Basket Implied Correlation Analysis for Dispersion Trading Applications

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Acknowledgments

This work builds upon the theoretical framework for dispersion trading presented by Marco Avellaneda and related academic literature on correlation risk premium and volatility arbitrage.

1 Objective

This project computes the **implied correlation** of an equity basket using options-market data from the Bloomberg Terminal. It extracts the market's forward-looking estimate of average pairwise correlation between large-cap equities for use in **dispersion trading** signal generation and **correlation risk premium** analysis.

2 Overview

Two Jupyter notebooks form the analytical core:

- `correl_matrix.ipynb`: Computes a 30-day rolling realized correlation matrix for the selected equity basket.
- `implied_correl.ipynb`: Calculates the basket-implied correlation time series using index and stock implied volatilities.
- `Disp.ipynb`: Has not been added yet as in the intial approach I was using atm straddles now I am experimenting with variance swaps and increasing the number of stocks.

All data—including historical prices, implied volatilities, and basket weights—were extracted from the **Bloomberg Terminal**.

3 Mathematical Framework

3.1 Portfolio Variance Decomposition

The total variance of a basket can be expressed as:

$$\sigma^2_{\text{basket}} = \sum_i w_i^2 \sigma_i^2 + \rho \left[\left(\sum_i w_i \sigma_i \right)^2 - \sum_i w_i^2 \sigma_i^2 \right]$$

where:

- σ_{basket}: index or basket volatility (proxied by VIX)
- σ_i: implied volatility of stock i
- w_i: weight of stock i in the basket
- ρ: average pairwise correlation among constituents

3.2 Implied Correlation Extraction

Rearranging yields:

$$\rho_{\text{implied}} = \frac{\sigma^2_{\text{basket}} - \sum_i w_i^2 \sigma_i^2}{\left(\sum_i w_i \sigma_i\right)^2 - \sum_i w_i^2 \sigma_i^2}$$

This isolates the implied correlation term from the variance equation, yielding the market's expectation of average pairwise correlation.

3.3 Realized Correlation

The realized correlation across N assets over a rolling window is given by:

$$\rho_{\text{realized}} = \frac{2}{N(N-1)} \sum_{i<j} Corr(r_i, r_j)$$

where r_i are the daily returns of each stock.

3.4 Dispersion Definition

Realized Dispersion is defined as:

$$D_{\text{realized}} = \sigma^2_{\text{Index}} - \sum_{i=1}^{n} w_i^2 \sigma_i^2$$

Implied Dispersion uses implied volatilities instead of realized:

$$D_{\text{implied}} = IV^2_{\text{Index}} - \sum_{i=1}^{n} w_i^2 IV_i^2$$

The **dispersion premium** is:

$$\text{Dispersion Premium} = D_{\text{implied}} - D_{\text{realized}}$$

4 Data

- **Source:** Bloomberg Terminal
- **Fields:** 30-day implied volatilities for S&P 500 constituents and index (VIX)
- **Frequency:** Daily

5 Basket Composition

Top 10 S&P 500 constituents (approximately 38% index weight):

Ticker	Weight (%)
NVDA	7.38
AAPL	6.63
MSFT	6.13
AMZN	4.27
GOOGL	2.88
GOOG	2.70
META	2.55
TSLA	2.37
BRK.B	1.79
LLY	1.36

Note: Static weights used. Expanding to top 50 names would improve representativeness (80% of index coverage).

6 Outputs

- Implied correlation time series
- Realized correlation series (30-day rolling)
- Comparative plots of implied vs realized correlation
- Rolling correlation matrices

7 Applications

Area	Use Case
Dispersion Trading	Detect mispricing between index and basket options
Correlation Risk Premium	Measure implied–realized correlation spreads
Volatility Forecasting	Identify correlation regime shifts
Risk Management	Monitor systemic correlation clustering

8 Interpretation

Correlation Range	Market Regime
0.0–0.3	Low correlation (diversified)
0.3–0.5	Normal
0.5–0.7	Elevated
0.7–1.0	Crisis co-movement

8.1 Signal Interpretation:

- $\rho_{\text{implied}} > \rho_{\text{realized}}$: index options rich → sell correlation / long dispersion
- $\rho_{\text{implied}} < \rho_{\text{realized}}$: index options cheap → buy correlation / short dispersion

9 Dispersion Trading Strategy Overview

9.1 Long Dispersion Trade

Position:

- Sell index volatility (short ATM straddle on SPX)
- Buy single-stock volatility (long ATM straddles on constituents)
- Match index weights to maintain dollar-neutrality

Profit scenarios:

1. Correlations decrease (dispersion widens)
2. Individual stocks realize more volatility than implied
3. Index realizes less volatility than implied

9.2 Short Dispersion Trade

Position: Reverse of long dispersion

- Buy index volatility
- Sell single-stock volatility

Profit scenarios:

1. Correlations increase (dispersion compresses)
2. Market stress events (flight to quality)
3. Elevated implied dispersion premium

10 Risk Factors

10.1 Correlation Risk

The primary risk in dispersion trading. Correlations exhibit:

1. **Mean reversion:** Extreme correlations tend to revert
2. **Asymmetry:** Faster increase in downturns than decrease in upturns
3. **Volatility clustering:** Correlation shocks are persistent

10.2 Greeks Exposure (would be negligible with variance swaps)

- **Vega:** Net vega determines vol sensitivity
- **Gamma:** Determines rebalancing frequency and transaction costs
- **Theta:** Time decay, especially near expiration

11 Requirements

```
pandas >= 1.5.0
numpy >= 1.24.0
openpyxl >= 3.0.0
matplotlib >= 3.7.0
```

12 Execution

1. Run `correl_matrix.ipynb` to compute realized correlations.
2. Run `implied_correl.ipynb` to calculate implied correlation.
3. Compare results for signal generation and visualization.

13 Limitations

- Static weights (no rebalancing)
- Limited universe (10 stocks, 38% index coverage)
- Requires Bloomberg data access
- No backtesting framework
- Transaction costs not modeled

14 Future Work

- Expand to top 50 constituents for better coverage
- Implement dynamic weight rebalancing
- Build backtesting framework with transaction cost model
- Add Greeks calculation and risk management module
- Incorporate variance swap replication

15 License

16 References

1. Driessen, J., Maenhout, P., Vilkov, G. (2009). *The Price of Correlation Risk: Evidence from Equity Options.* Journal of Finance.
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3. Bossu, S., Strasser, E., Guichard, R. (2005). *Just What You Need to Know About Variance Swaps.* JPMorgan Equity Derivatives Report.