AR-GARCH Forecasting Writeup

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1 Overview

This strategy applies a rolling AR-GARCH model to forecast LULU price movements around index inclusion dates. My goal was to capture short-term price dislocations triggered by forced flows from passive funds. The logic relies on the fact that such dislocations are typically shock-driven (AR behavior) and exhibit volatility clustering (GARCH behavior). I designed a one-day holding strategy triggered by rolling return forecasts. Unlike my momentum and mean reversion strategies, which execute a single trade per inclusion event, this strategy targets a single stock (LULU) and operates at higher frequency, generating signals continuously over a full year starting from the inclusion date.

2 Data

- Polygon.io: Daily OHLCV data for LULU
- FRED API: Daily Fed Funds Rate (https://fred.stlouisfed.org/docs/api/fred/)

The dataset covered 180 days before and 365 days after the S&P 500 announcement. Any windows shorter than 60 days were skipped.

3 Trade Logic and Filters

Signal construction:

- At each step, fit an AR(5)-GARCH(1,1) model on the past 60 days of returns.
- Forecast the next day return, convert to price.
- Compute forecast error = forecasted price - actual price.
- Buy at open. Go long if error > 2.2; short if error < -2.2.
- Hold 1 day unless stop loss is hit by closing time

Why AR-GARCH: LULU showed clear volatility clusters and reactive behavior, consistent with post-inclusion flows. AR(5) captures autocorrelation from price shocks. GARCH(1,1) captures conditional variance. Modeling returns avoids non-stationarity and preserves percent-based scaling.

Why LULU: LULU was selected due to its high predicted trade flow following its S&P 500 inclusion and its strong liquidity profile within a large-cap index. Beyond practical factors like slippage minimization and data availability, this choice is further supported by the theory of inelastic markets. Gabaix and Koijen (2022) show that aggregate demand shocks (such as those from passive index funds) can have persistent and disproportionate effects on asset prices due to low elasticity in

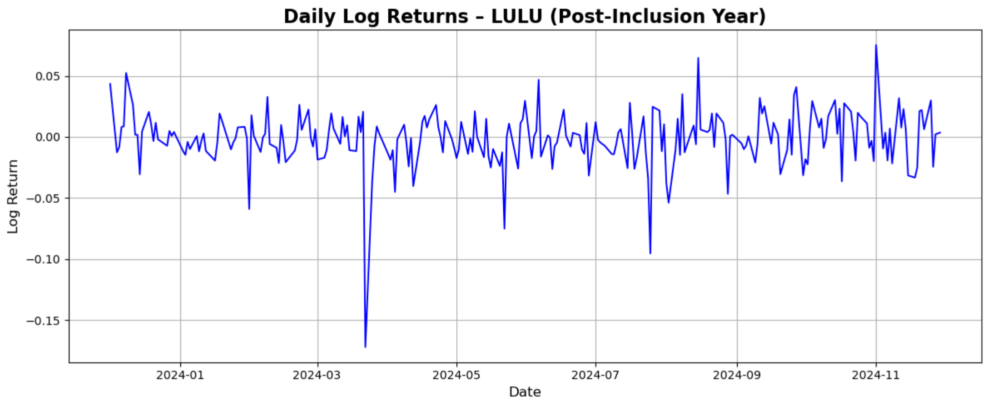

Figure 1: Daily log returns of LULU over the 1-year trading period. Volatility clustering is evident where large return magnitudes are followed by further large moves.

equity markets. Their framework helps explain why large-cap, high-liquidity names like LULU may still experience nontrivial price dislocations around inclusion events, making them viable candidates for short forecasting strategies

Model Validation Visual analysis of the AR-GARCH forecast shows that the model was well suited. The autocorrelation function (ACF) showed statistical outliers outside of the confidence band, enough to know that it was not due to sampling bias or white noise. However, this is only prevalent when the ACF is plotted for the entire trading interval. In shorter intervals, the ACF looks well suited with no outliers, which likely means that volatility spikes during the trading window may contribute to the outlandish ACF when modeled over the entire interval.

4 Risk Management

- Risk per trade: 1% of portfolio ($50k max loss)
- Stop loss: 10% adverse move from entry
- Sizing: min(1% ADV, $risk / (entry × stop_loss_pct))
- Overnight cost: Fed Funds + 1.5% (long) / +1.0% (short)

5 Capital Constraints + Fees

- Portfolio: $5M
- Execution fees: $0.01/share
- Daily overnight fees included

6 Hedging

No hedging was applied. Because this model is designed to trade only a single stock based on short-term statistical inefficiencies, adding ETF hedges would dilute alpha. The model benefits from unfiltered exposure to LULU's flow-induced pricing effects.

7 Sharpe Ratio and PnL

The Sharpe ratio was computed using the daily returns:

$$\text{Sharpe Ratio} = \frac{\bar{r}_d - r_f}{\sigma_d} \cdot \sqrt{252}$$

Note that daily returns were computed using the daily PnL divided by the capital **risked** per trade—not capital **invested** per trade.

- Total Net PnL: `$2,168,050.60`
- Sharpe Ratio: `2.75`
- Trades: 125

Returns are measured net of transaction and overnight costs. Equity curve is computed cumulatively from daily net PnL.

Figure 2: AR-GARCH net PnL over a year, starting on inclusion date (LULU).

Note: This strategy executes frequently on high-confidence signals. The Sharpe ratio is annualized using 252 trading days.

8 Holding Period Experiments

- 1-day hold: best performing setup
- Multi-day hold: added exposure to reversal risk
- Re-entry: possible if new signal triggers after flat

9 Future Improvements

- Add cointegrated cross-signals for multi-asset models
- Dynamic thresholds based on implied volatility regime

10 Conclusion

This AR-GARCH forecasting strategy was developed to capitalize on temporary dislocations caused by predictable fund flows around index inclusion events. By focusing on a liquid S&P 500 stock with large projected flows (LULU), and using a statistically grounded signal framework, the model delivered a Sharpe ratio of 2.71 and consistent profits over a year of trading. The structure is flexible enough to scale across other names and inclusion cycles, and could serve as a foundation for more robust event-driven models with cross-asset signals or even options overlays in conjunction with stochastic volatility models.

References

[1] Gabaix, X., & Koijen, R. S. J. (2022). In search of the origins of financial fluctuations: The inelastic markets hypothesis. *Journal of Financial Economics*, 146(2), 527–553.

Also: "Advanced Algorithmic Trading" by Michael Moore