025521	0.679	0.4970
ΔCBAR rate$_{t-1}$	0.069328	0.024827	2.792	0.0052***
Sigma	0.000128	0.000013	9.860	0.0000***

Note I: For calculation of z-stat and p-values asymptotic normal distribution was used (Wald).

Note II: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

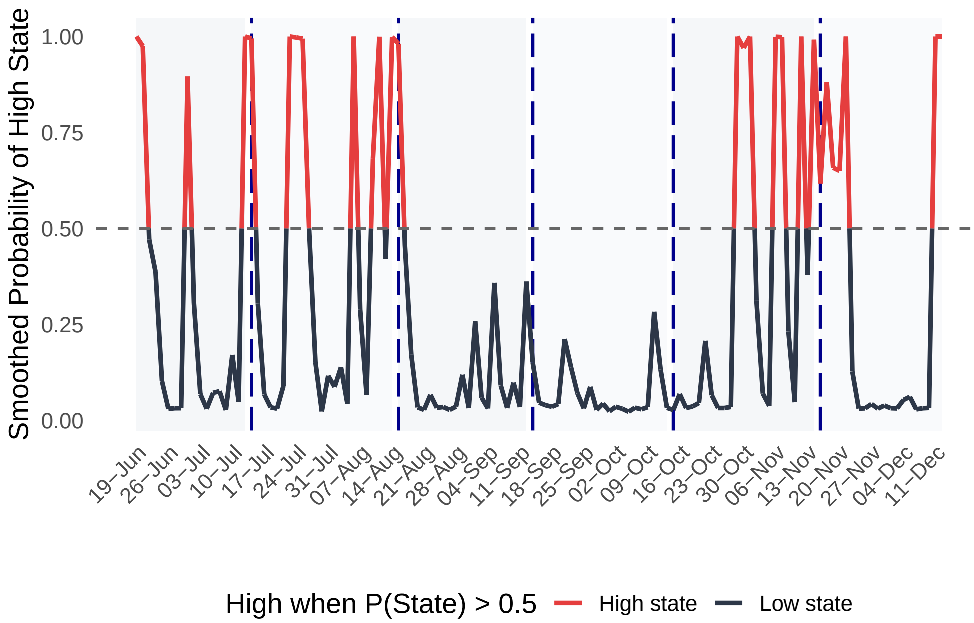
Table 4 reports the estimated transition probability matrix. The probability of remaining in the low state (state 2) is 0.87, which is substantially higher than the probability of remaining in the high state (state 1), 0.67. Consequently, the low state is more persistent, leading to a greater frequency of low state days in the smoothed (ex-post) regime probability series, as illustrated in Figure 5.

Table 4: Transition Probability Matrix

	To	
From	State 1	State 2
State 1	66.7%	33.3%
State 2	13.2%	86.8%

Note: Entries are $100 \times \Pr(S_t = j \mid S_{t-1} = i)$.

Figure 5: Markov-Switching Regime Probabilities



The results of the first stage show us that interbank rates generally respond sluggishly to shifts in liquidity conditions. The incidence of high state days varies considerably across maintenance periods. While some periods exhibit a substantial number of high state days, others contain none. Although high state days frequently occur toward the end of the maintenance period, as predicted by reserve-averaging theory, they are also observed early in some periods. Consequently, the second stage of the analysis investigates the determinants of the probability of entering or remaining in the high state.

4.2 Stage II: Drivers of the High Volatility

Once the high state probabilities are obtained from the first-stage Markov-switching regression, the second stage examines the determinants of these probabilities using a binary logit model, with the probability of the high state serving as the dependent variable.

The continuous posterior probabilities generated by the Markov-switching model are transformed into a binary indicator for logit estimation. Specifically, the binary dependent variable takes the value 1 if the smoothed probability exceeds 0.5, and 0 otherwise. This threshold-based discretization entails a modest loss of information but is justified by the substantial gain in model simplicity and interpretability afforded by the logit framework.

The logit specification naturally constrains fitted values to the [0, 1] interval and introduces nonlinearity, which aligns with the theoretical expectation that the relationship between liquidity-related covariates and the likelihood of entering or persisting in the high state is nonlinear. All explanatory variables are stationary at levels (as confirmed by unit root tests).

Independent variables used in the second stage reflect our main hypotheses. From theory, we know that the following factors may contribute: deviation of cumulative reserve position from its trend, day-specific count of main liquidity operations remaining before the maintenance period ends, and sterilization level by the central bank.

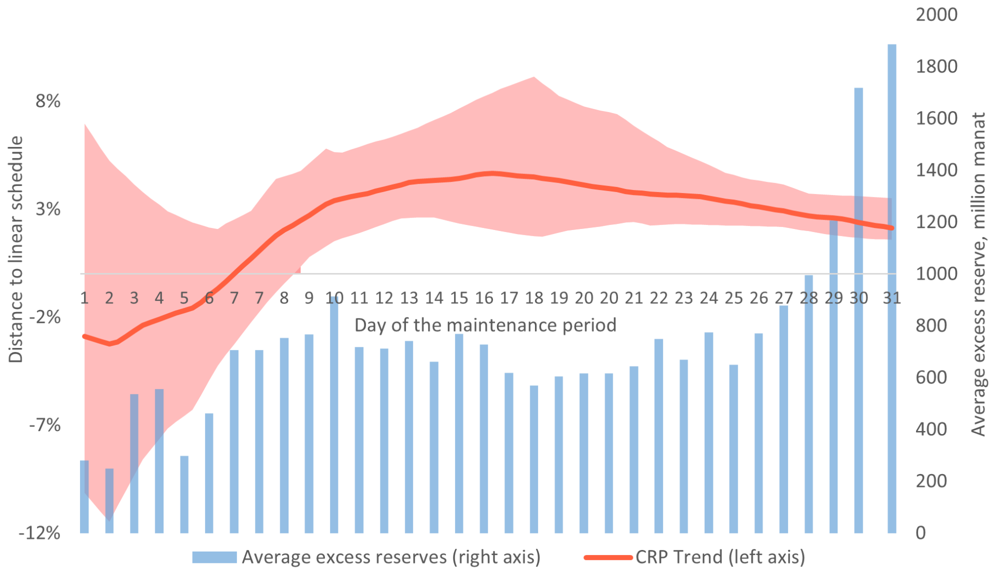
4.2.1 Cumulative Reserve Position Gap

As illustrated in Figure 3 earlier, CRP exhibits a characteristic pattern across maintenance periods: it typically rises steeply in the early days and then gradually declines toward levels of approximately 2–3% by the final day. This pattern, while subject to some period-specific variation, is broadly consistent with front-loading behavior under reserve averaging. Figure 6 formalizes this observation by averaging the CRP across all maintenance periods in the sample, aligned by the day of the period. The resulting series, which is termed the CRP trend, represents the average reserve position on each corresponding day of the maintenance cycle [8]. This stylized pattern raises several key questions.

First, why does the CRP trend begin the maintenance period in negative territory? This initial shortfall can be explained by the fact that, as a result of front-loading, banks substantially increase volumes in MLOs in the final days of the maintenance period to avoid the opportunity cost of excess reserves. Consequently, some duration of these MLOs "spills over" into the subsequent maintenance period, creating a temporary reserve deficit that manifests itself as negative CRP in the early days of the new period.

[8]For instance, a CRP trend value of 4.6% on day 15 indicates that, on average, banks hold reserves equivalent to 104.6% of their required reserves during the first half of the maintenance period.

Figure 6: CRP Trend and Average Excess Reserves within Maintenance Period



Source: Central Bank of the Republic of Azerbaijan and authors' calculations.
Note I: Red area along the CRP trend represents the minimum and maximum CRP level occured within the period. *Note II:* Excess reserves are defined as the sum of correspondent accounts and net standing facility, minus the average required reserves needed to hold through the end of the maintenance period.

A second key question concerns why the banking sector typically ends the maintenance period with an average cumulative reserve position (CRP) of approximately 2.1%, rather than reducing it closer to zero. In theory, banks could deposit substantially larger amounts at the overnight standing deposit facility on the final day and minimize opportunity costs associated with excess reserves. In practice, however, this does not occur fully.

The primary reason is that banks must maintain a certain buffer of reserves in their correspondent accounts to meet day-to-day operational and settlement requirements. Toward the end of the maintenance period, the need to hold reserves to satisfy the required reserve obligation diminishes significantly due to front-loading earlier in the period. This reduction is only partially offset by the continuing operational demand for liquidity. Consequently, the sector becomes effectively "locked in": the heavy front-loading of reserves earlier in the period leaves banks with a structural excess that cannot be fully unwound on the settlement day without risking operational disruptions. As a result, banks incur de facto opportunity costs even when holding only the minimum reserves necessary for operational purposes.

We believe that the CRP plays a fundamental role in the volatility of AZIR. To account for its effect in the second stage, we develop a variable called "cumulative reserve position gap (CPR gap)", which is computed as[9]:

$$CRP\ \text{gap}_t = CRP_t - \overline{CRP}_{d(t)} \tag{5}$$

$$\overline{CRP}_j = \frac{1}{M}\sum_{m=1}^{M} CRP_{m,j} \tag{6}$$

Let t index calendar days. Each day t corresponds to a maintenance period $m \in \{1, 2, \ldots, M\}$ and a day within the maintenance period $j \in \{1, 2, \ldots, J\}$. The function $d(t)$ represents the mapping of each day t to a specific m and j.

If the banking sector finds itself at a higher CRP level than usual, this should theoretically increase the likelihood of high states, especially towards the end of the maintenance period.

Due to its cumulative averaging nature, CRP (and its trend/gap) is more volatile early in the maintenance period. Furthermore, "spillovers" from the last maintenance period's MLOs further add volatility. To mitigate these sources of noise and ensure more reliable inference, observations affected by the "spillovers", which are the first four to six days of each period, are excluded from the analysis.

4.2.2 The Number of Remaining Main Liquidity Operations

CBAR typically conducts two main liquidity operations per week, resulting in approximately 8 or 9 MLOs during each reserve maintenance period. Consequently, the number of remaining MLOs before the period's conclusion emerges as a critical control variable.

When the banking sector has limited opportunities to place excess liquidity, the impact of excess reserves on interbank market rates becomes more pronounced. An extreme case arises when no MLO remains available prior to the end of the maintenance

[9]Essentially, it represents the deviation of the CRP at day t from the average (of the last 6 months) CRP on the same day of all 6 maintenance periods in the sample. For example, on the 14th of September, CRP stood at 2.25%, which is above the average CRP on the last day of the maintenance period over our sample period, 2.14%. As a result, on that day, the CRP gap variable is equal to 0.11 percentage points.

period [10].

Excluding these extreme instances, the remaining number of MLOs exhibits a systematic decline as the maintenance period advances. However, the marginal effect of this decline is not uniform. For example, a reduction from 8 to 7 remaining operations differs qualitatively from a reduction from 2 to 1. It is hypothesized that the relationship between the number of remaining MLOs and the probability of entering or persisting in the high state is nonlinear. Specifically, the effect strengthens substantially as the number of available operations approaches zero.

This nonlinearity arises from increased market sensitivity to liquidity constraints when sterilization buffers are nearly depleted, compelling banks to adjust interbank rates more aggressively to fulfill reserve requirements. To account for this nonlinearity, we use the following variable in the second stage:

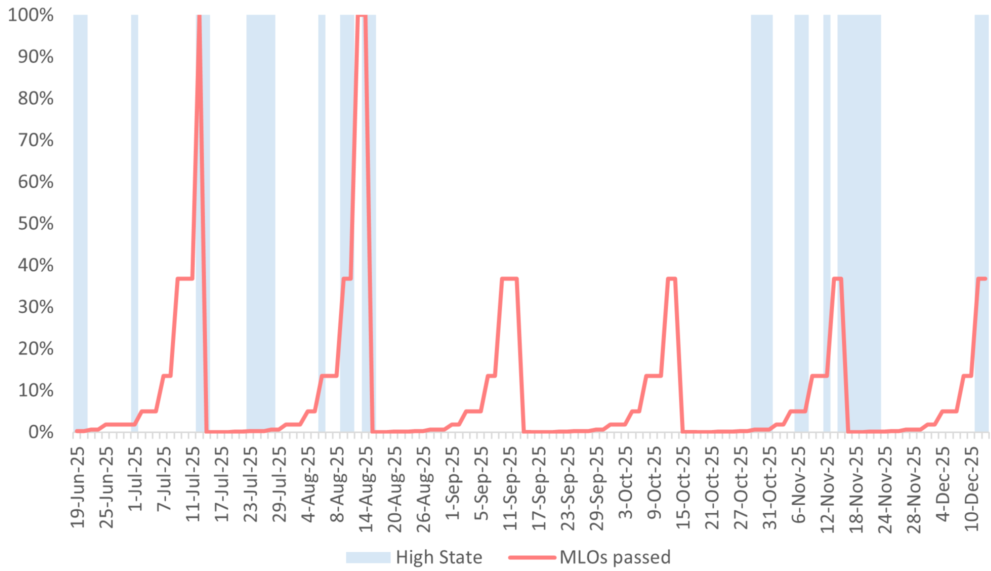
$$MLOs \;\; \text{passed} = \frac{1}{e^i}, \quad \text{where } i = \text{number of } MLOs \text{ remaining.} \tag{7}$$

To ensure that all explanatory variables exert effects in a theoretically consistent direction, we divide by the exponent over the number of MLOs remaining (i.e., $1/e^i$). In the theoretical framework, a decrease in the number of remaining MLOs (i.e., an increase in $1/e^i$) should raise the probability of the high state. Incorporating the exponential form of this transformation further allows us to capture the hypothesized nonlinearity in the relationship.

Figure 7 displays the time series of the exponential inverse specification.

[10] In the sample period, this scenario occurred on only two occasions, 14 July and 13–14 August, both of which were identified as high states in the first-stage Markov-switching regression. This pattern aligns closely with the hypothesis that liquidity pressure intensifies sharply when sterilization capacity is exhausted near the settlement date

Figure 7: MLOs passed, exponential



Source: Central Bank of the Republic of Azerbaijan and authors' calculations.

4.2.3 Sterilization Level by the Central Bank

The third factor is the level of sterilization by the CBAR. The partial sterilization ratio quantifies the proportion of banks' excess reserve demand that remains unaccommodated by the CBAR via MLOs. It is calculated as:

$$Partial\ Sterilization_t = 1 - \frac{Supply_t}{Demand_t} \tag{8}$$

where supply represents the quantity of sterilization offered by the Central Bank, demand represents the total quantity demanded by the banks, and t is the date of the latest auction.

For instance, a level of 20% indicates that 20% of the aggregate placement demanded by banks in the MLOs went unmet. A rate of 0% means full sterilization.

In a standard symmetric interest rate corridor system, such as the one implemented by the CBAR, the central bank is generally expected to fully sterilize structural excess liquidity through appropriately calibrated MLOs. At first glance, therefore, including partial sterilization ratio as an explanatory variable might seem superfluous. However, it plays a crucial role as a control in the present analysis.

The CBAR transitioned to using 7-day deposit auctions as its primary liquidity-management tool in mid-2025, replacing earlier reliance on repo operations and longer-term notes. This operational shift, while enhancing short-term liquidity control (with 7-day deposits comprising 87% of the sterilization portfolio by late 2025), was accompanied by transitional frictions. These included inaccuracies in liquidity forecasting and episodes of volatile placement demand from banks, which periodically led to substantial under-sterilization.

Thus, the partial sterilization ratio is designed to capture these residual liquidity imbalances and their independent effects on interbank rate dynamics and Markov regime shifts. By accounting for these implementation challenges during the transition period, the variable helps isolate the role of incomplete sterilization in amplifying rate sensitivity within the high state.

4.2.4 Heterogeneous Borrowing Pattern

The interbank market in Azerbaijan has heterogeneous borrowing behavior among its participants. It is observed that some banks are present on the market irrespective of their own liquidity position or the liquidity position of the system as a whole. The rates of these banks do not react to changing liquidity conditions, as the same overnight contract is rolled for an extended period of time. We call these banks less elastic participants.

As opposed to less elastic participants, the rest of the banks (called more elastic participants) enter and leave the market on a day-by-day basis. The counterparties, rates, and volumes of their contracts vary substantially as the liquidity conditions change. Therefore, the presence of more elastic banks becomes an important factor as their entry and exit likely contribute to volatility in AZIR. As a control, we develop a time-series called participation-driven volatility (PDV), which combines the extent of more elastic banks' presence in the market with the size of the rate-differential. The identification of less elastic/more elastic participants and the control variable used for their effect is explained in greater detail in Appendix A.

4.2.5 Logit Regression

The four factors mentioned above and their lags and interactions are used as independent[11] variables in logit regressions. Standard errors are computed using the Huber–White (sandwich) covariance estimator to ensure robustness against potential heteroskedasticity or misspecification. Following Hosmer et al. (2013), we estimate[12] the following relationship:

$$E\big(Y \mid X_1, X_2, \ldots, X_n\big) = \frac{\exp\big(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n\big)}{1 + \exp\big(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n\big)}. \tag{9}$$

where, Y is the high state dummy variable, and X_n are the four factors mentioned above.

Results are given in Table 5, where the first column represents the initial regression, the second column adds lags, and the last column adds interaction terms. The results in the first column appear counterintuitive: a lower level of partial sterilization is associated with an increased probability of the high state, which contradicts economic intuition. This apparent puzzle is resolved in the second column upon the inclusion of lagged variables.

We argue that lags are essential for most of our explanatory variables. First, the CRP reflects the banking sector's end-of-day liquidity position; thus, the previous day's closing position can substantially influence interbank contracting on the current day. Second, the lag of MLOs passed is necessary because, even on the day of the final MLO, some interbank transactions occur before the auction settles, thereby partially mitigating the immediate impact of autonomous liquidity shocks on AZIR. The following day, however, all contracts are negotiated in an environment where the sector can no longer offset shocks via 7-day operations. Third, lagging the participation-driven volatility is warranted, as volatility induced by more elastic banks may spill over into the subsequent day through rate adjustments. For consistency, we also include the lag

[11] All independent variables used within the regression were normalized using a Z-score transformation. The approach was used to ensure comparability of the effect sizes without altering statistical inference or model fit.

[12] The binary logit model is estimated using EViews 14 software. Parameters are obtained through the maximum likelihood estimation. The Newton-Raphson optimization algorithm, augmented with Marquardt steps, is employed for iterative convergence.

of the partial sterilization.

Table 5: Logit Regression Results

	Dependent variable:		
	High State Dummy		
	Model 1	Model 2	Model 3
	(1)	(2)	(3)
Constant	−1.4071	−1.7661	−1.5868
	(0.2616)***	(0.3966)***	(0.435)***
CRP Gap	0.4415	−0.5814	−0.6293
	(0.239)*	(0.596)	(0.643)
MLOs Passed	0.1517	−0.1394	0.2005
	(0.262)	(0.315)	(0.382)
Partial Sterilization	−0.779	−0.293	−0.023
	(0.363)**	(0.606)	(0.898)
PDV	1.3337	1.2819	1.8149
	(0.403)***	(0.663)*	(0.624)***
CRP Gap (-1)		1.4742	1.91
		(0.831)*	(0.886)**
MLOs Passed (-1)		0.6958	0.60
		(0.314)**	(0.291)**
Partial Sterilization (-1)		−0.9295	−1.3742
		(0.726)	(1.086)
PDV (-1)		1.2572	1.3193
		(0.494)**	(0.505)***
CRP Gap x PDV			0.624
			(0.742)
MLOs Passed x PDV			−0.5145
			(0.322)
Partial Sterilization x PDV			−0.909
			(0.648)
Observations	123	120	120
R^2	0.183	0.345	0.379
AIC	0.957	0.835	0.849
BIC	1.072	1.044	1.128
Note: Huber-White Robust SEs		*p<0.1; **p<0.05; ***p<0.01	

The results from the second column are more intuitive. The probability of a high state increases with PDV and MLOs passed (which means a smaller number of MLOs remaining before the end of the maintenance period).

The third column incorporates interaction terms between the PDV and the other three factors. This specification aims to capture the high stickiness of transactions by less elastic banks, which exhibit limited responsiveness to changing liquidity conditions. Consequently, when the PDV is low (i.e., the market is dominated by less elastic banks), the effects of the CRP gap, partial sterilization, and number of MLOs remaining on the probability of the high state should be attenuated.

The results from the third column are as follows:

- A baseline probability (B) of 17%;
- A two-day cumulative effect of the PDV amounting to 65.5%;
- A lagged effect of a 1 percentage point increase in the CRP gap of 27.8%;
- A lagged effect of a 1 percentage point increase in the MLOs passed of 0.56%.

We place primary emphasis on the third model, as it best aligns with the institutional features of the Azerbaijani interbank market. The PDV exerts a strong influence: participation by less elastic banks in the interbank market frequently triggers the high state. A cumulative reserve position gap exceeding 1.2% is sufficient to elevate the probability of the high state (including the baseline probability) above 50%. This highlights the need for CRP monitoring and potentially utilizing fine-tuning operations when necessary. Figure 8 illustrates the marginal effects of the CRP gap and highlights the nonlinear nature of this response.

Figure 8: Marginal Effect of CRP Gap over High State Probability

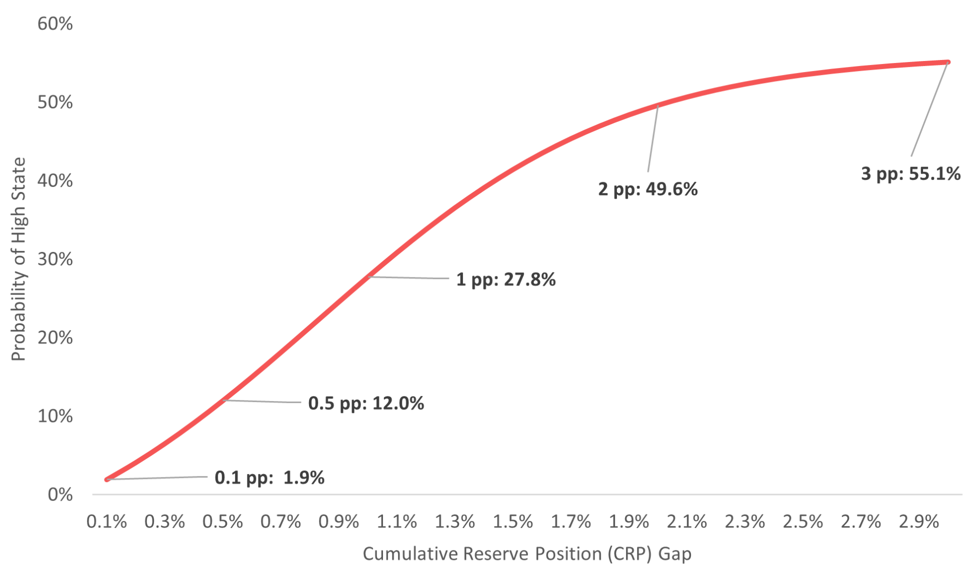


Table 6 presents the same nonlinear response for the number of MLOs remaining. As discussed earlier, the marginal effect of this variable is strongest when no further MLOs remain until the end of the maintenance period. In such circumstances, the predicted probability of the high state exceeds 50% when combining the baseline probability and the effect at this point (35.6% + 17% = 52.6%). This pattern underscores the importance of conducting fine-tuning operations at the end of the maintenance period, particularly when the last working day of the maintenance period does not coincide with an MLO. Such operations ensure that the marginal contribution of the "number of MLOs remaining" factor remains bounded at a maximum of 13.1%.

Table 6: Marginal Effect of MLOs Remaining over High State Probability

Change in number of MLOs remaining	**Change in exponential variable**	**Marginal change in probability of high state**
9 to 8	0.02 pp.	0.01%
8 to 7	0.06 pp.	0.03%
7 to 6	0.16 pp.	0.09%
6 to 5	0.43 pp.	0.24%
5 to 4	1.16 pp.	0.65%
4 to 3	3.15 pp.	1.77%
3 to 2	8.55 pp.	4.82%
2 to 1	23.25 pp.	13.1%
1 to 0	63.21 pp.	35.6%

5 Conclusion

The empirical analysis identifies key drivers of interbank rate volatility in Azerbaijan's symmetric interest rate corridor framework and provides practical recommendations for the CBAR to improve liquidity management, enhance policy transmission, and maintain price stability in a persistent structural surplus environment.

Deviations of the CRP from its historical trend strongly predict shifts to high states, where AZIR becomes much more sensitive to liquidity conditions. A 1.2-percentage-point deviation above trend raises the probability of a high state above 50%. Excessive front-loading early in the maintenance period creates imbalances that concentrate toward settlement, amplifying volatility even in a liquidity-abundant system. The final days of each maintenance period are especially prone to volatility, with risks peaking when sterilization capacity (remaining MLOs) is exhausted before settlement. Observed cases of zero remaining MLOs coincided with high state classifications, reflecting concentrated uncertainty and forced rate adjustments. Lastly, the entry and exit of more elastic banks affect liquidity distribution and rate formation, contributing significantly to volatility on affected days. Considering this, the CBAR has been encouraging broader participation of the banks in the interbank market.

Recently, the CBAR has started to integrate CRP monitoring (relative to its trend) into liquidity assessments, and as a result, has been efficiently managing liquidity. Proactive calibration of 7-day deposit auctions and other sterilization tools to keep the CRP close to its trend led to the reduction of high state frequency. This minimized the volatility of AZIR and led to a tighter alignment with the refinancing rate. To further improve control over the volatility of AZIR, the CBAR may consider the conduct of fine-tuning operations in order to guide CRP. Additionally, fine-tuning operations can also serve to prevent cases when there are no MLOs before the end of the maintenance period.

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Appendix

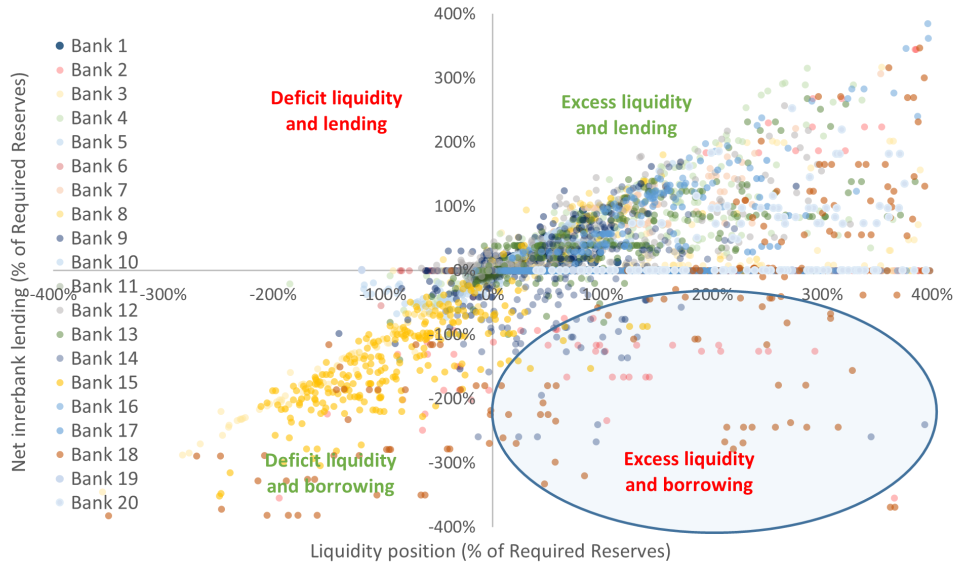
A Participation-Driven Volatility

A distinctive feature of the interbank market, consistently observed throughout the sample period, is a certain degree of concentration in trading activity. On most working days in the sample, transactions are dominated by a small number of banks that repeatedly execute comparable deals with the same counterparties.

Figure 9 presents a scatter plot with banks' daily liquidity positions on the horizontal axis and their net interbank lending volumes on the vertical axis. The liquidity position is defined as the net amount a bank must borrow from (or lend to) the interbank market to bring its cumulative reserve holdings in line with its historical average trend relative to required reserves.

In line with standard interbank market expectations, the bulk of observations fall into the anticipated quadrants: the first quadrant (excess liquidity and net lending) or the third quadrant (liquidity deficit and net borrowing). However, a non-negligible subset of points lies in the fourth quadrant, reflecting excess liquidity combined with net borrowing. These observations are attributable to four banks that systematically borrow in the interbank market despite maintaining surplus reserves, even after accounting for their front-loading.

Figure 9: Heterogenous Borrowing Patterns



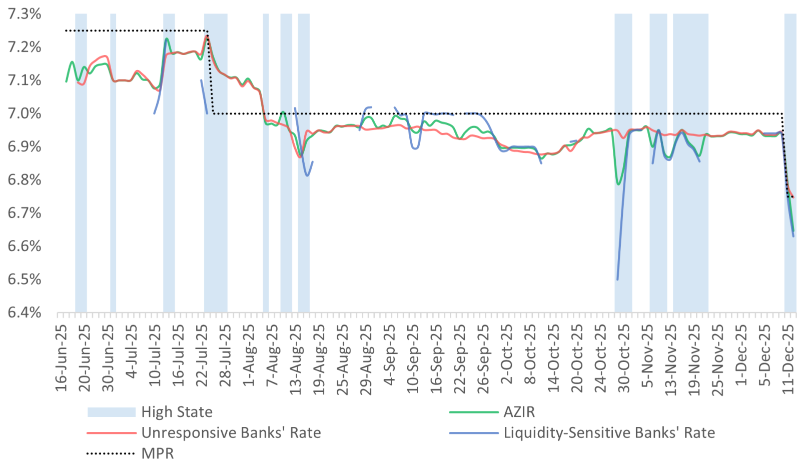
Source: Central Bank of the Republic of Azerbaijan and authors' calculations.

These four banks assume particular importance in the analysis owing to the exceptional stability of their borrowing activity. Both the interest rates and volumes associated with their contracts display very limited day-to-day variation. This regularity strongly suggests that their interbank participation is motivated primarily by operational or structural factors rather than by the need to satisfy reserve requirements and that they operate under pre-arranged, bilateral agreements featuring fixed rates and volumes. All such contracts are overnight and are routinely rolled over for prolonged periods, frequently extending across weeks. As a result, unlike the borrowing behavior of other market participants, these transactions remain largely insensitive to changes in aggregate liquidity conditions or maintenance period effects.

This structural borrowing segment introduces heterogeneity into interbank rate formation and state dynamics, as these stable, non-responsive contracts may dampen or distort the transmission of liquidity pressures to overall interbank pricing. Controlling this factor thus helps isolate the effects of the other variables on rate sensitivity and Markov regime switches.

The lower elasticity of these four banks to prevailing liquidity conditions is clearly evident in Figure 10. To illustrate this segmentation, we compute two distinct interbank overnight lending rates.

Figure 10: Less Elastic Banks’ and More Elastic Banks’ Rates



Source: Central Bank of the Republic of Azerbaijan and authors’ calculations.

We observe that the interest rate of less elastic banks (four banks mentioned above) is substantially more stable than the rest. In contrast, the interest rate of other banks (called more elastic banks) exhibits considerable volatility and is exposed to changes in liquidity. Moreover, this rate is less continuous, as the interbank market experiences limited activity on most days during our sample period. Consequently, the volatility of AZIR is largely driven by whether more elastic banks participate in the interbank market on a given day. This binary participation factor emerges as a key variable to control for in the second-stage analysis. To address this binary participation effect, we construct a control variable defined as the product of (i) the share (weight) of more elastic banks in total interbank market volume and (ii) the absolute difference between the less elastic rate and the more elastic rate. The variable captures both the extent of more elastic banks’ presence in the market and the size of the rate differential, thereby helping to isolate the contribution of participation-driven volatility in the second-stage analysis:

$$participation - driven\ volatility \;=\; (1 - w_{more\,elastic}) \times (|i_{more\,elastic} - i_{less\,elastic}|) \quad (10)$$

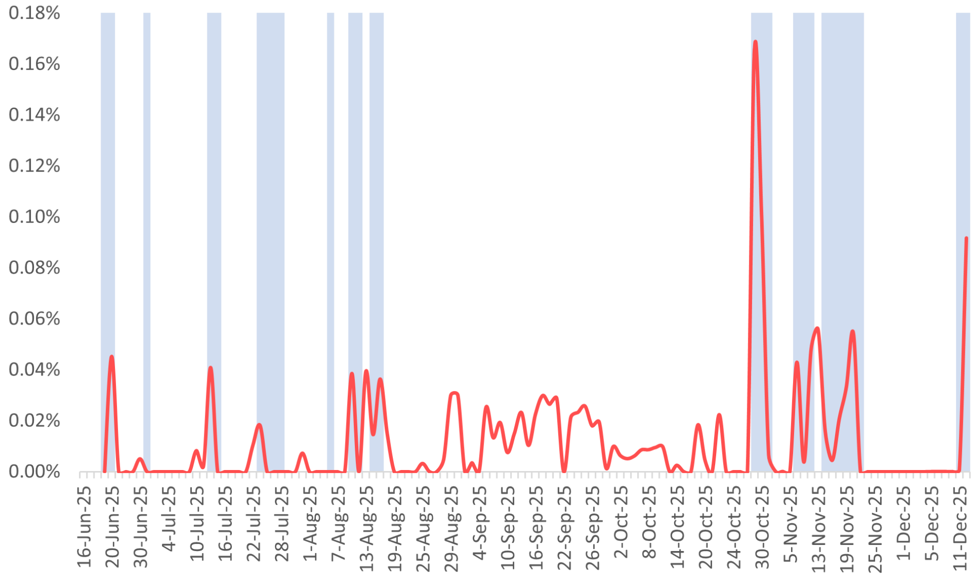
where

- $w_{\text{more elastic}}$ represents the weight of the unresponsive banks each day,
- $i_{\text{more elastic}}$ represents the interbank rate of more elastic banks,

- $i_{\text{less elastic}}$ represents the interbank rate of less elastic banks.

As can be seen from figure 11, the participation-driven volatility (PDV) variable plays a role in most of the high state observations.

Figure 11: Participation-Driven Volatility and High States



Source: Central Bank of the Republic of Azerbaijan and authors' calculations.