When Does Volatility-Informed Position Sizing Matter Most? Policy-Rate Dependence and Diversification Arithmetic of Multi-Strategy Trading in Moex Index Stocks

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Abstract: *This paper decomposes the performance of volatility-informed multi-strategy trading in constituents of the MOEX index, using six systematic strategies on 17 liquid stocks that account for about 80% of Russian equity market capitalization, evaluated walk-forward over 2022–2025. Two results emerge. First, diversification arithmetic: with an average pairwise return correlation of 0.09 and negatively correlated trend and counter-trend blocks (−0.24 to −0.11), the six strategies deliver approximately 4.2 effective independent bets and a diversification ratio near 2.0, so the choice of weighting scheme is second-order, and equal weights are best for four of six strategy portfolios. Second, policy-rate dependence: as the Bank of Russia key rate rose from 9.9% to 21.0%, the annual Sharpe ratio of the unassisted system fell from 2.99 to 0.40 while the regime-filtered system never fell below 1.87, widening the relative advantage of forecast-based position sizing from about 1.7 to 4.7 times. Volatility-informed sizing matters most when a high policy rate makes unassisted active trading hardest.*

Keywords: Multi-Strategy Portfolio; Volatility Forecasting; Position Sizing; Diversification; Effective Number Of Bets; Policy Rate; Moex Index; Emerging Markets.
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Introduction

This paper openly extends a companion study published in Russian. Lysenok (2026) established, on 17 liquid MOEX index stocks over 2022–2026, that the value of volatility forecasts in a multi-strategy book is concentrated in position sizing: regime filtering and volatility targeting raise the portfolio Sharpe ratio by +1.19 and +1.22 ($p < 0.001$), against +0.15 ($p = 0.009$) for scaling trade parameters, and the resulting portfolio beats the IMOEX index by ΔSharpe = +2.05. Those levels are established there and are reproduced here, with attribution, only as background. The present paper serves a different audience and adds two results the companion does not report: the diversification arithmetic behind the construction, and the dependence of the sizing advantage on the policy-rate environment. The underlying computations form part of the author's doctoral research at HSE University, and no text is reused from the companion publications.

The question matters beyond the Russian setting. The volatility-managed portfolio literature has largely studied a single channel, scaling market exposure by forecast volatility (Moreira and Muir, 2017; Harvey et al., 2018), applied to a passive index. A practitioner running a book of heterogeneous systematic strategies faces a richer menu: the forecast can resize positions, filter trading regimes, or reshape the parameters of individual trades, and the strategies themselves can be combined into a portfolio whose diversification properties are a design choice. Which of these margins carries the value is an empirical question, and the answer determines where model-improvement effort should be spent.

Three hypotheses organize the paper.
H1 (diversification structure). Strategies built on distinct market mechanisms deliver near-orthogonal daily returns: the average pairwise correlation is below 0.2, the counter-trend and trend blocks are negatively correlated, and the effective number of independent bets materially exceeds the number of strategy blocks.
H2 (weighting is second-order). Given the designed correlation structure, the choice of weighting scheme contributes little: the naive equal-weighted scheme is not dominated by inverse-volatility, risk-parity, or maximum-Sharpe weights.
H3 (policy-rate dependence). The advantage of forecast-based position sizing over the unassisted system widens as the policy rate rises, because sizing protects capital in the environment where unassisted active trading deteriorates most.

All three are supported. The average pairwise correlation of the six strategies is 0.09, the trend and counter-trend blocks hedge each other (−0.24 to −0.11), and the six strategies supply approximately 4.2 effective bets (H1). Equal weights deliver the best result for four of the six strategy portfolios, consistent with DeMiguel, Garlappi, and Uppal (2009), so weight optimization adds little on top of the built-in structure (H2). Across 2022–2025 the Sharpe ratio of the unassisted system falls from 2.99 to 0.40 as the key rate rises from 9.9% to 21.0%, while the sized approaches never fall below 1.12, widening their relative advantage from roughly 1.7 to 4.7 times (H3).

The remainder of the paper proceeds as follows. Section 2 positions the contribution in the literatures on strategy diversification, volatility-managed trading, and the Russian market. Section 3 describes the sample, the strategies, and the construction of portfolios and tests. Section 4 reports the three results. Section 5 discusses mechanisms and practical implications, Section 6 states limitations and directions for further work, and Section 7 concludes.

Related work

2.1. Diversification and portfolio construction

The multi-strategy construction descends from the hedge-fund literature. Fung and Hsieh (1997) show that dynamic trading strategies generate return styles largely orthogonal to asset-class factors, so combining styles diversifies along a dimension unavailable to asset allocation; Newton et al. (2021) confirm in a stochastic-discount-factor framework that allocating across hedge-fund strategy types yields material diversification gains. The six-strategy book studied here is a transparent single-market laboratory of the same principle: the blocks are constructed on opposing mechanisms, and the full correlation structure is observable, with an average pairwise correlation of 0.09 against within-block values of 0.67–0.86. DeMiguel, Garlappi, and Uppal (2009) show across seven datasets that estimation error lets the naive 1/N rule match or beat fourteen optimizing models out of sample; the present setting is a strategy-space analogue, and with cross-block correlations this low the theoretical gain from weight optimization is small to begin with, which is why equal weights win for four of six strategy portfolios. The degree of diversification itself is quantified with the standard toolkit: the diversification ratio of Choueifaty and Coignard (2008) and the effective number of bets of Meucci (2009), which Section 4.1 applies to the strategy correlation matrix.

DeMiguel, Garlappi, and Uppal (2009) show that estimation error routinely erases the theoretical gains of optimized weights, so that the naive equal-weighted rule is hard to beat out of sample. Our setting offers a complementary observation at the level of strategies rather than assets: when the building blocks are strategies designed on distinct market mechanisms, the diversification benefit is created at the design stage, in the correlation structure itself, and the choice of weighting scheme becomes second-order. Consistent with this reading, the equal-weighted scheme delivers the best result for four of the six strategy portfolios in our sample, and the paper therefore focuses on the structure that makes weights unimportant rather than on the weights themselves. The degree of diversification itself is quantified with the standard toolkit: the diversification-ratio perspective of Choueifaty and Coignard (2008) and the effective number of bets of Meucci (2009), which Section 4.1 applies to the strategy correlation matrix.

2.2. Volatility-managed trading and the channel question

Moreira and Muir (2017) document that scaling factor exposures by inverse forecast variance raises Sharpe ratios and earns alpha for major equity factors; approach D of the companion design is exactly this rule applied inside an active book, and it lifts the multi-strategy Sharpe ratio from 1.32 to 2.54. Harvey et al. (2018) find that the principal effect of volatility targeting across asset classes is stabilization of realized risk rather than higher returns, and the pattern here matches: approach D leaves returns nearly unchanged (19.6% to 20.9%) while cutting portfolio volatility from 4.4% to 2.9% and the maximum drawdown from −2.8% to −1.1%. Fleming, Kirby, and Ostdiek (2001; 2003) estimate that a mean-variance investor would pay 50–200 basis points per year for volatility-timing information; the companion certainty-equivalent estimates for the Russian book sit at the top of that range, ΔCE = +2.07% per year for regime filtering and +1.79% for volatility targeting at $\gamma = 10$ (Lysenok, 2026). Cederburg et al. (2020), evaluating 103 equity strategies, caution that volatility-managed versions rarely beat their originals out of sample, which is why this paper asks when sizing pays rather than whether it does.

Each element of the design has its own literature, and each prediction is testable against the companion numbers. The counter-trend block rests on the mean-reversion evidence of Poterba and Summers (1988); the trend block on time-series momentum, documented by Moskowitz, Ooi, and Pedersen (2012) across 58 futures markets. Trend-following returns are strongly state-dependent: Daniel and Moskowitz (2016) show that momentum crashes cluster in high-volatility states, and Barroso and Santa-Clara (2015) show that scaling momentum by forecast risk removes the crashes and nearly doubles its Sharpe ratio. The companion results reproduce this hierarchy on Russian data: volatility-informed sizing lifts the trend block most, tripling the Donchian strategy's Sharpe ratio from 0.62 to 1.81, while the counter-trend and range blocks gain moderately. For the trade-parameter channel, Kaminski and Lo (2014) prove that stop-loss rules add value under momentum dynamics but predict the gain to be modest; the observed +0.15 ($p = 0.009$) matches the predicted order of magnitude. This channel hierarchy is not visible in studies of a single passive exposure, which is what the within-system design adds.

2.3. The Russian market and the companion studies

Research on Russian equity volatility includes Aganin (2017), who compares GARCH and HAR-family models, Aganin (2020), who links index volatility to oil and sanctions, and Pogorelova and Peresetsky (2020), who extract a global stochastic trend from non-synchronous volatility observations; Berzon and Lysenok (2021) assess the investment attractiveness of BRICS markets. Recent Russian-language work remains forecasting-oriented: Glebova and Kovaleva (2024) forecast market volatility under sanctions, and Patlasov (2025) develops hybrid deep-learning models for realized ETF volatility. The economic-value and portfolio side of the question has so far developed only through the author's companion studies, discussed next. The two direct predecessors are the companion studies. Lysenok (2025) builds the hybrid HAR-J–boosting forecasting model and the three-level aggregation from instruments to the multi-strategy portfolio. Lysenok (2026) evaluates the four integration approaches end-to-end and reports the headline levels used as background here: the channel comparison (+0.15 / +1.19 / +1.22) and the outperformance of the IMOEX index (ΔSharpe = +2.05, $p = 0.001$). Neither reports the effective-bets arithmetic, the weighting-scheme comparison, or the year-by-year decomposition against the policy rate; those are the contributions of the present paper.

Taken together, these literatures leave three questions open on emerging-market data. How much diversification does a designed set of strategies actually deliver, measured in effective independent bets rather than asserted from block labels? Through which channel do volatility forecasts transmit into performance when parameter scaling, regime filtering, and position targeting operate on the same book? And does the transmission depend on the policy-rate environment, the dimension along which emerging markets differ most sharply from the developed markets of the existing evidence? Sections 4.1–4.3 answer these questions in turn.

Data and methodology

3.1. Sample and evaluation design

The sample comprises 17 liquid constituents of the MOEX index, the headline equity index of the Moscow Exchange, jointly accounting for roughly 80% of Russian equity market capitalization; concentration of the Russian market makes this compact sample economically representative, and the restriction to continuously traded large caps is acknowledged as a selection choice in Section 6. Daily data cover 2014–2026; all performance evaluation is walk-forward on 2022–2026, with model training and parameter calibration strictly preceding each evaluation year. Transaction costs of 0.05% per side are applied throughout; free capital is placed in money-market instruments at the Bank of Russia key rate, which averaged 10.6–21.0% per year over the window. Daily OHLCV data are drawn from the MOEX ISS API; replication code for the derived calculations of this paper is available at https://github.com/nilysenok/PhD_Vol_trading. The volatility forecast is the hybrid econometric–gradient-boosting model of Lysenok (2025), built on a HAR-J core in the tradition of Corsi (2009) with the jump components of Andersen, Bollerslev, and Diebold (2007); its construction and accuracy are documented there and are not re-estimated here.

3.2. Strategies and forecast-integration approaches

Table 1. Six systematic strategies in three blocks

Strategy	Block	Signal	Risk management
S1 MeanReversion	Counter-trend	Z-score of price vs SMA	ATR stop-loss / take-profit
S2 Bollinger	Counter-trend	Bollinger Bands	ATR stop-loss / take-profit
S3 Donchian	Trend	Donchian channel breakout	Trailing stop
S4 Supertrend	Trend	Supertrend (ATR-based)	Trailing stop
S5 PivotPoints	Range	Pivot levels S1/R1	Pivot / ATR stops
S6 VWAP	Range	VWAP ± deviation band	VWAP band / ATR stops

Source: compiled by the author.

Each strategy is run under four integration modes. Approach A is the base system without volatility forecasts. Approach B (trade-parameter channel) scales stop-loss and take-profit distances proportionally to forecast volatility and holding time inversely to it. Approach C (regime filtering) computes the percentile rank of the forecast and zeroes positions in unfavorable volatility regimes: counter-trend strategies trade in low-volatility regimes, trend strategies in high-volatility regimes. Approach D (volatility targeting) scales position size inversely to forecast volatility with a binary gate at extreme levels.

3.3. Portfolio construction and statistical inference

For each strategy, a portfolio across the 17 instruments is formed under four weighting schemes: equal weights; inverse volatility; risk parity, in the sense of Maillard, Roncalli, and Teïletche (2010); and maximum Sharpe. Weights are estimated on training data and re-estimated annually; the six strategy portfolios are then combined into the multi-strategy portfolio. Statistical inference on Sharpe-ratio differences (Sharpe, 1994) uses paired bootstrap comparisons, in the spirit of Ledoit and Wolf (2008) with stationary-bootstrap resampling (Politis and Romano, 1994).

Results

4.1. Correlation structure and effective bets (H1)

Table 2. Correlation matrix of daily strategy returns (approach A, 2022–2026)

	S1	S2	S3	S4	S5	S6
S1	1.00	0.67	−0.24	−0.16	0.20	0.16
S2		1.00	−0.22	−0.11	0.19	0.20
S3			1.00	0.86	−0.10	−0.16
S4				1.00	−0.03	−0.15
S5					1.00	0.21
S6						1.00

Source: reproduced from Lysenok (2026, Figure 4); effective-bets calculation by the author.

The structure is block-diagonal in an economically interpretable way. Within blocks, correlations are high: 0.67 between the two counter-trend strategies and 0.86 between the two trend strategies, confirming that strategies sharing a mechanism share a return stream. Across blocks, the counter-trend and trend strategies are negatively correlated, from −0.24 to −0.11 with a block average of −0.18, providing a built-in hedge: strong trends that damage mean-reversion trades are precisely the episodes in which breakout strategies profit. Range strategies are weakly correlated with both blocks (0.16 to 0.21). The average pairwise correlation across all fifteen pairs is 0.09. Under equal weights and comparable strategy volatilities, the effective number of independent bets in the sense of Meucci (2009) reduces to $N / (1 + (N - 1)\cdot\bar{\rho}) = 6 / 1.44 \approx 4.2$ from six strategies, equivalently a diversification ratio of about 2.0 in the sense of Choueifaty and Coignard (2008), an unusually high ratio for strategies driven by a single family of signals on the same seventeen instruments. H1 is supported: the diversification benefit is engineered by pairing mechanisms with opposite exposures to trending regimes, not discovered by weight optimization.

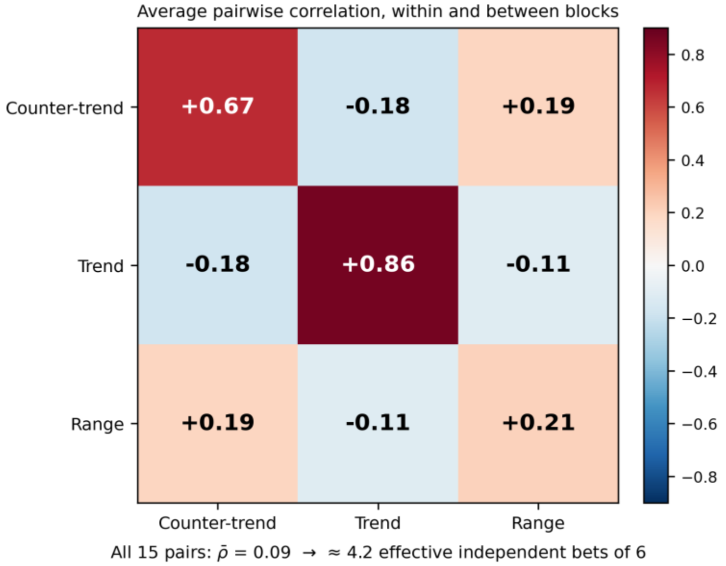

Figure 1. Block-level structure of the strategy correlation matrix: within-block and between-block average pairwise correlations; the average across all fifteen pairs is 0.09, implying approximately 4.2 effective independent bets. Source: author's calculations from the matrix of Table 2 (reproduced from Lysenok, 2026).

4.2. Background: the sizing channel, reproduced from the companion study

Table 3. Multi-strategy portfolio by integration approach (commission 0.05% per side)

Approach	Sharpe	Return, %	Vol., %	MDD, %	Exposure, %	ΔSharpe vs A	p
A (no forecasts)	1.32	19.6	4.4	−2.8	15.7	—	—
B (adaptive stops)	1.47	19.5	3.8	−1.6	13.0	+0.15	0.009
C (regime filter)	2.51	21.2	3.0	−0.9	7.2	+1.19	< 0.001
D (volatility targeting)	2.54	20.9	2.9	−1.1	12.2	+1.22	< 0.001

Source: reproduced from Lysenok (2026), Tables 8–9; bootstrap N = 10,000.

These levels are established in the companion study and are reproduced here only as the platform for what follows. Their reading is unambiguous: the trade-parameter channel is statistically detectable but economically minor (+0.15), while the two position-sizing channels dominate (+1.19 and +1.22), cutting portfolio volatility by a third, reducing the maximum drawdown to −0.9% and −1.1%, and, in the regime-filter case, halving average market exposure from 15.7% to 7.2%. The question this paper adds is when this sizing advantage matters most, and the answer, in the next section, is state-dependent.

4.3. The policy-rate environment (H3)

Table 4. Multi-strategy portfolio Sharpe ratio by year, average key rate, and the relative advantage of the regime filter

Year	A	B	C	D	Key rate, % (avg)	C / A
2022	1.68	1.82	2.86	3.69	10.6	1.70
2023	2.99	2.97	5.09	3.89	9.9	1.70
2024	1.56	1.78	2.98	2.29	17.4	1.91
2025	0.40	0.49	1.87	1.12	21.0	4.68

Source: author's calculations.

The four annual observations preclude formal regression, so the pattern is reported descriptively. As the key rate roughly doubled from 9.9% to 21.0%, the unassisted system deteriorated monotonically after 2023, from a Sharpe ratio of 2.99 to 0.40; the trade-parameter channel followed it down (0.49 in 2025). The sizing approaches also weakened but retained economically meaningful performance in every year, with the regime filter never below 1.87. In relative terms, the C/A ratio of the regime filter to the unassisted system widened from about 1.7 in 2022–2023 to 1.9 in 2024 and 4.7 in 2025. Two forces plausibly combine: high rates raise the return on the capital that sized approaches release into the money market, and the volatility environment that accompanies tight policy is the very regime in which the filter removes the least productive trades. Whichever force dominates, the practical message is the same: forecast-based position sizing is most valuable when a high policy rate makes unassisted active trading hardest, which is when an institutional investor benchmarked against the money-market rate needs it most. H3 is supported at descriptive strength.

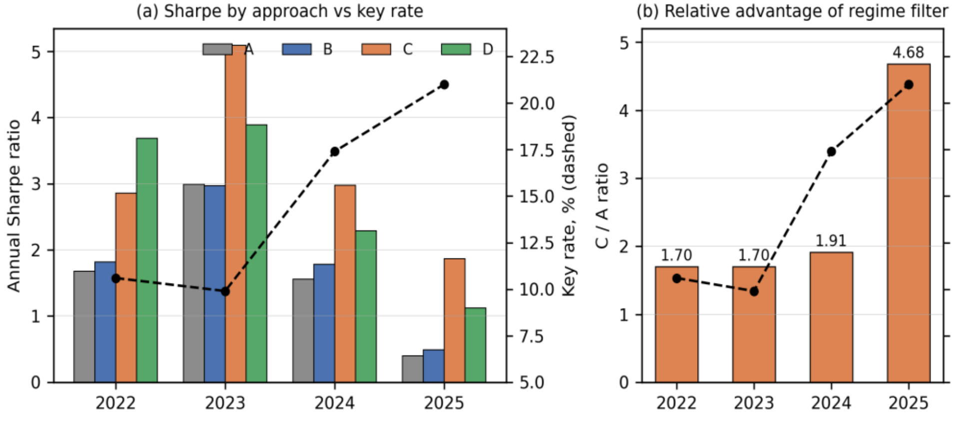

Figure 2. Policy-rate dependence of multi-strategy performance: annual Sharpe ratios by integration approach against the average Bank of Russia key rate (panel a) and the relative advantage of the regime filter, C/A (panel b). Source: author's calculations.

Discussion

Read together, the three results locate the value of a volatility forecast in a multi-strategy system. The forecast is not primarily a trade-tuning device: reshaping stops and holding periods yields a statistically significant but small improvement. Its value is concentrated where it controls capital at risk, through regime filtering and volatility targeting, and this value is amplified by the portfolio architecture, because six strategies built on opposing market mechanisms supply 4.2 effective bets whose combination stabilizes the aggregate return stream before any forecast is applied. The rate analysis then shows that the sizing channels are not a fair-weather refinement: their relative contribution grows as the environment worsens, quadrupling in the 21% key-rate year in which the unassisted system barely cleared zero.

The findings connect to two strands of literature. The dominance of sizing over parameter tuning parallels the conclusion of the volatility-managed portfolio literature that exposure control, rather than signal refinement, is the operative margin (Harvey et al., 2018); our within-system design shows that the same hierarchy holds inside an active multi-strategy book, not only for passive factor exposures. The second connection is to DeMiguel, Garlappi, and Uppal (2009): the observation that equal weighting is best for four of six strategy portfolios, combined with the deliberate near-orthogonality of the blocks, suggests that in strategy space, as in asset space, diversification design dominates weight optimization, and the productive locus of effort is the correlation structure of the building blocks.

For practice, the decomposition implies an allocation of research effort. Improving forecast accuracy feeds all channels, but the marginal value of accuracy flows overwhelmingly through sizing decisions; a desk that spends its modelling budget on trade-parameter refinement is optimizing the weak channel. And for an institutional investor evaluated against the money-market rate in a high-rate economy, the rate-dependence result implies that volatility-informed sizing functions as protection of the performance benchmark precisely in the years when active equity trading is least rewarding.

Limitations and future research

Four limitations bound the conclusions. First, the sample of 17 continuously traded large caps covers roughly 80% of market capitalization but is a selection of liquid survivors; the decomposition describes the investable core of the market, and extending it to a survivorship-free universe including delisted and suspended stocks is the natural next step. Second, the window contains four annual observations of the policy rate, so the rate-dependence result is descriptive rather than inferential. Third, all results condition on one forecasting model and one family of strategy specifications, documented in the companion studies; the channel hierarchy could differ for other signal families. Fourth, the evaluation window 2022–2026 is a structurally unusual period for the Russian market, which strengthens the paper as a stress test of the construction but cautions against extrapolating the levels of performance.

Three extensions follow naturally. First, rebuilding the universe without the survivorship screen, including the stocks delisted or suspended in 2022, would test whether the decomposition survives on the full cross-section. Second, intraday data would sharpen both the volatility forecast and the regime classification. Third, replication in other high-rate emerging markets, with Brazil under a 13–15% Selic as the natural candidate, would show whether the policy-rate channel generalizes beyond the Russian setting.

Conclusion

This paper asked why, and under what conditions, volatility forecasts create value in an active multi-strategy book, extending the companion evidence of Lysenok (2026) on MOEX index stocks with a decomposition that the companion does not report: the diversification arithmetic of the construction and the dependence of the sizing advantage on the policy-rate environment. The findings are three. First, the diversification benefit is engineered rather than discovered: six strategies built on opposing market mechanisms exhibit an average pairwise correlation of 0.09 with a natural hedge between the trend and counter-trend blocks, delivering approximately 4.2 effective independent bets and a diversification ratio of about 2.0; as a direct consequence, the choice of weighting scheme is second-order, and equal weights are best for four of six strategy portfolios. Second, against this background the companion channel hierarchy stands: position sizing dominates trade-parameter tuning by an order of magnitude (+1.19 and +1.22 versus +0.15 in Sharpe terms, or ΔCE of +2.07% per year at $\gamma = 10$). Third, the sizing advantage is state-dependent in the direction that matters: as the key rate rose to 21%, the unassisted system's annual Sharpe ratio collapsed from 2.99 to 0.40 while the regime-filtered system never fell below 1.87, widening the relative advantage from roughly 1.7 to 4.7 times.

The implications are practical. A desk allocating research effort should direct it to the sizing decision, where forecast information is transmitted, rather than to trade-parameter refinement; and for an institutional investor benchmarked against the money-market rate in a high-rate economy, volatility-informed sizing functions as protection of the benchmark in the very years when unassisted active equity trading is least rewarding. Establishing whether these conclusions survive on a survivorship-free universe and on intraday data is the natural next step.

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