Estimation of risk interaction structure in financial networks

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Introduction

What is the Risk Interaction Structure

Risk Interaction Structure

1

Definition

Risk interaction structure is a framework that describes how risks are propagated through dynamic dependencies among stocks within a financial network.

2

Why it is important?

Modeling and analyzing risk interaction structures can help market participants better predict systemic risks.

3

Stock risk

Stock risk refers to the uncertainty or volatility in the returns of a stock investment. In this study, the risk of a stock is represented by its volatility and its variations.

4

Volatility

An indicator used to measure the magnitude of fluctuations in stock returns

$$\text{Volatility}_t = \log((\text{Log Return}_t)^2)$$

$$\text{Log Return}_t = \log(P_t) - \log(P_{t-1})$$

Research Challenges

Unknown Network Structure

1

In financial markets, the interactions between assets are typically unobservable, making it challenging to directly determine the degree of dependence and transmission mechanisms between assets.

Structural Breaks

2

Stock time series often exhibit sudden changes, such as market crashes or policy adjustments, which can significantly impact the dynamic propagation of risks.

Volatility Dynamics

3

Risk propagation within financial networks requires modeling both temporal and **spatial dependencies**.

The spatial dependence of stocks refers to the phenomenon where a stock's volatility is not only determined by its own historical returns but also influenced by other stocks

Basic Steps

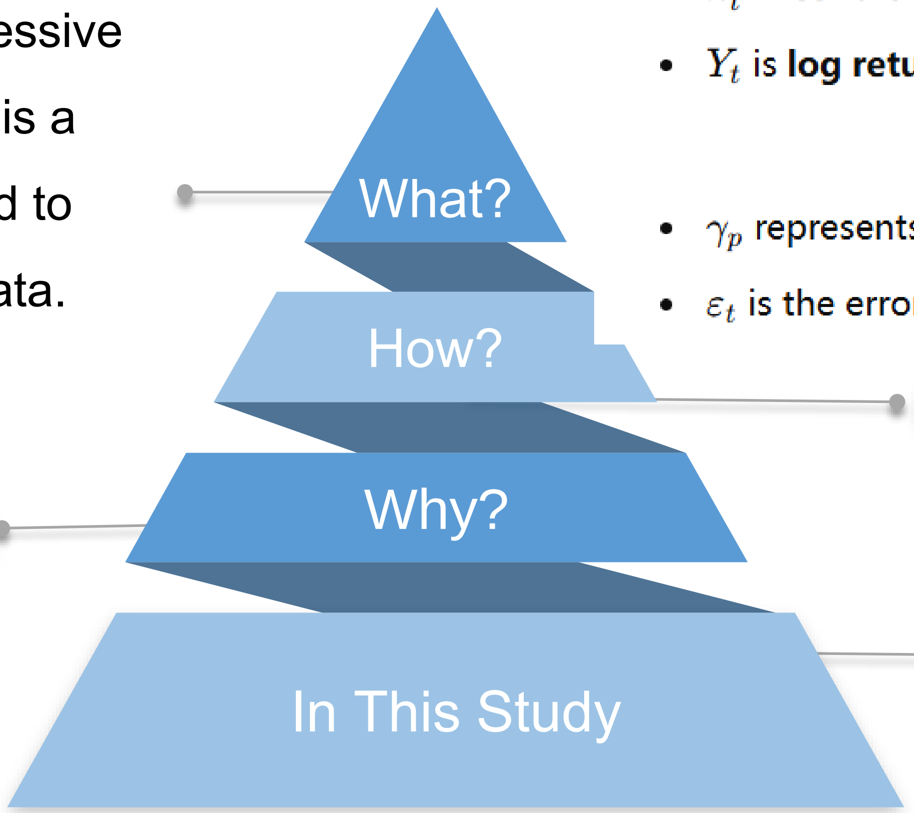
1. Data selection
2. Constructing Log-ARCH Models
3. Removing Heteroskedasticity
4. Applying Spatiotemporal Model and 2-stage LASSO

What is Log-ARCH?

$$\log h_t^2 = \omega + \sum_{p=1}^{P} \gamma_p \log Y_{t-p}^2 + \varepsilon_t$$

What is Log-ARCH?

Log-ARCH (Logarithmic Autoregressive Conditional Heteroskedasticity) is a variant of the ARCH model used to model volatility in time series data.



Mathematical Representation

where:

- h_t^2 is **conditional variance (volatility)**.
- Y_t is **log return**:

$$Y_t = \log(P_t) - \log(P_{t-1})$$

- γ_p represents the autoregressive coefficients.
- ε_t is the error term.

Why Use Log-ARCH?

1. Improving model stability.
2. Better captures volatility clustering effects in financial markets.

Log-ARCH in Research

1. Estimate volatility for individual stocks.
2. Calculate standardized residuals

Basic Steps

1 Data selection

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4 Applying Spatiotemporal Model and 2-stage LASSO

Two-Stage LASSO

Stage 1- Identifying Candidate Change Points

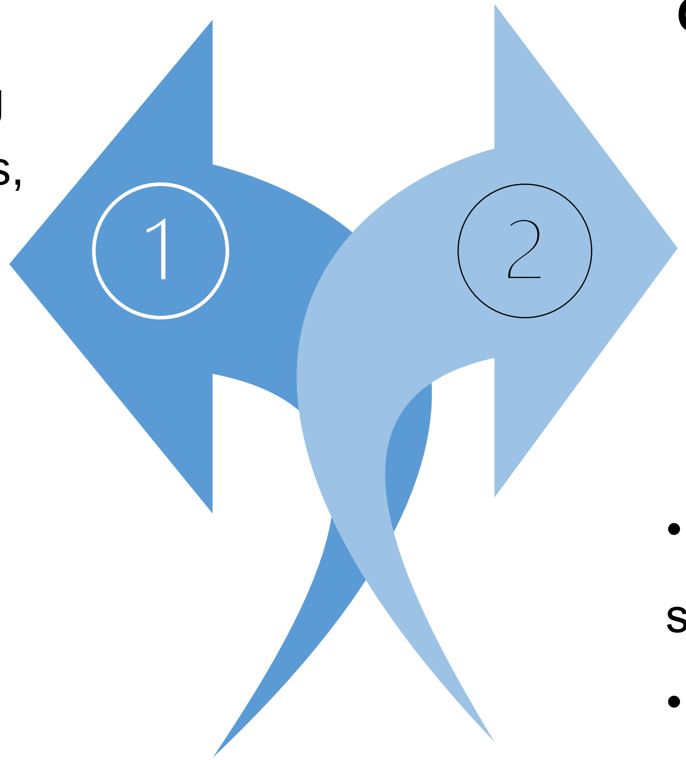
- **Objective**: Instead of directly estimating the spatial dependencies between assets, the first step detects potential structural breaks in financial time series.

- Given a time series Y_t:

$$Y_t = X_t\beta + \epsilon_t$$

$$\hat{\beta} = \arg\min_{\beta} \sum_t (Y_t - X_t\beta)^2 + \lambda \sum |\beta|$$

The penalty parameter λ ensures that only significant breakpoints are retained.



Stage Two: Estimating the Spatial Weight Matrix

Objective: Given the candidate change points, the second stage estimates risk interaction relationships among stocks through the spatial weight matrix $\boldsymbol{W}$.

$$Y = \underbrace{\Psi a}_{\text{mean shifts}} + \underbrace{Z\xi}_{\text{spatial dependence}} + \varepsilon,$$

- a captures change-point-based mean shifts at each station
- $\xi = vec(W)$ are the spatial weights.
- Constraint**:** Each row of $\boldsymbol{W}$ sums to 1 to ensure interpretability in financial flows.

Advantages of 2-stage LASSO

ARCH with known weight matrix

Manually defines the distance calculation method.

Does not consider structural breaks in the data.

Assumes that all stocks have some level of connection.

Does not explicitly address endogeneity issues.

VS

2-STAGE LASSO

Data-driven

Identifies and adjusts for structural breaks in the data.

Encourages sparsity, retaining only the most important weights.

Addresses endogeneity issues effectively.

Suitable for high-dimensional, irregular, or non-geographically dependent data.

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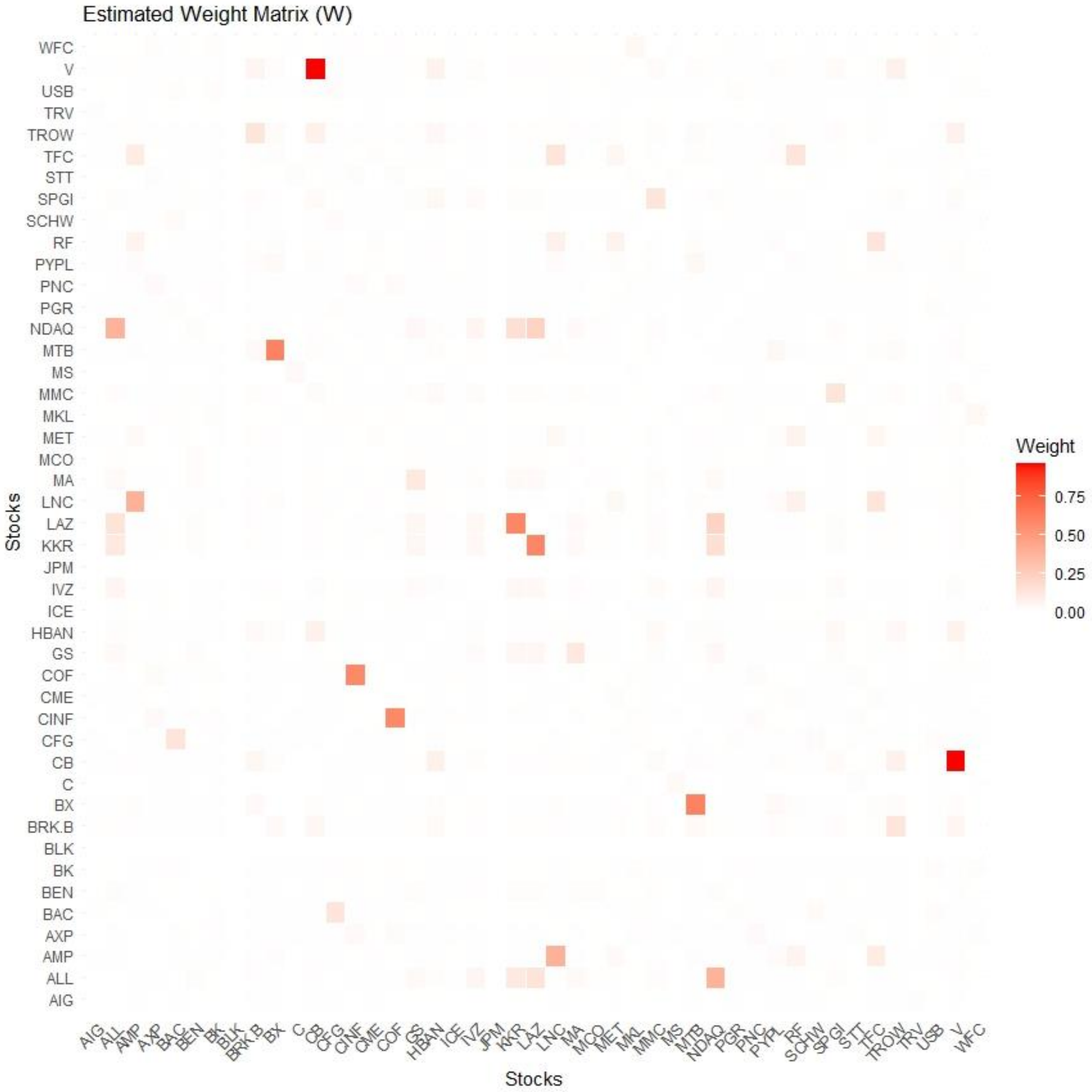
Data

Data selection

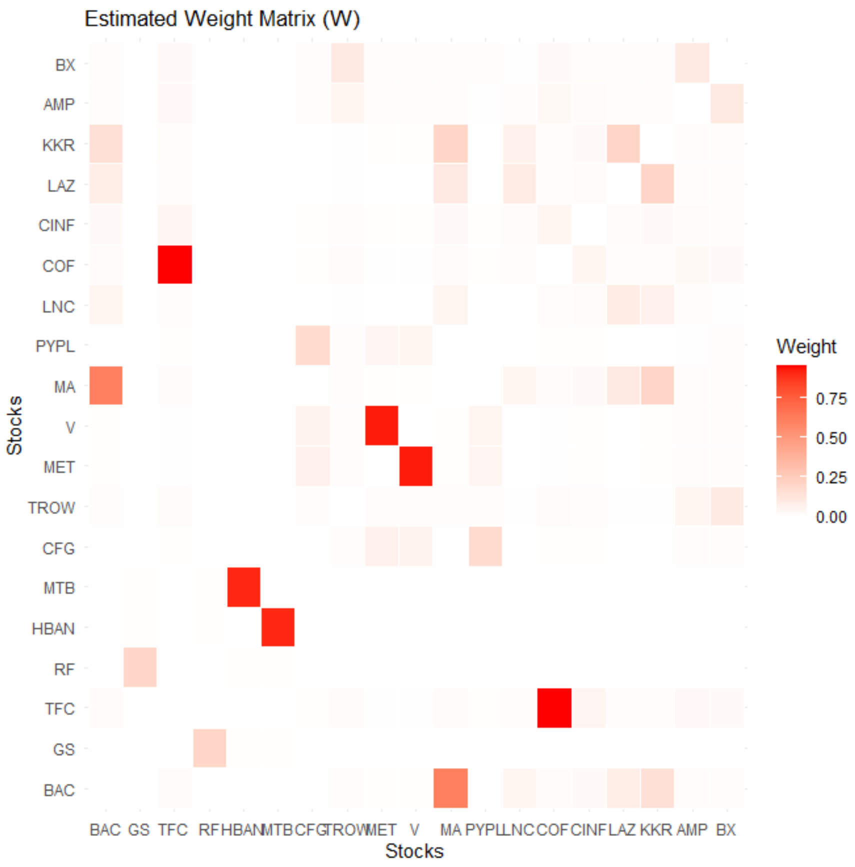


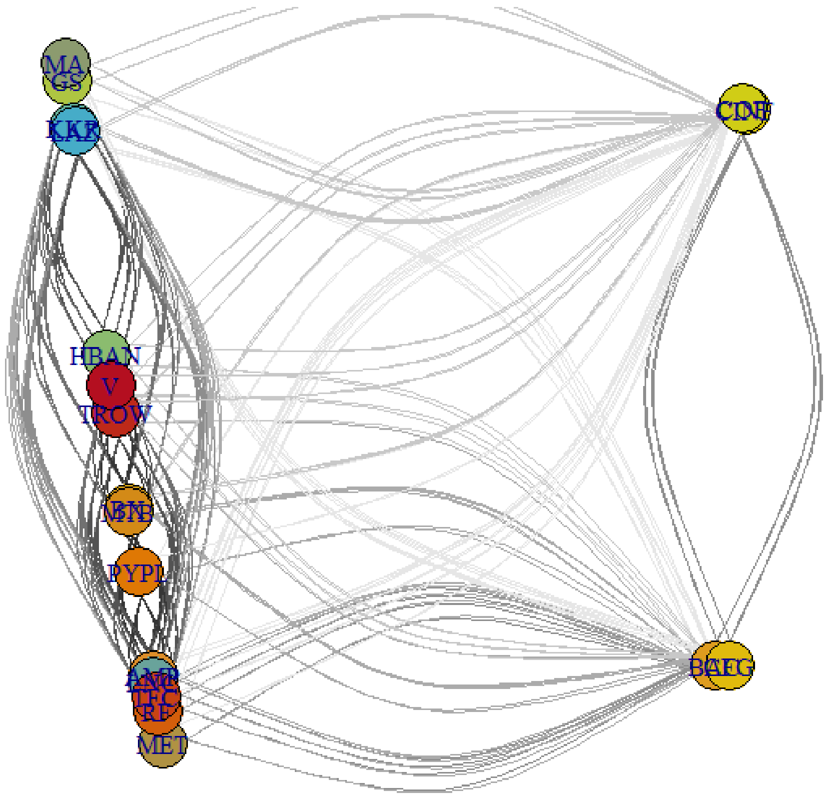
At the beginning, we selected the stocks of 50 financial companies in the United States. Get daily log returns from January 2022 to January 2025 from Yahoo Finance.

Then, the log-squared returns of each stock are computed.

Next, the distance between stocks is defined using the Autoregressive Principal Component (AR.PIC) method.
By applying the log-squared return time series to the AR.PIC approach, the similarity or distance between stock time series is calculated.

Data selection

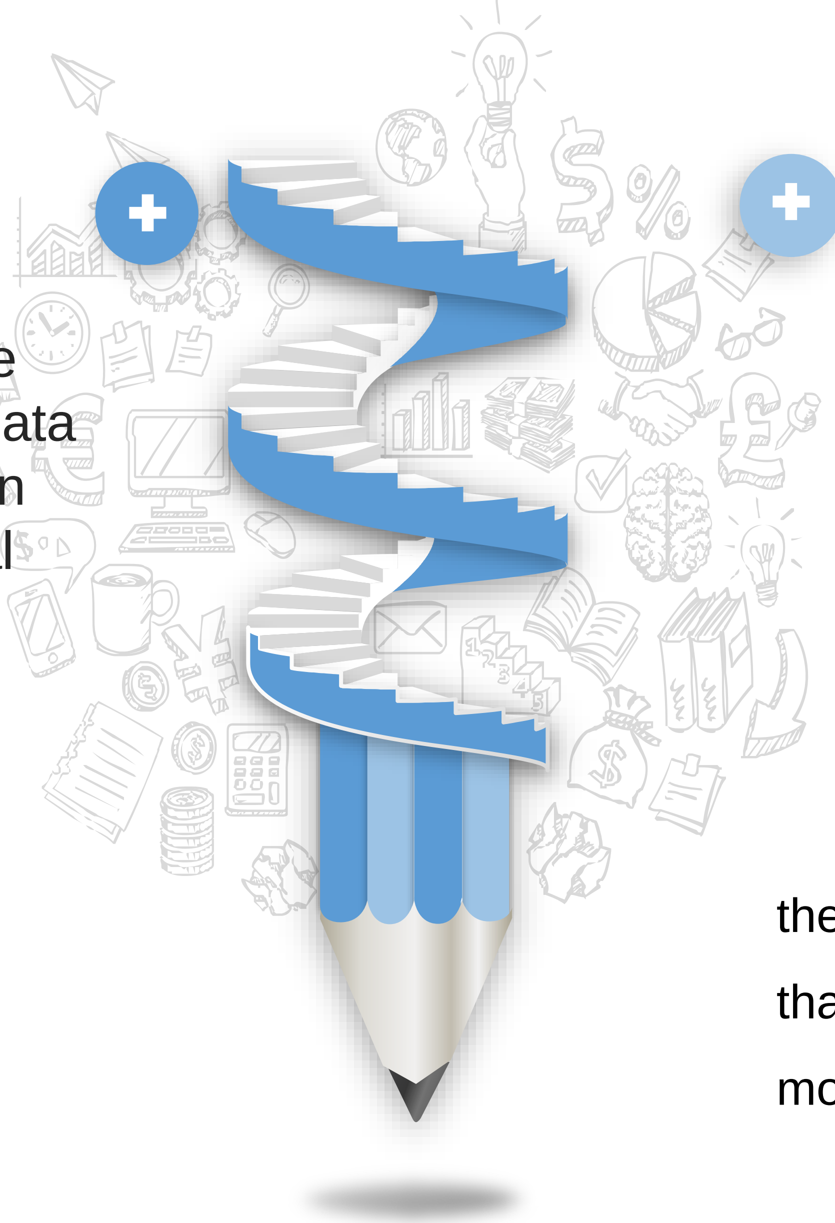




Monte Carlo simulation

Step 1: Generate data

Randomly rearrange the variable values y to generate a pseudo data set y (j). Keep the spatial position unchanged and break the spatial structure.



Step 2: Calculate the semi-variogram for the new data

$$\hat{\gamma}(h) = \frac{1}{2|N(h)|} \sum_{(i,j)\in N(h)} (y_i - y_j)^2$$

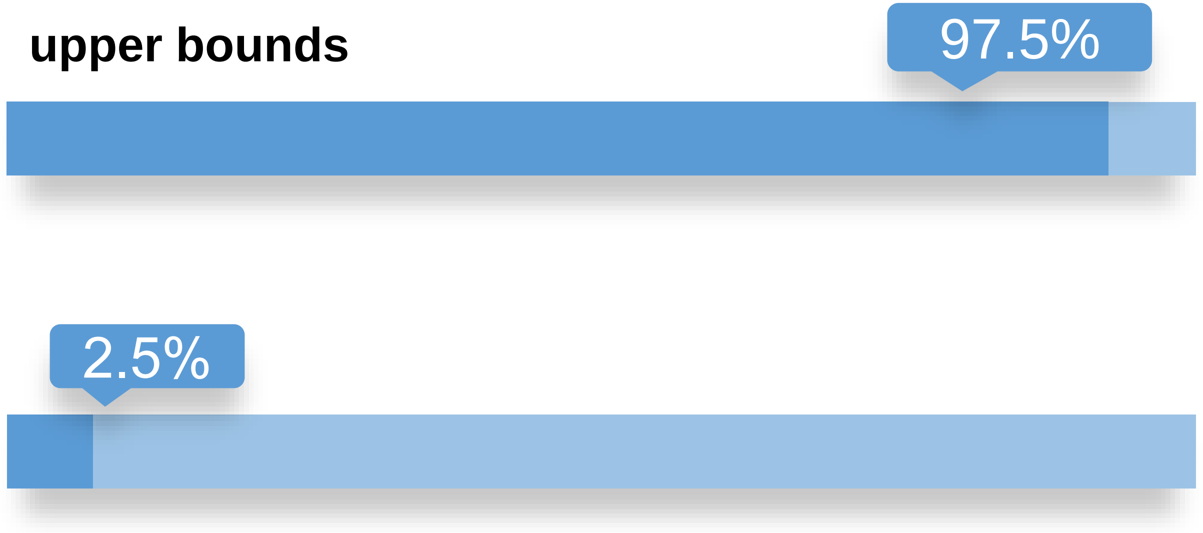
h: Distance range (grouping).
$N(h)$: All pairs of data points.
$y_i y_j$: Variable values (e.g., stock returns).

the semi-variance value is low, indicating that stock pairs with close distances are more similar. vice versa.

Monte Carlo simulation

Step 3: Generate lower and upper bounds

upper bounds



lower bounds

Form confidence intervals under the "no spatial autocorrelation assumption

within the upper and lower limits → there is no significant spatial autocorrelation.

exceeds the upper and lower limits → there is significant spatial autocorrelation.

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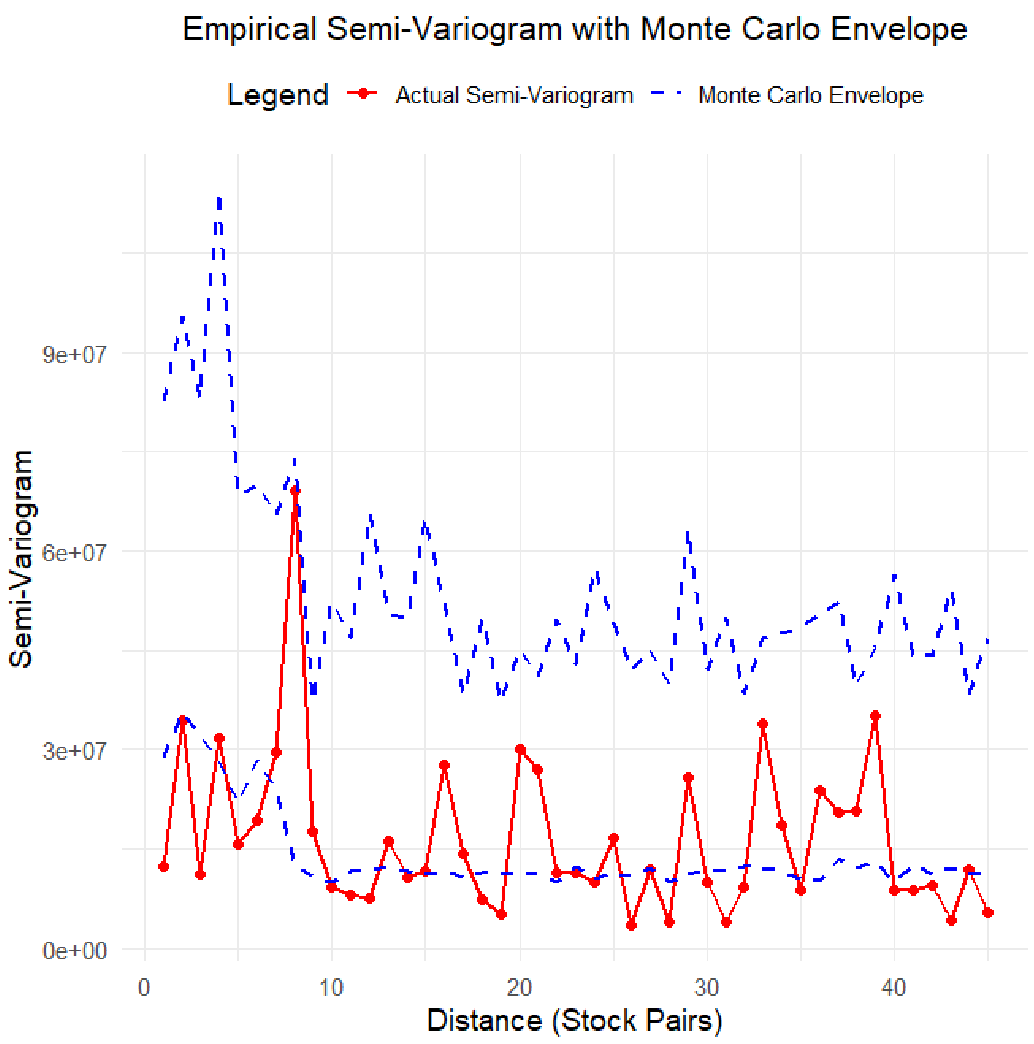
Monte Carlo simulation



Red line (Actual Semi-Variogram):

Represents the difference in returns of actual stock pairs and the pattern of changes with distance.

Blue dotted line (Monte Carlo Envelope):

Represents the expected range of yield differences (95% confidence interval) under the assumption of "no spatial autocorrelation"

Conclusion

The red line **significantly exceeds** the blue dashed line, indicating that there may be spatial autocorrelation between these stock pairs.

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Conclusion

Basic Steps

1. Exploratory data analysis
2. Constructing Log-ARCH Models
3. Removing Heteroskedasticity
4. Applying Spatiotemporal Model and LASSO

Exploratory data analysis

- Data Collection
- Logarithmic rate of return calculation

$$\text{Log Return}_t = \log(\text{Price}_t) - \log(\text{Price}_{t-1})$$

$$\text{Log-Squared Log Return}_t = \log\left((\text{Log Return}_t)^2\right)$$

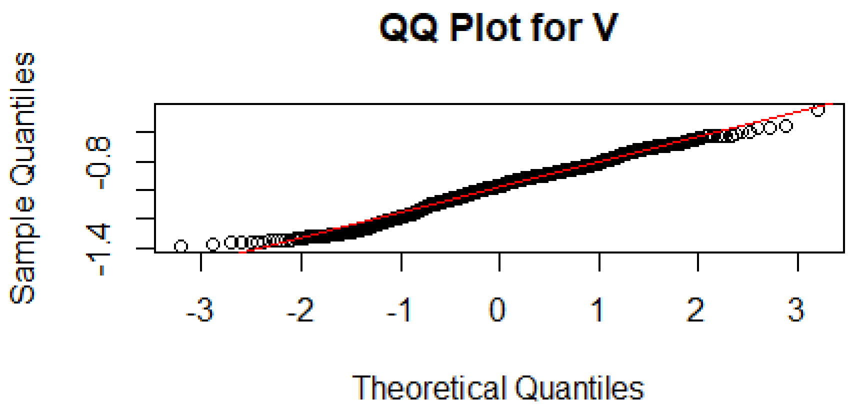
- Remove missing values

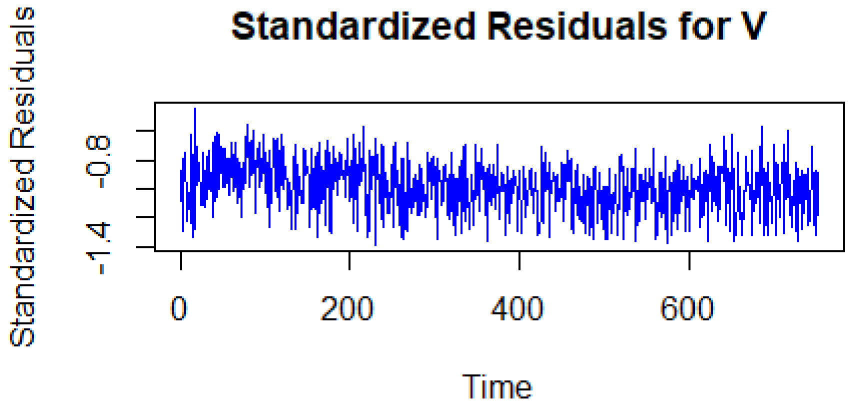
Sub-Sector	Companies
Banking	Bank of America, Goldman Sachs, Truist Financial, Regions Financial, Huntington Bancshares, M&T Bank, Citizens Financial, Capital One
Insurance	MetLife, Lincoln National, Cincinnati Financial
Payment Processing	Visa, Mastercard, PayPal
Investment Management	T. Rowe Price, Lazard, Ameriprise Financial
Private Equity	KKR & Co., Blackstone


Price Trend for V
[2022-01-03/2024-12-31]
Last 316.040008544922
300
250
200
Volume (millions):
3,963,800
25
15
5
Jan 03 2022
Jul 01 2022
Jan 03 2023
Jul 03 2023
Jan 02 2024
Jul 01 2024
Dec 31 2024


Price Trend for MA
[2022-01-03/2024-12-31]
Last 526.570007324219
500
450
400
350
300
Volume (millions):
1,942,600
10
6
2
Jan 03 2022
Jul 01 2022
Jan 03 2023
Jul 03 2023
Jan 02 2024
Jul 01 2024
Dec 31 2024

Constructing Log-ARCH Models





Aim

Constructed individual Log-ARCH models for each stock to capture short-term volatility dynamics and temporal autoregressive effects.

Specific Procedures

Defined the specifications of the Log-ARCH model and set the variance and mean structures and fitted the Log-ARCH model for each stock , applied it to each stock’s log return series, and extracted the standardized residuals.

Conclusion

These residuals measure the deviation after model fitting and reflect the portion of volatility not explained by the model, which is the temporal autoregressive effects.

Removing Heteroskedasticity

Aim

To address the issue of heteroskedasticity in the return series by standardizing the residuals using the volatility components estimated from the Log-ARCH models.

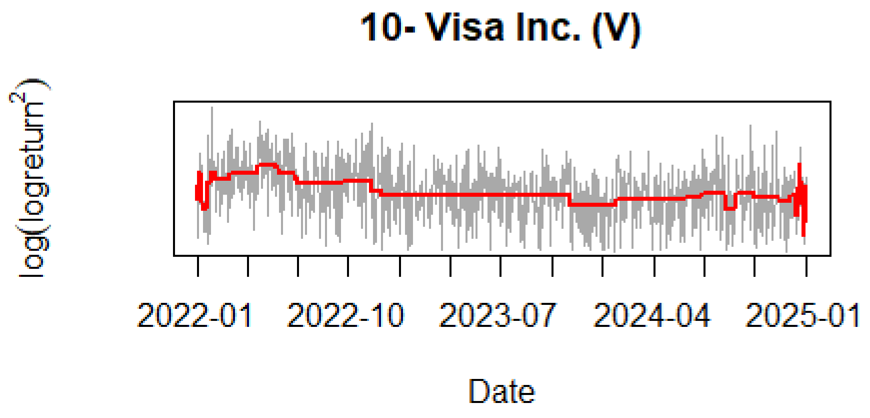
Specific Procedures

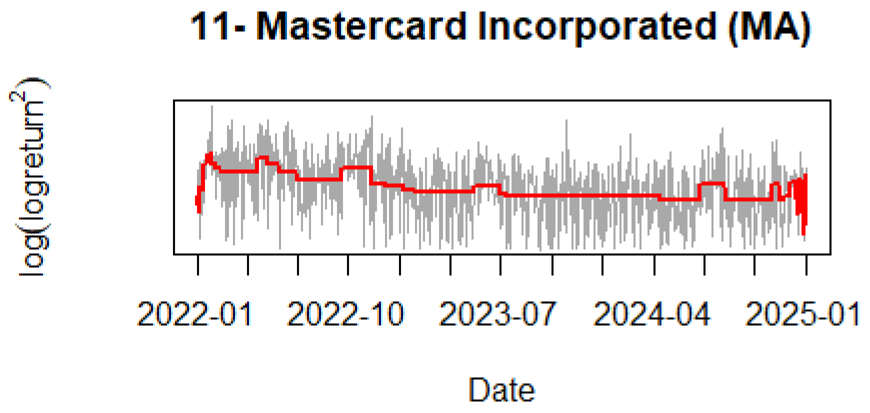
Volatility components estimated from the Log-ARCH models were used to calculate standardized residuals by subtracting the original log returns by their corresponding volatility estimates.

Effect

The transformation removed heteroskedasticity from the return series, resulting in residuals with consistent variance over time and a more stable dataset for subsequent analysis.

LASSO-stage 1 (Change Point Detection)





Ridge Regression

Initial selection of change points using Ridge with optimized λ.

Adaptive LASSO

Adaptive LASSO was applied to refine change point positions by computing weighted factors to adjust variable importance and re-estimating for optimized locations.

Cross-validation

Conducted cross-validation to optimize the regularization parameter λfor reliable detection results.

LASSO-stage 2 (Full Model Construction)

Objective

- To estimate spatial dependency relationships ($\widehat{W}$) across stocks.
- To balance model complexity and accuracy through cross-validation.

1.Identifying Change Points

- Extracted potential change points for each stock from Stage 1.
- Assembled change-point information into a matrix $X.CP$.

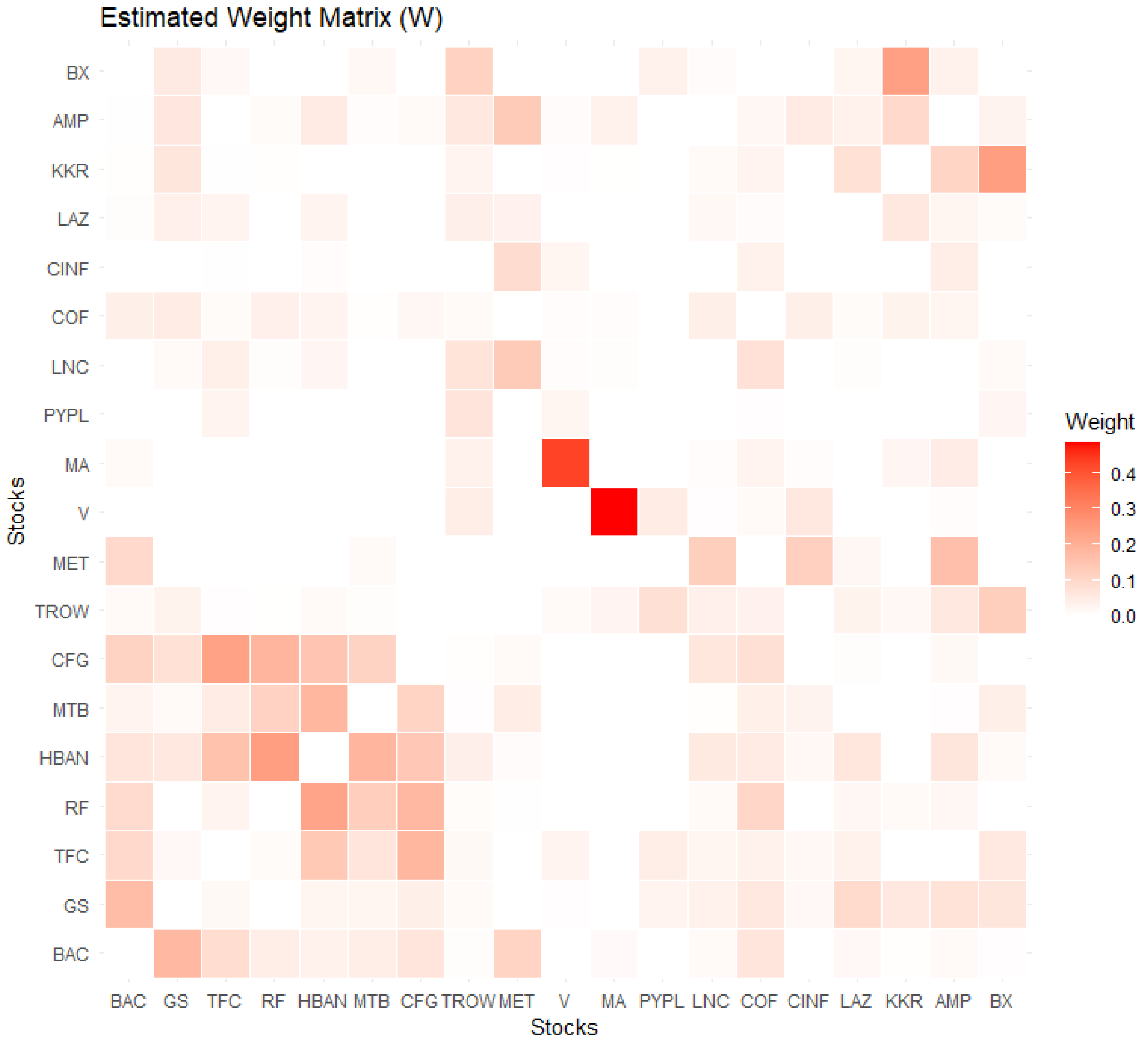
2.Looping Over Penalty Parameters (λ)

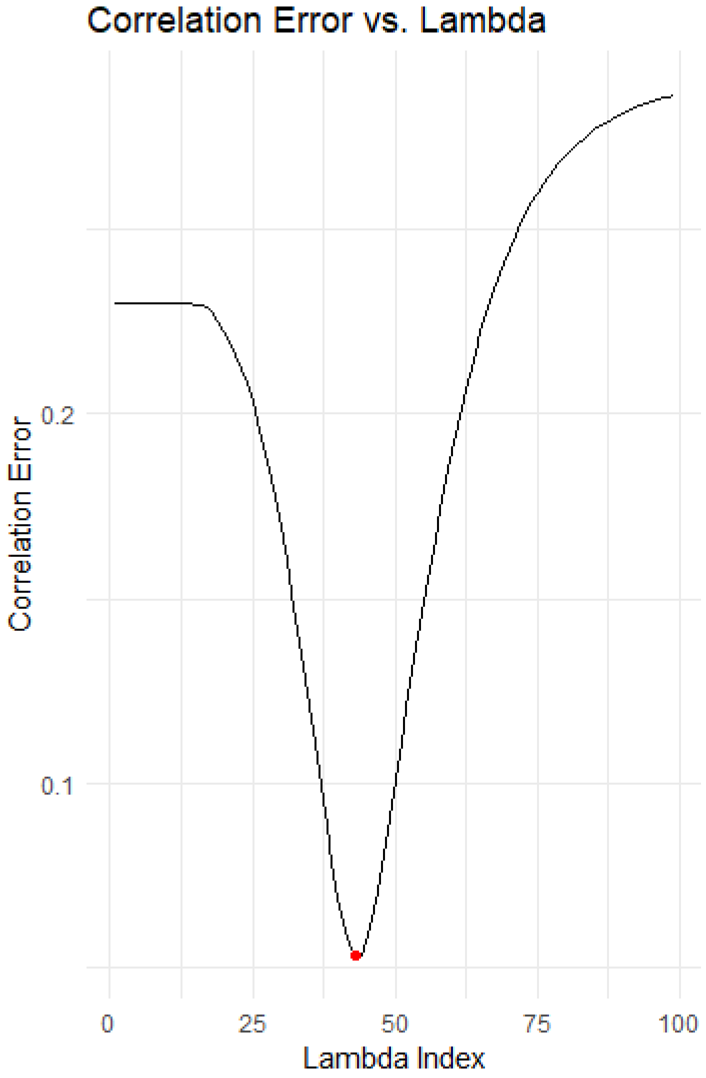
- **Extraction:** Extracted relevant columns of X for change points and spatial weights.
- **Model Training:** A penalized regression model is trained under **custom constraints**
- **Storage:** Fitted coefficients from the model are stored back into the parameter vector (β).

3. Selecting Optimal λ

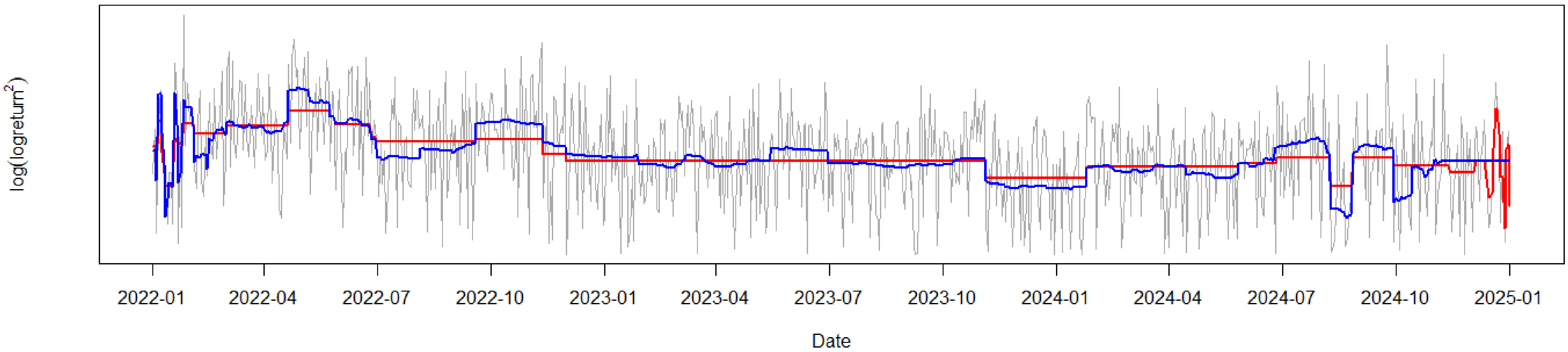
Chose λ minimizing mean correlation error across folds.

LASSO-stage 2 (Full Model Construction)

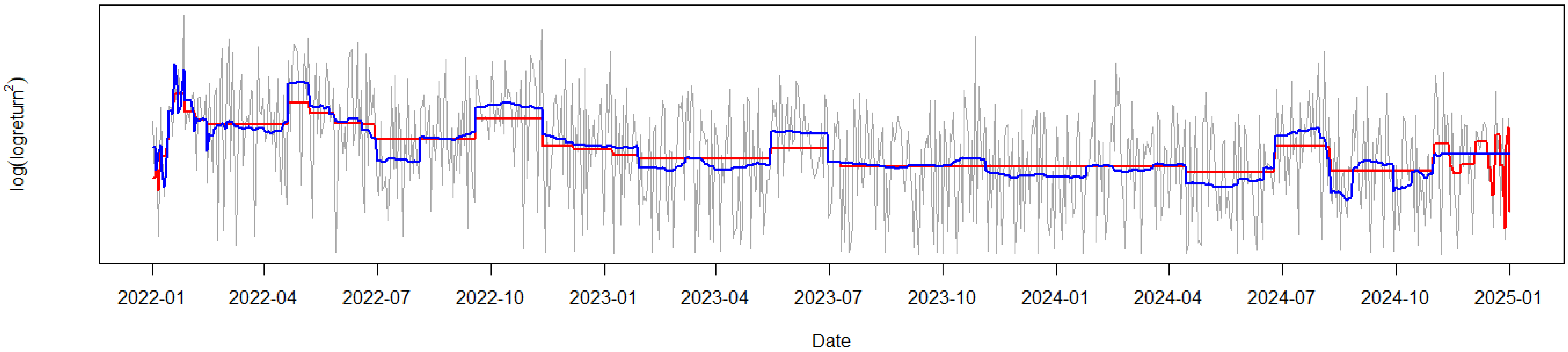




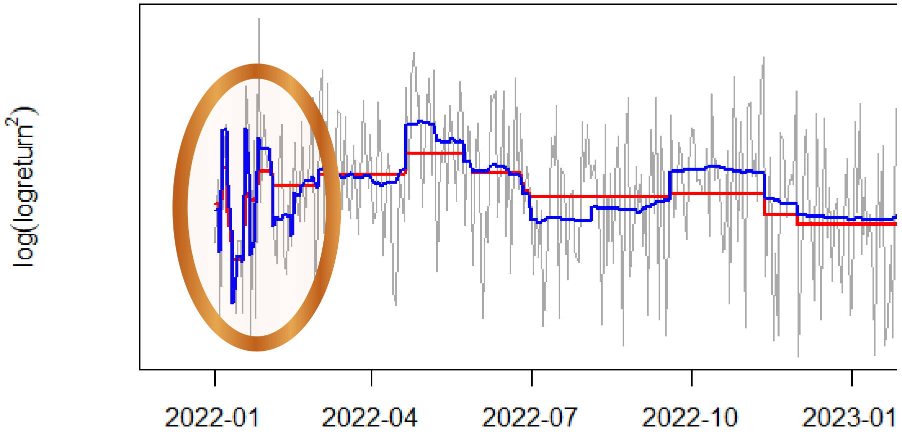
10- Visa Inc. (V)



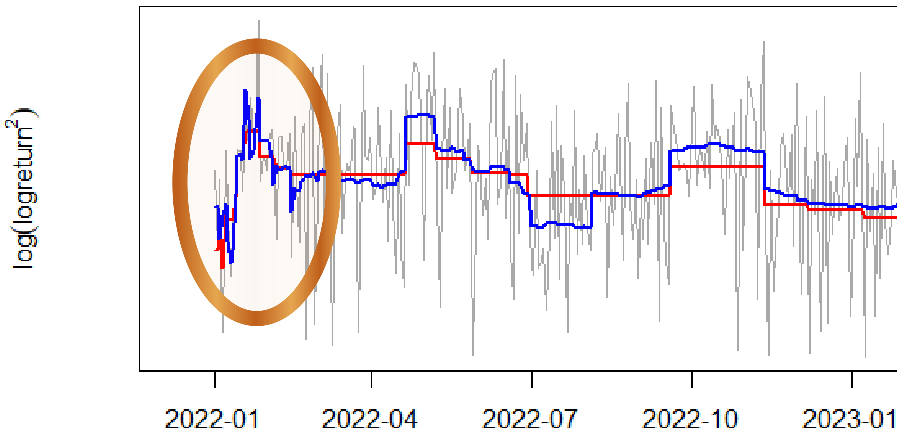
11- Mastercard Incorporated (MA)



First Quarter 2022 Fed Tightening & Russia-Ukraine Conflict

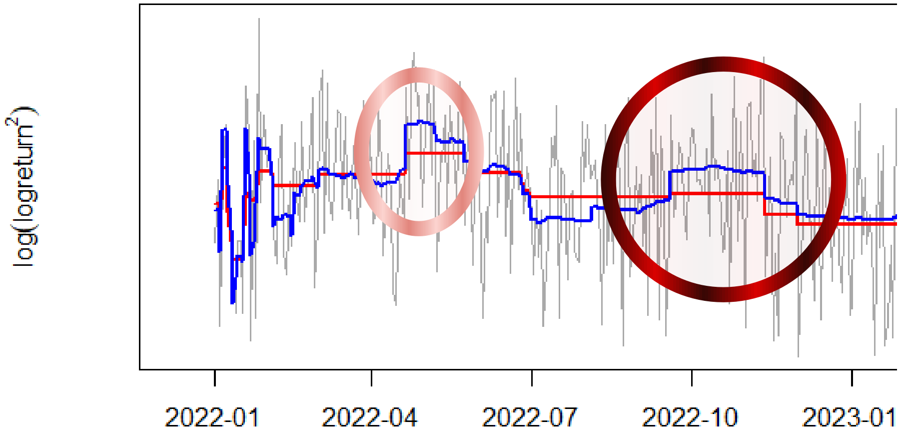


- **January 2022**: Fed′ s announcement of faster rate hikes and balance sheet reduction triggered a sell-off in high-valuation stocks.
- Impact: Visa (-3.3%), Mastercard (-2.7%) experienced significant declines in early January.



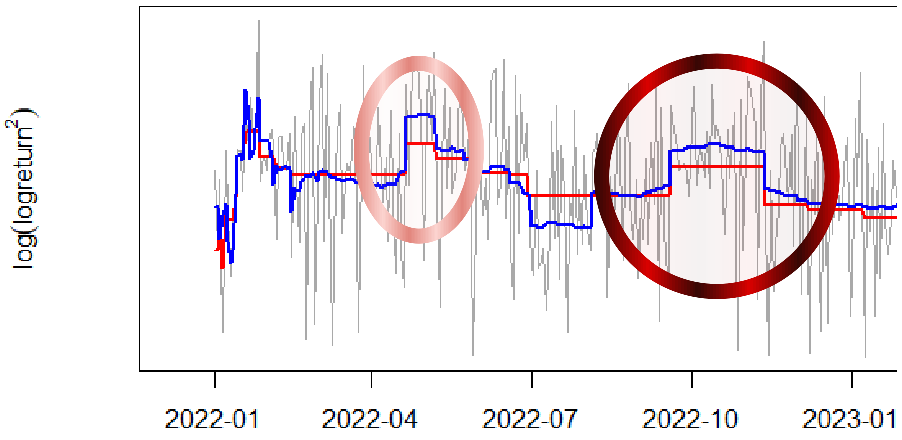
- **February to March**: Russia-Ukraine conflict escalated, with financial sanctions disrupting global payment systems.
- Impact: Visa (-2.4%), Mastercard (-2.1%) declined.
- Post-announcement of Russian operations suspension in early March, further drops were noted (Visa: -4.1%, Mastercard: -3.9%).

Second & Third & Fourth Quarters 2022



Second & Third Quarters: Inflation Concerns & Travel Recovery

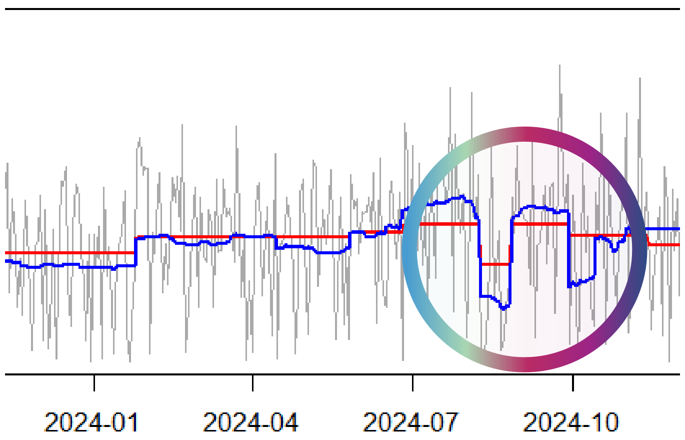
- **May 2022:** U.S. CPI showed persistent inflation, initially depressing stock prices. However, signs of travel recovery lifted market optimism.
  - **Impact:** Visa (-1.8% on May 11, +2.1% next day), Mastercard (-2.2% on May 11, +2.5% next day) showed notable volatility.



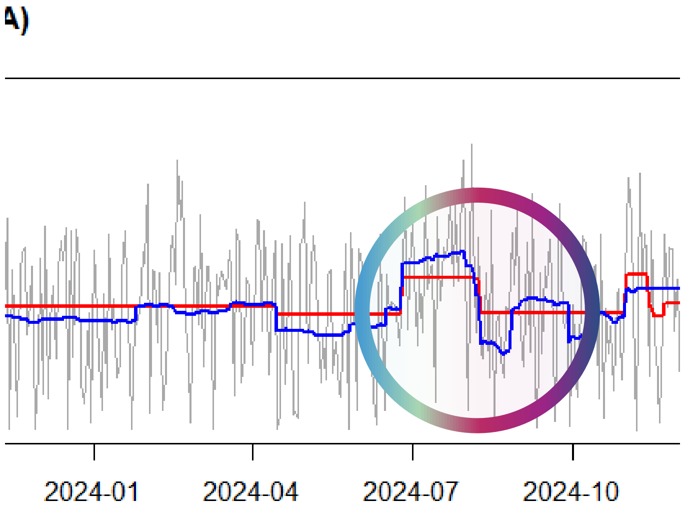
Fourth Quarter: Fed's Rate Hike Slowdown & Holiday Season Boost

- **October 2022:** Market sentiment improved with expectations of slower Fed rate hikes and peak inflation.
  - **Impact:** Reduced volatility and upward trends for Visa (+2.5%) and Mastercard (+2.7%).
- **November 2022:** Below-expected CPI data spurred a market rally, strengthening payment sector performance.
  - **Impact:** Visa (+4.3%), Mastercard (+5.2%) saw sharp single-day gains in mid-November.

Third Quarter 2024: Market Turmoil and Legal Challenges



- **August 2024: Global Financial Market Turbulence**
  - **Event:** On August 5, 2024, global financial markets experienced significant volatility, with major indices sharply declining due to fears of a slowing global economy and escalating geopolitical tensions.
  - **Impact:** Visa and Mastercard both faced sell-offs amid broader market declines, with Visa losing 3.2% and Mastercard down 2.9% on the same day.



- **September 2024: DOJ Antitrust Lawsuit Against Visa**
  - **Event:** On September 24, 2024, the U.S. Department of Justice (DOJ) filed an antitrust lawsuit against Visa, alleging monopolistic practices in the U.S. debit card market since 2012.
  - **Impact:** Visa's stock dropped 5.4% on the news, as concerns about legal penalties and regulatory changes mounted. Mastercard saw a smaller decline of 2.7%, reflecting fears of broader scrutiny on payment processors.


Thank
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