



UNIVERSITÀ
DI TRENTO

Dipartimento di
Economia e Management

Master of Science in
FINANCE

STUDY OF DYNAMIC CORRELATION FOR RISK ASSESSMENT IN FINANCE: AN ANALYSIS OF THE NASDAQ 100 WITH AND WITHOUT THE EFFECT OF COVID-19

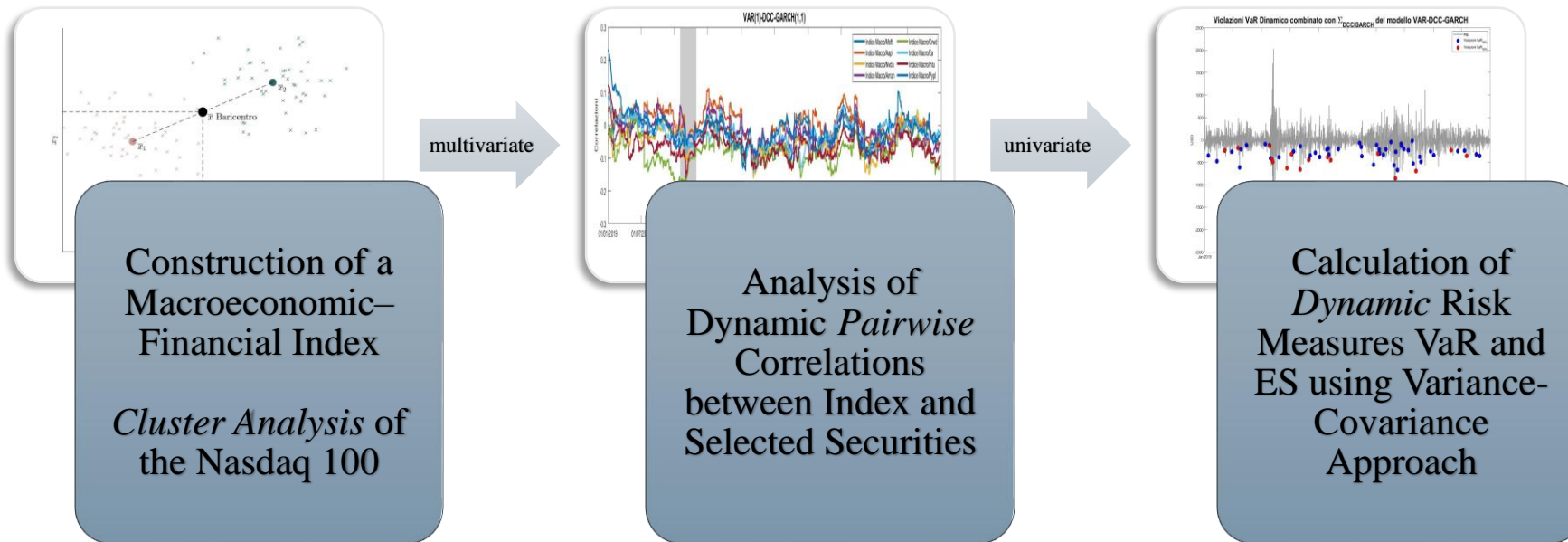
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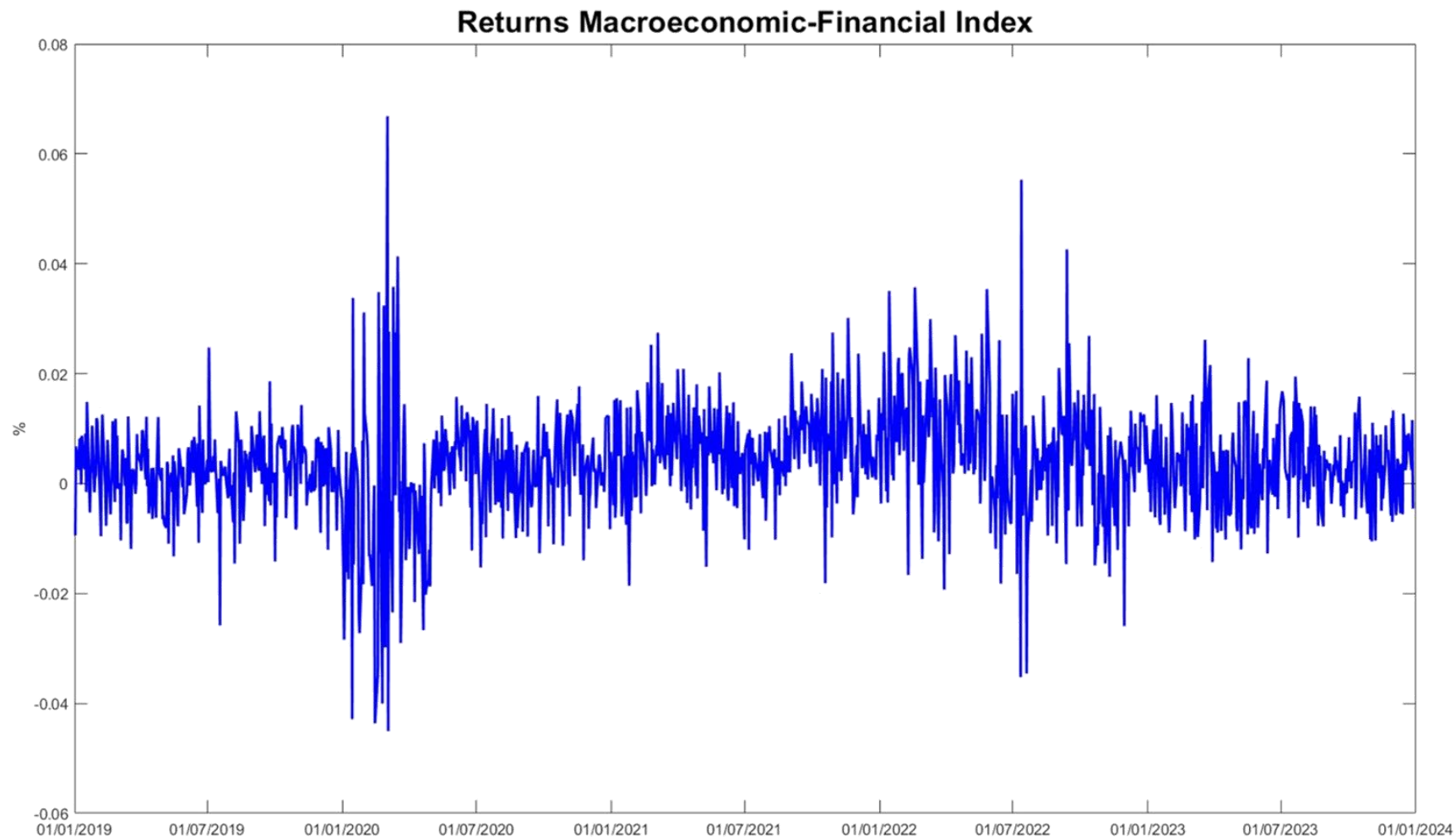
Purpose

The objective is to analyse the dynamic pairwise correlations between an aggregated index and selected securities from the Nasdaq 100, with a view to applying them to portfolio risk calculations using Value at Risk (VaR) and Expected Shortfall (ES)





Macroeconomic-Financial Index

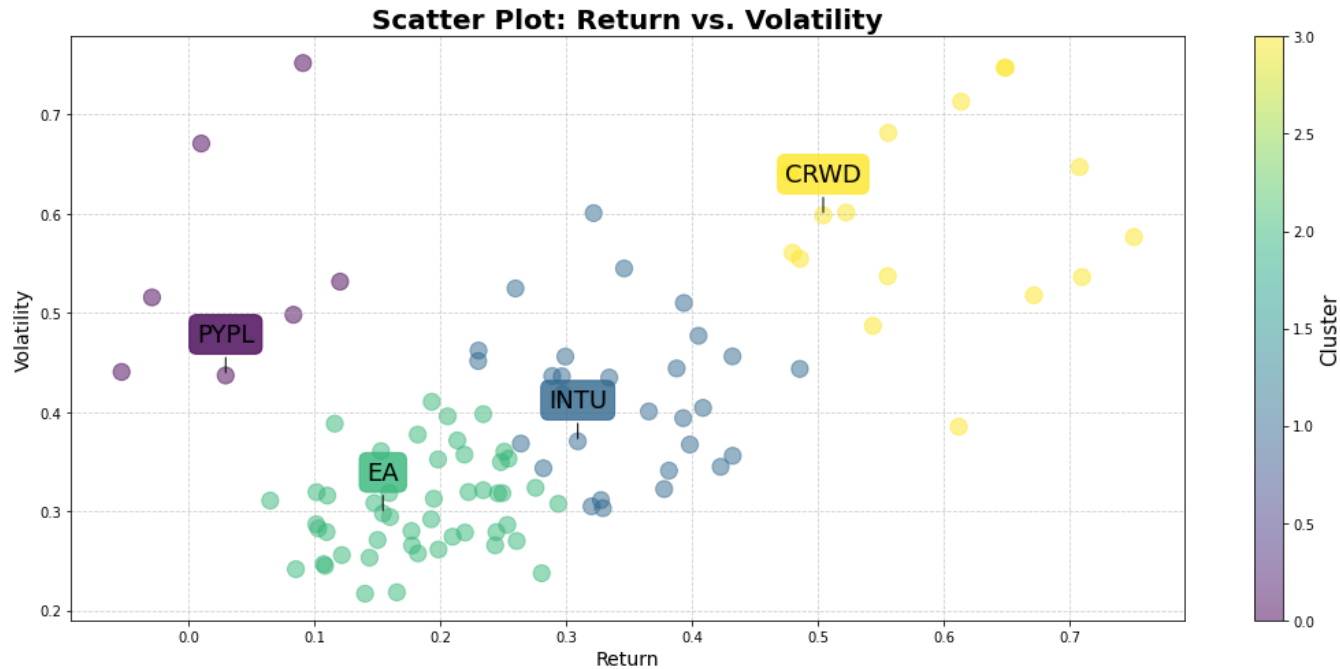


GOLD	Commodity	<i>Return</i>
WTI	US Oil	<i>Return</i>
VIX	Proxy Vol. Impl.	<i>Return</i>
FVX	Treasury 5Y	<i>Difference</i>
CPI	Consumer Price Index	$\Delta\%log(Cpi)$
LOIS	LIBOR–OIS Spread	<i>Difference</i>

All data are on a daily basis.



Cluster Analysis Results



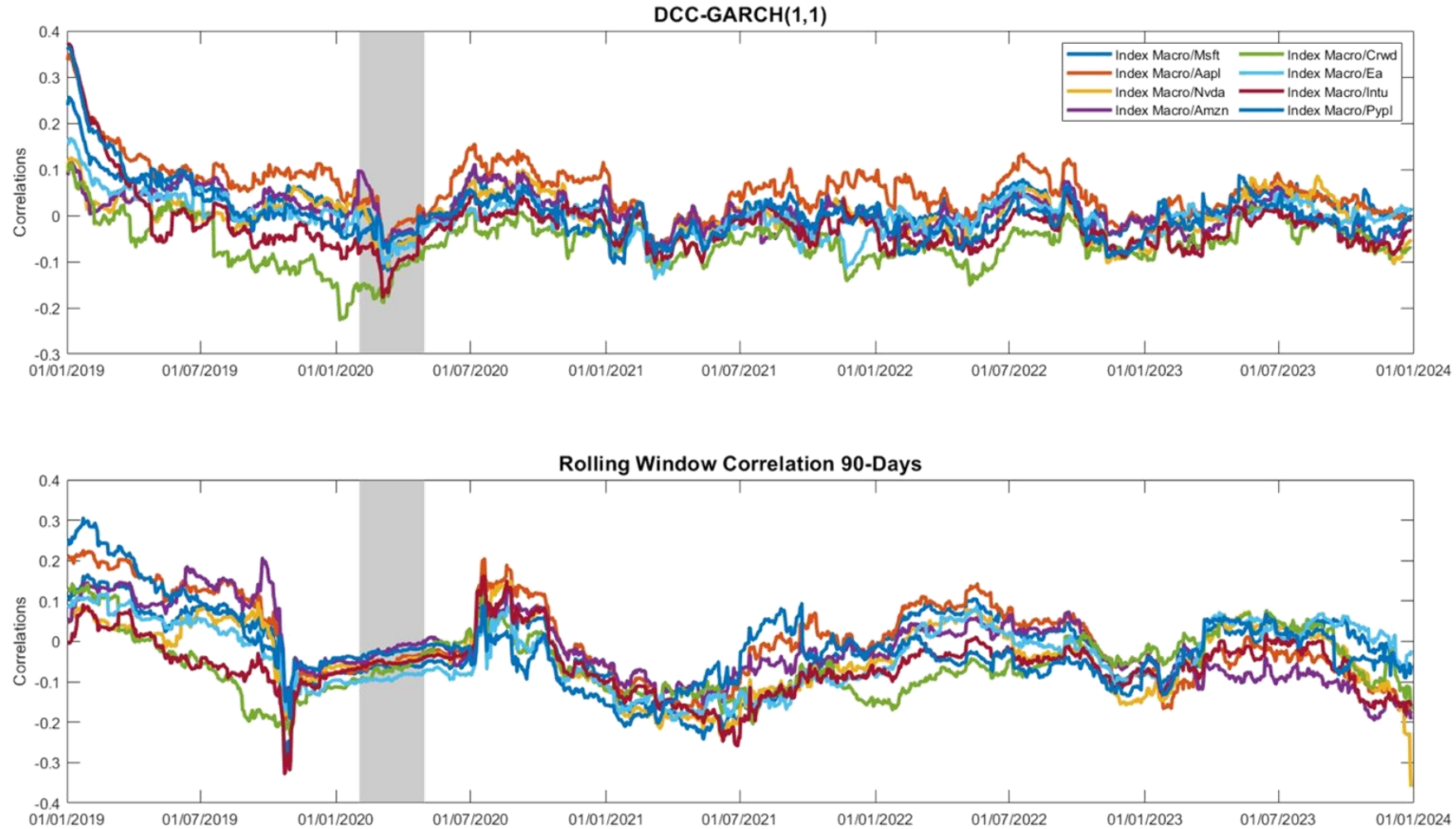
Cluster	Closest Ticker	Average Returns	Volatility	Ret-Vol
0	INTU	0.3093	0.3705	mid-mid
1	CRWD	0.5044	0.5984	high-high
2	PYPL	0.0296	0.4369	low-high
3	EA	0.1546	0.2978	low-low

To make the group as representative as possible of the Nasdaq 100, we have added the four largest capitalisation stocks of the index to the results: **Microsoft (MSFT)**, **Apple (AAPL)**, **Nvidia (NVDA)**, **Amazon (AMZN)**.



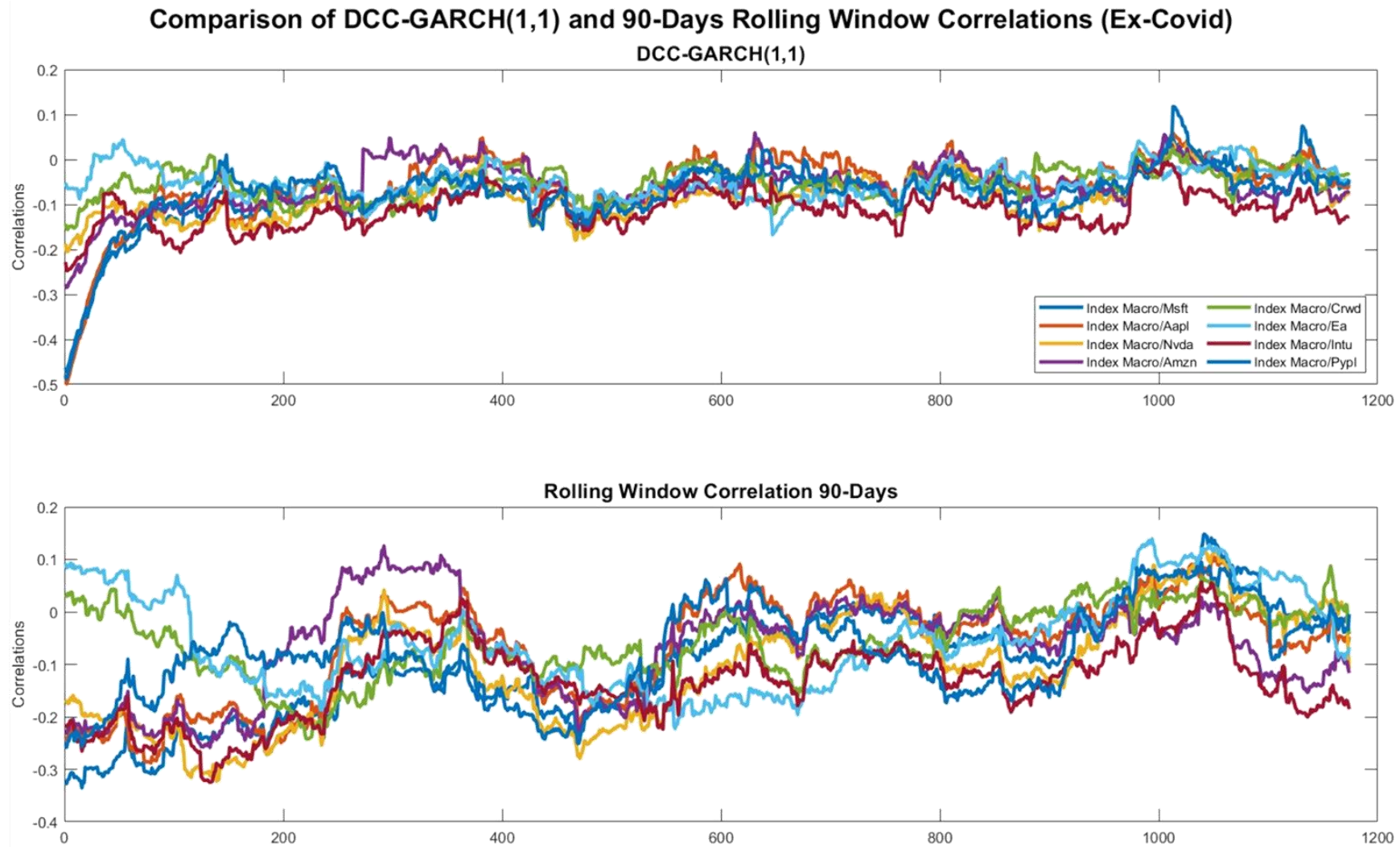
Dynamic Correlations ($\hat{\Gamma}_t^{DCC}$)

Comparison of DCC-GARCH(1,1) and 90-Days Rolling Window Correlations





Dynamic Correlations ($\hat{\Gamma}_t^{DCC}$), Ex-Covid*

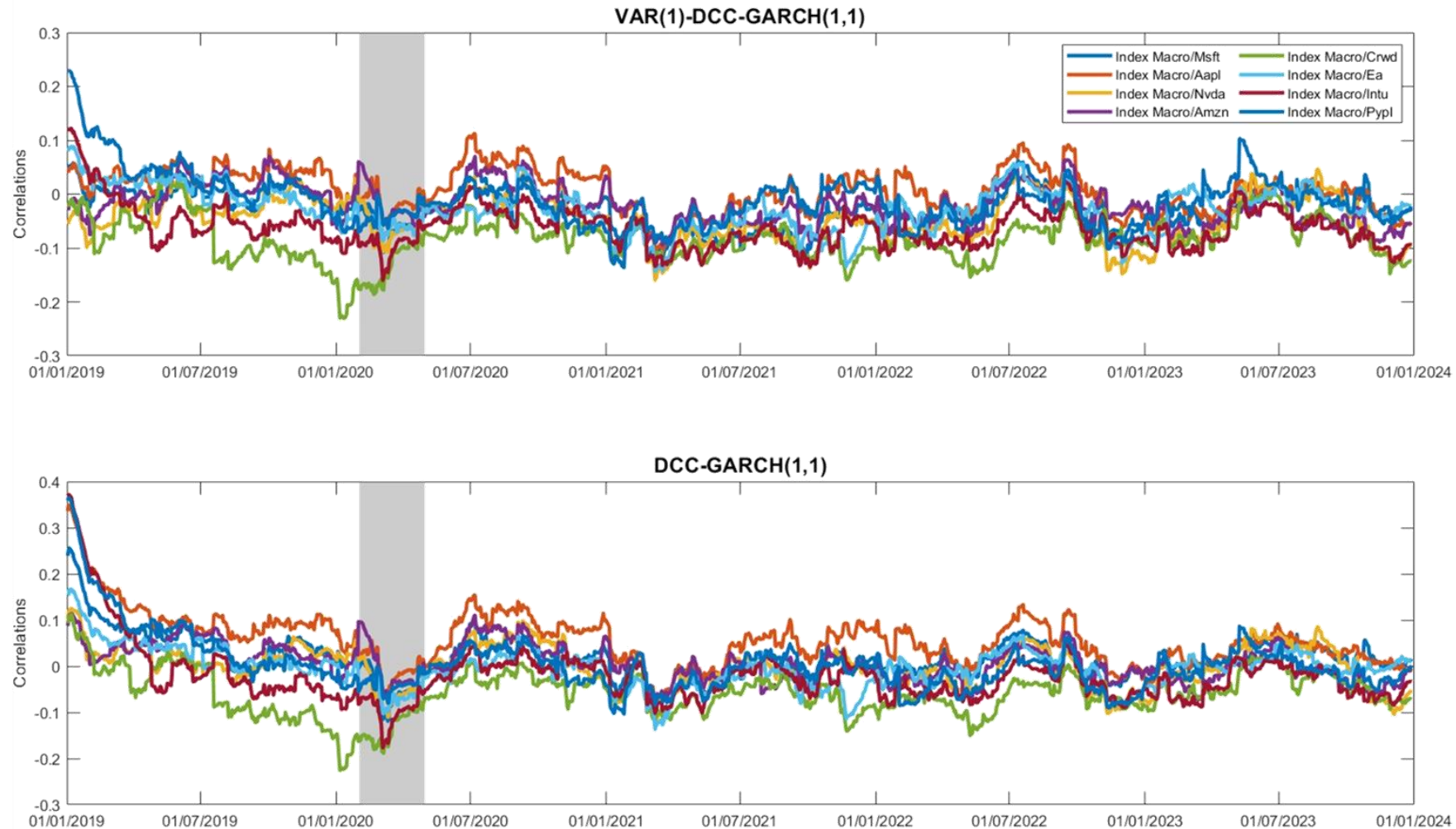


*The term 'Ex-Covid' denotes the exclusion of data relating to the months of February, March and April 2020 from the dataset.



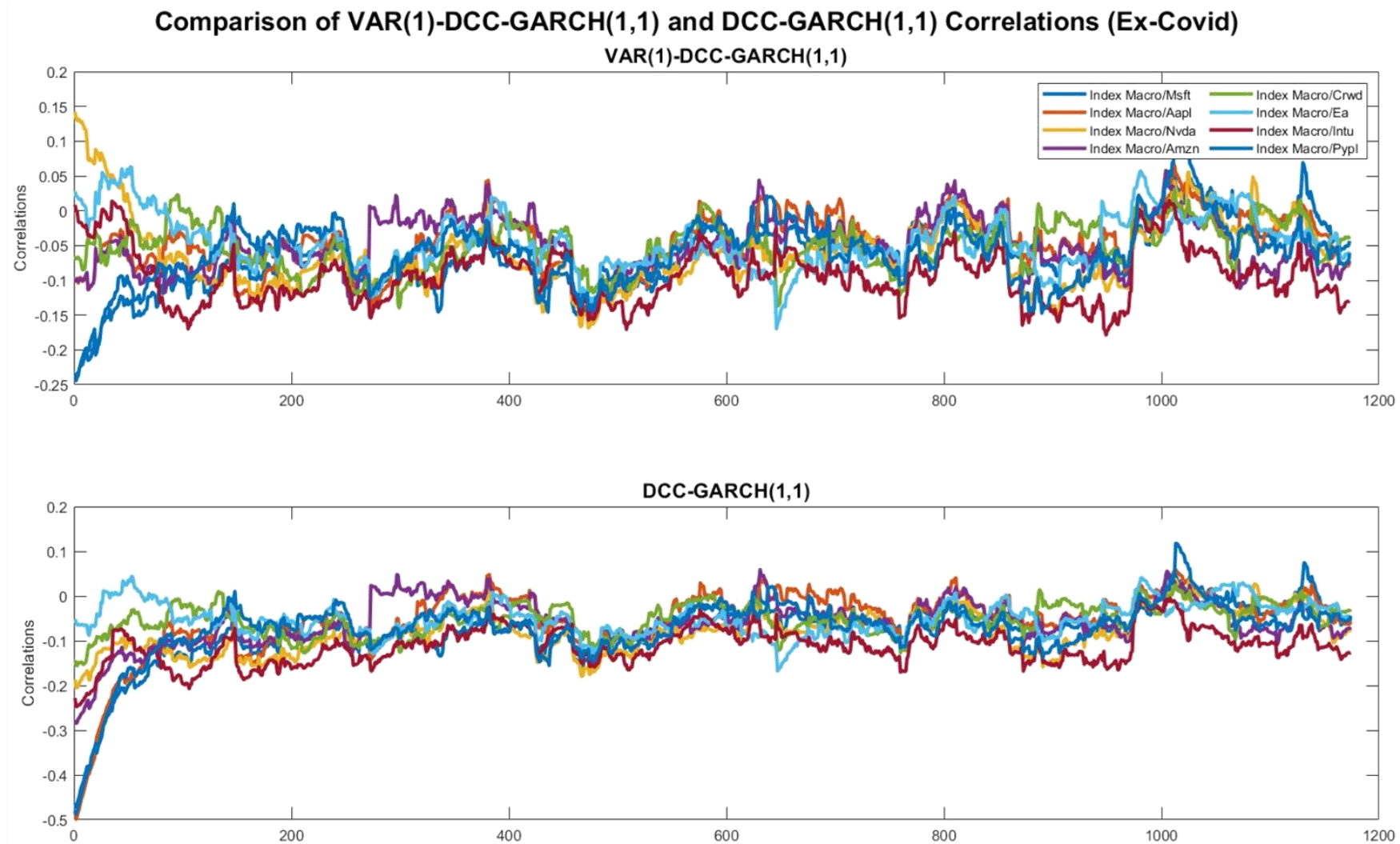
Dynamic Correlations ($\hat{\Gamma}_t^{VAR-DCC}$)

Comparison of VAR(1)-DCC-GARCH(1,1) and DCC-GARCH(1,1) Correlations





Dynamic Correlations ($\hat{\Gamma}_t^{VAR-DCC}$), Ex-Covid





Model Selection

	α (Alpha)	β (Beta)
<i>DCC-GARCH (1,1)</i>	0.0091 (0.0001)	0.9701 (0.0000)
<i>VAR(1)-DCC-GARCH (1,1)</i>	0.0089 (0.0024)	0.9702 (0.0000)

As seen for the trend in correlations, the parameter estimates also differ **marginally**: in particular, for both models, the impact of new information on correlations (α) is limited, while the persistence of correlations (β) tends to remain stable over time. The results are corroborated by the significant *p-values*.

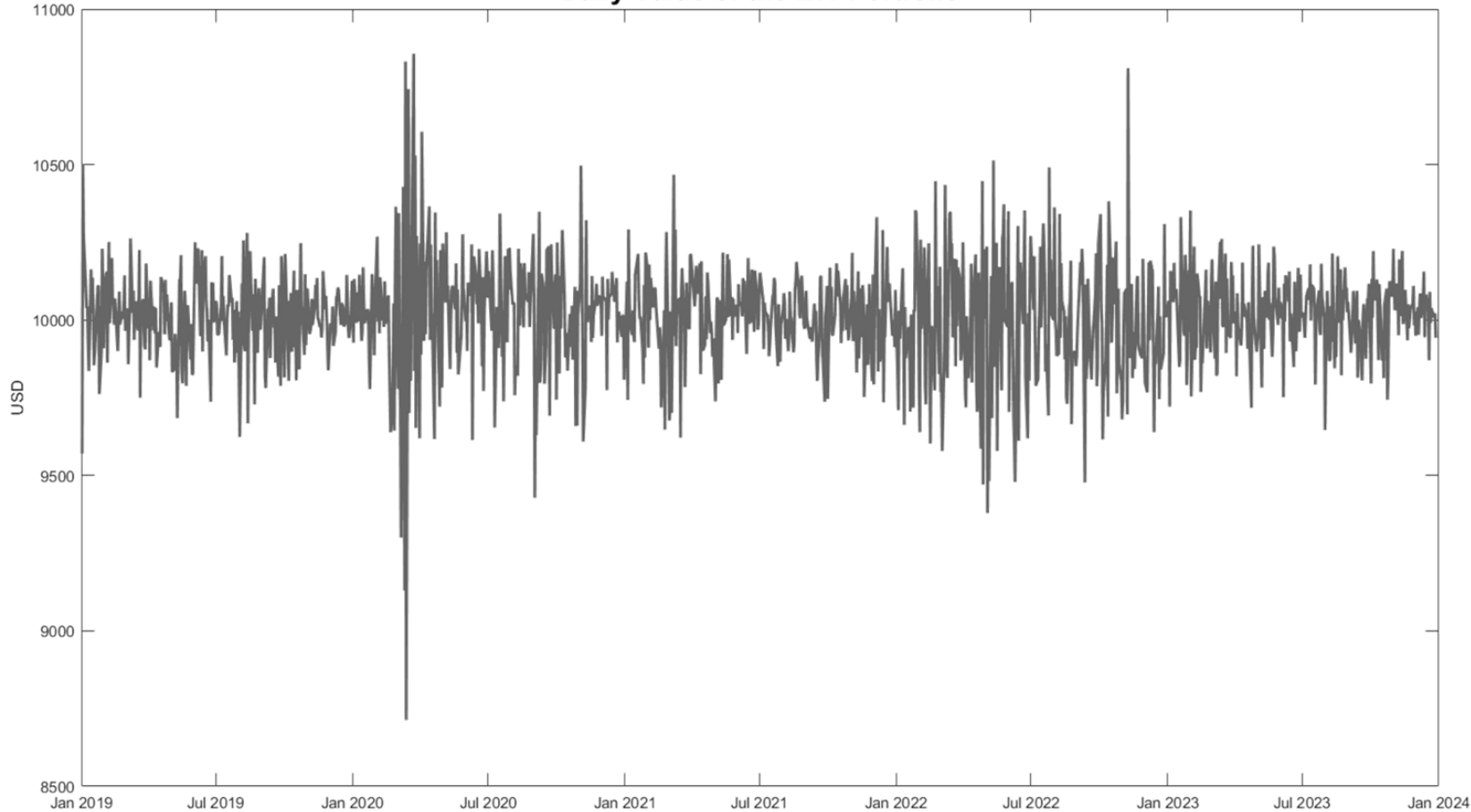
Comparing the log-likelihood, however, the results confirm that the **VAR(1)-DCC-GARCH(1,1)** model offers a better fit to the data:

<i>Likelihood Ratio Test</i>	
H_0	1
<i>p-value</i>	0



Empirical Results: Portfolio Construction

Daily Value of the EW Portfolio



Assumptions

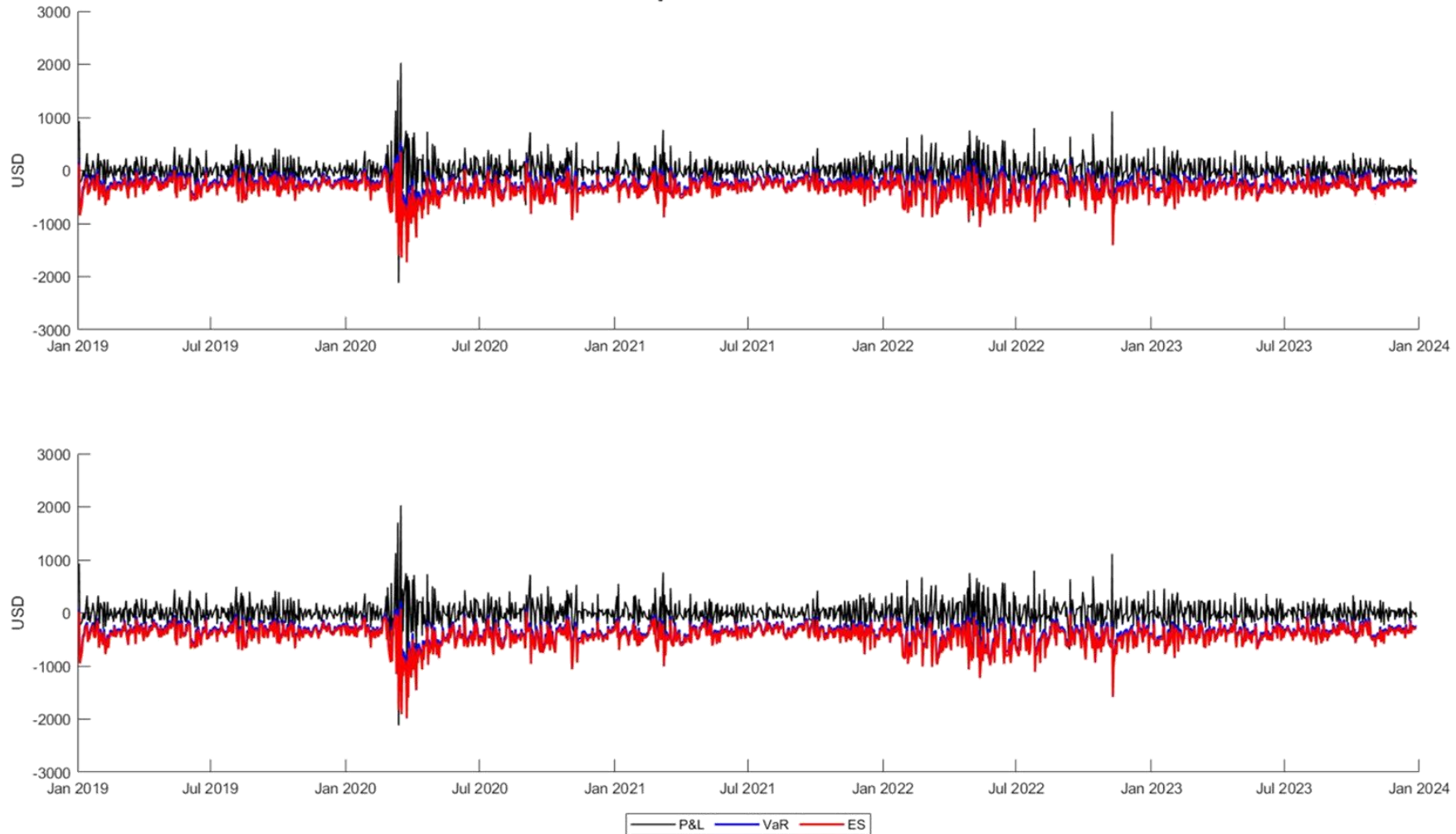
- US investor, no foreign exchange risk..
- Initial investment: \$10.000.
- No transaction costs.
- Same weight for all assets.

$$E(r_P) = \sum_{i=1}^n w_i E(r_i) = w^T r$$



Empirical Results: Parametric Approach

Losses compared to VaR and ES



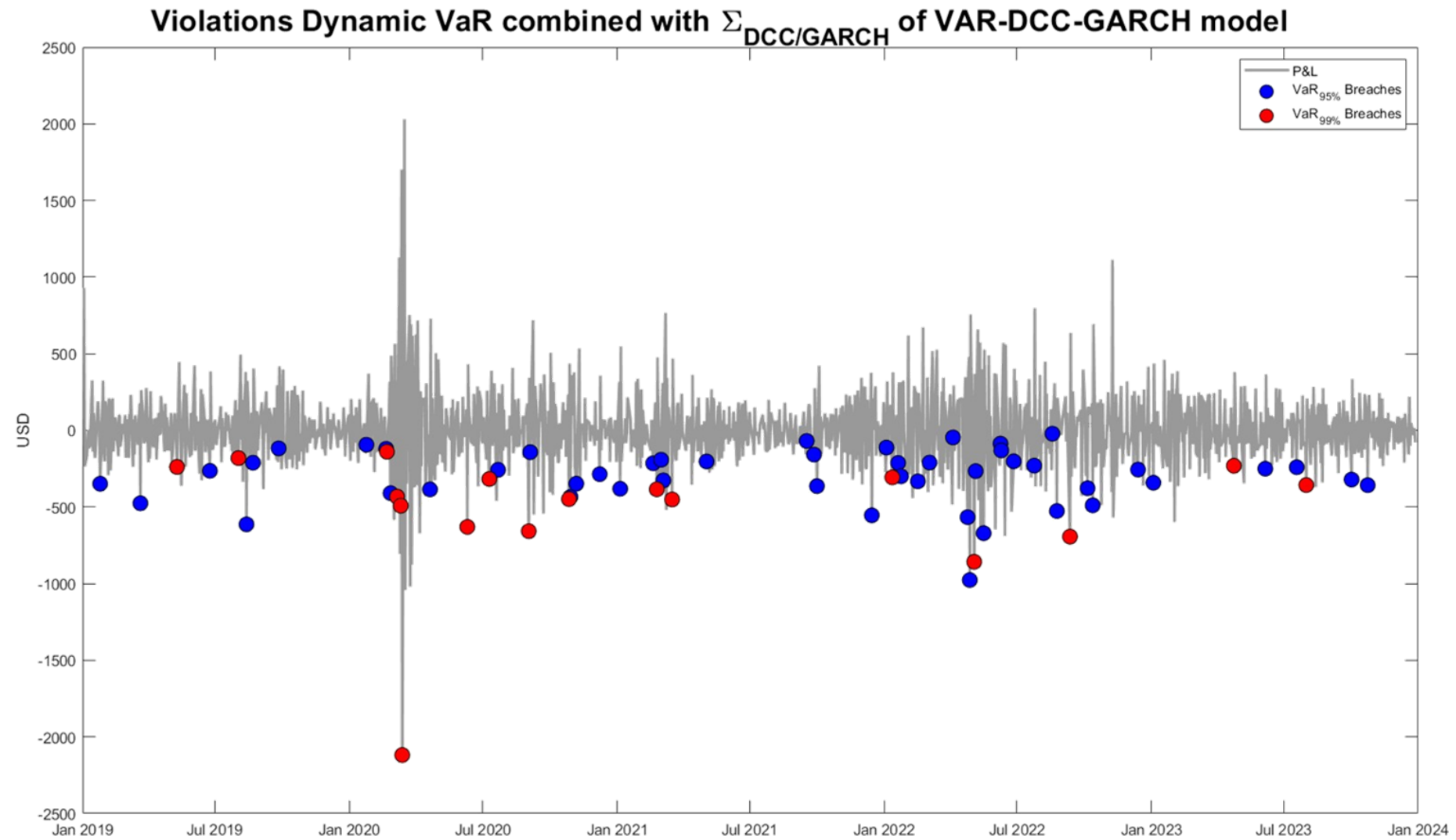


Empirical Results: Parametric Approach (cont'd)

<i>Measures of Risk</i>	Average	
	<i>Covid</i>	<i>Ex-Covid</i>
VaR_{95%}	−271.34	−338.05
VaR_{99%}	−378.82	−466.59
ES_{95%}	−337.24	−416.86
ES_{99%}	−423.27	−530.50

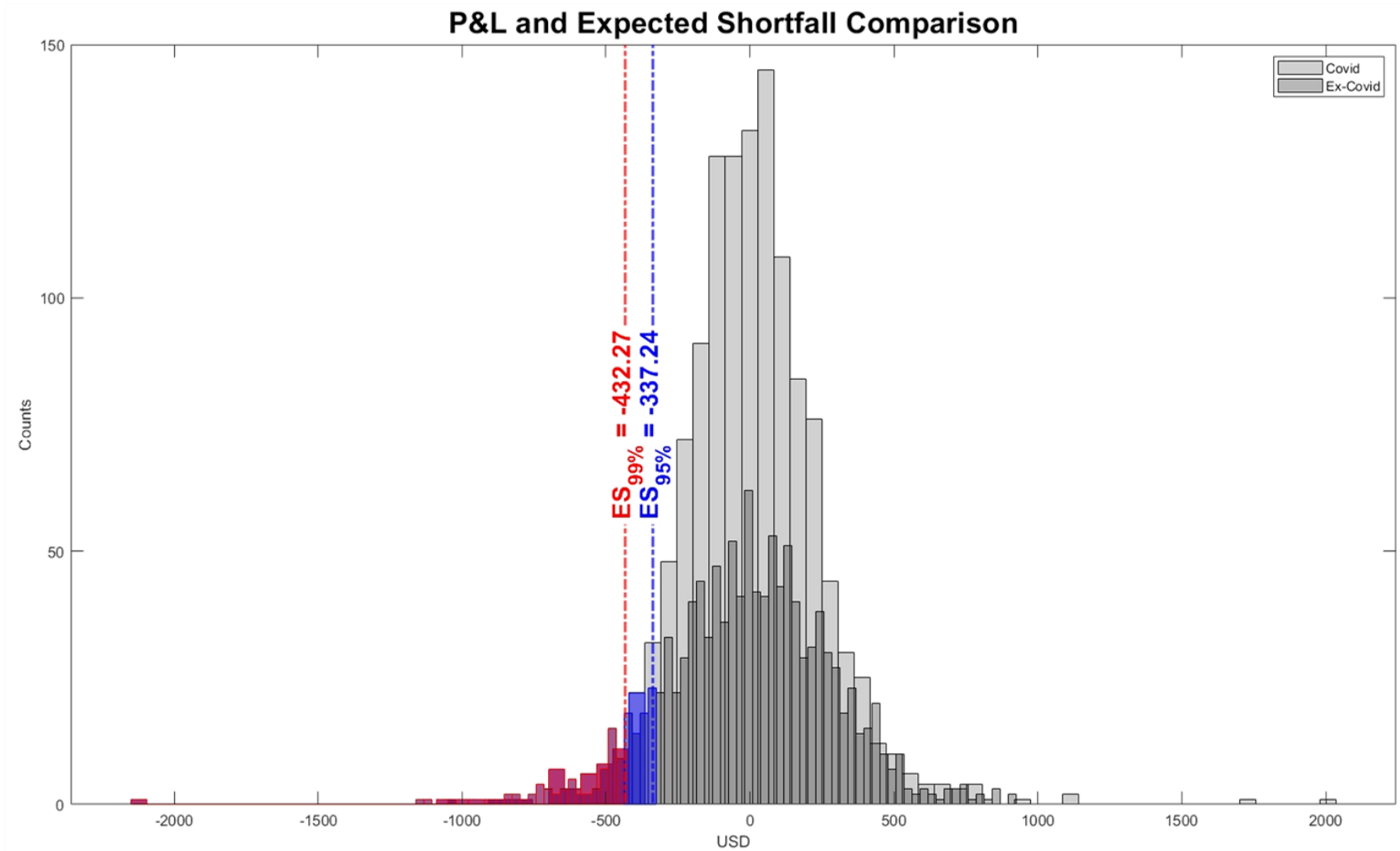


Empirical Results: VaR Breaches



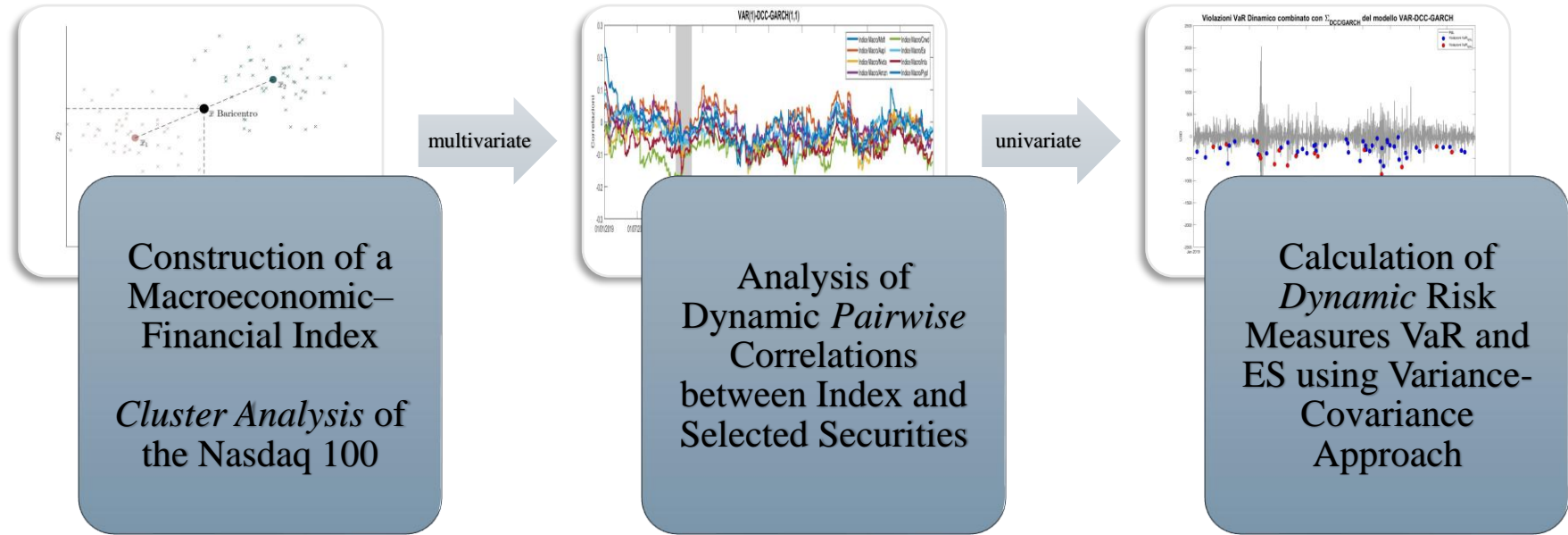


Empirical Results: Expected Shortfall





Conclusions



- Importance of **data analysis** methodologies.
- More sophisticated econometric techniques are decisive for more **accurate** modelling of *second-order conditional moments*.
 - The exclusion of the most volatile months of the pandemic *reduced* the frequency of regime shifts between positive and negative correlations, stabilizing the correlation dynamics.
- The adoption of ES provides, compared to VaR, a more **precise** view of potential risk.
 - The exclusion of the most volatile months of the pandemic showed *higher* potential losses, suggesting the presence of other risk dynamics.