GROUP WORK PROJECT # 1 MScFE 692: Capstone Review
GROUP NUMBER: 10750

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N/A

Group Work Project 1

0.1 Student A - Extend the PCA monitoring framework in lesson 4.3 with the goal of obtaining a systemic risk indicator combining signals of correlation breakdown and of widening credit spread

The computational framework adopted in lesson § 4.3 made use of nine ETFs of the SPDR series, issued by State Street to target specific industry and service sectors in the economy, with each ETF composed exclusively of stocks that are within the S&P500 index. The computations start from January 2007 and extend until the present date. That is why only the nine ETFs already existing in 2007, out of the full suite of eleven SPDR ETFs, were used in the analysis.

Beyond the SPDR ETFs, extra tickers were tracked to follow the volatility of the markets (^VIX), the 10-year Treasury bonds yields (^TNX), and an ETF from iShares reproducing the yield of investment grade corporate bonds (LQD).

All of the data series above are taken with a daily frequency at markets closing time.

Further, we gather daily yield series from the FRED database, for Baa investment grade $\geq$ 20-year corporate bonds as graded by Moody's (BAA) and again the 10-year Treasury bond yields (DGS10).

To summarise:

Ticker	Description
	SPDR ETFs
`XLB`	S&P500 Materials stocks
`XLE`	S&P500 Energy stocks
`XLF`	S&P500 Financial stocks
`XLI`	S&P500 Industrial stocks
`XLK`	S&P500 Technology stocks
`XLP`	S&P500 Consumer Staples stocks
`XLU`	S&P500 Utilities stocks
`XLV`	S&P500 Healthcare stocks
`XLY`	S&P500 Consumer Discretionary stocks
	Other market data
`^VIX`	Market volatility index
`^TNX`	10-year Treasury yields index
`LQD`	Liquid, investment-grade corporate bond yields
	FRED data
`BAA`	Moody's Baa-rated corporate bond yields
`DGS10`	10-year Treasury yields

Below, the shape of the `pandas` DataFrame for the 9 SPDR ETFs downloaded, sporting for dimensions the number of daily observations for the period 2007-2025 (after data cleaning and rolling windows) $\times$ the 9 ETFs.

```
Shape of downloaded market data of SPDR ETFs:  (4688, 9)
```

We see that the number of observations for the remaining data series extracted from markets agrees with the previous database at 4688 datapoints:

```
Shape of downloaded market data of volatility and fixed income indices:  (4688,
3)
```

FRED series `BAA`, although nominally taken with daily frequency as declared on the FRED website, in reality exhibits monthly frequency when extracted from the database.

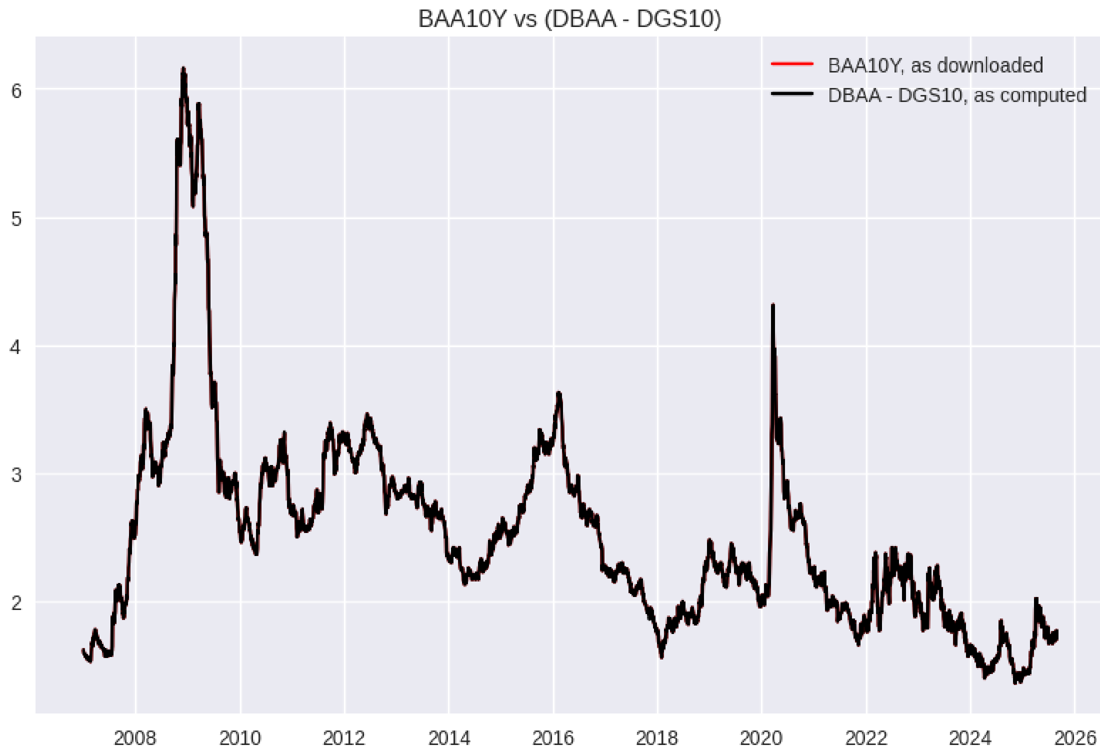
```
id                                                                  BAA
realtime_start                                               2025-08-21
realtime_end                                                 2025-08-21
title                             Moody's Seasoned Baa Corporate Bond Yield
observation_start                                            1919-01-01
observation_end                                              2025-07-01
frequency                                                       Monthly
frequency_short                                                       M
units                                                           Percent
units_short                                                           %
seasonal_adjustment                              Not Seasonally Adjusted
seasonal_adjustment_short                                           NSA
last_updated                                     2025-08-01 10:16:05-05
popularity                                                           71
notes                        These instruments are based on bonds with matu…
dtype: object
```

A workaround is found in downloading FRED's `DBAA` series instead, with the initial letter D evidently standing for *daily*.

Given that the Treasury yields data `DGS10` have more observations than all other series downloaded, in fact spanning over days when markets were closed, we will fill the missing datapoints in `DBAA` with the previous most recent observation available.

There also exist a FRED series `BAA10Y` = `DBAA - DGS10` which tracks the credit spread of investment-grade corporate bonds out of the box. The graph below shows `BAA10Y` is obtained exactly as `DBAA - DGS10`.

```
Shape of spread data from Fred:  (4866, 3)
```



For the sake of comparing the credit spread obtained from FRED data (`BAA10Y`) with the one obtained from market data (`LQD - ^TNX`), we first adapt the former to have the same number of observations of the latter.

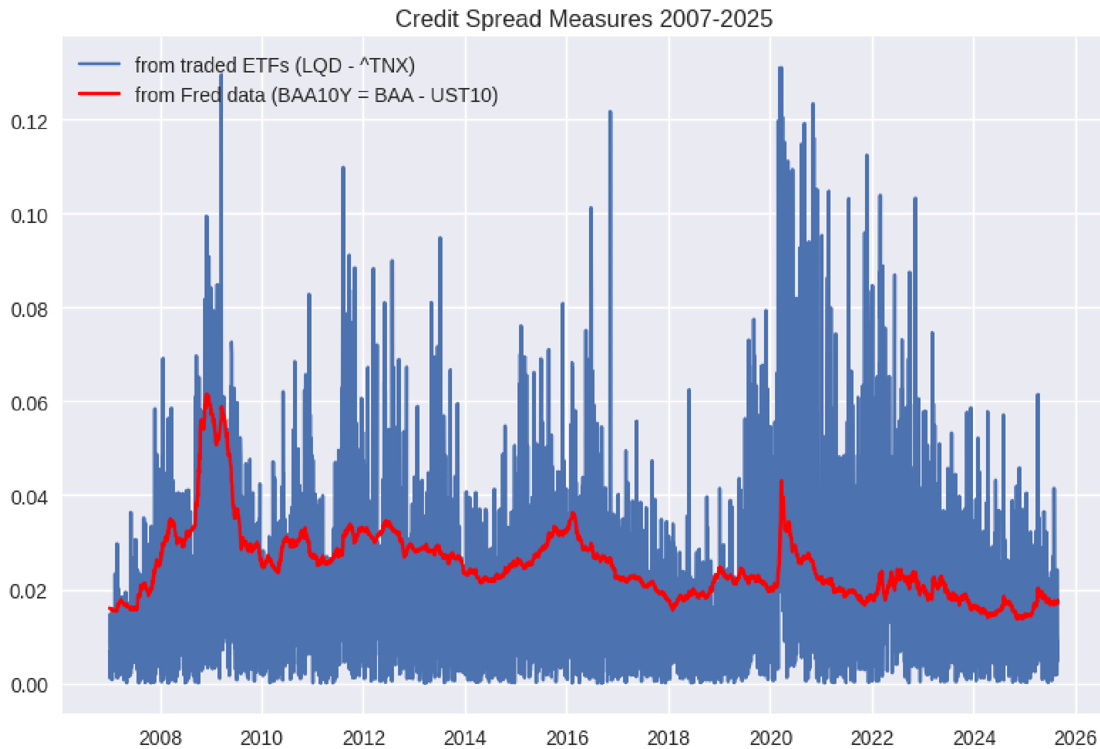
```
shape of spread data from markets:  (4688,)
```

```
shape of spread data from FRED:  (4688,)
```

The credit spreads so obtained by two different sources are plotted in the figure below.

It is evident that the market measure (blue) is much more noisy than that obtained from FRED data (red). We attribute this to the nature of `LQD` as a liquid (highly traded) instrument. Its price is determined by supply and demand dynamics, rather than by the yields of the corporate bonds undergirding it. In turn, this price will reflect the bonds' yields, but only indirectly through market participants' behaviour.

In support of the previous observation, we observe that the absolute value of the noisy market data seems to follow the same patterns as the more regular FRED data. The two measures of credit spread seem to be correlated.



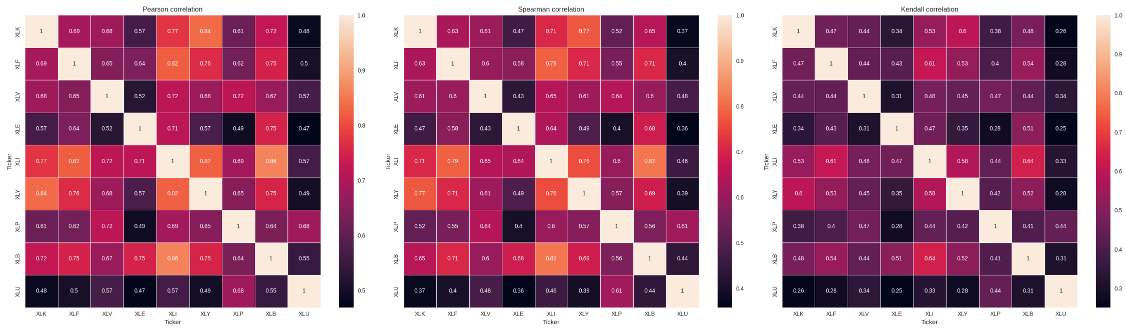
Now, in order to observe the correlations amongst the SPDR ETFs during the selected 2007-25 time window, we compute rolling correlation matrices for time windows of 60 trading days, advancing one day at the time.

The spectral decomposition (or PCA) of these rolling correlation matrices will yield the eigenvalues of the matrices. The largest eigenvalue is found to represent the *market factor* that affects all securities, determining parallel shifts in stock prices.

Its *explained variance ratio* (EVR), i.e. the fraction of total portfolio variance it explains, grows in times of increased market uncertainty. This consists in an undesirable increase in global correlation that could be exploited as a signal for a possibly incipient financial crisis.

We have updated the code in lesson §4.3 to compute the rolling correlation matrices to include not just computing the Pearson (linear) correlation, but also Spearman and Kendall correlations, to track nonlinear effects.

Below, we show the three correlation matrices for the 9 SPDR ETFs, not limited to a few days rolling window, but across the whole time period 2007-25:



We can see from the colorbars in the figures above, showing extreme values, that if nonlinear effects are included (Spearman and Kendall matrices), then the 9 ETFs are overall less correlated than the linear correlation matrix (Pearson) would imply.

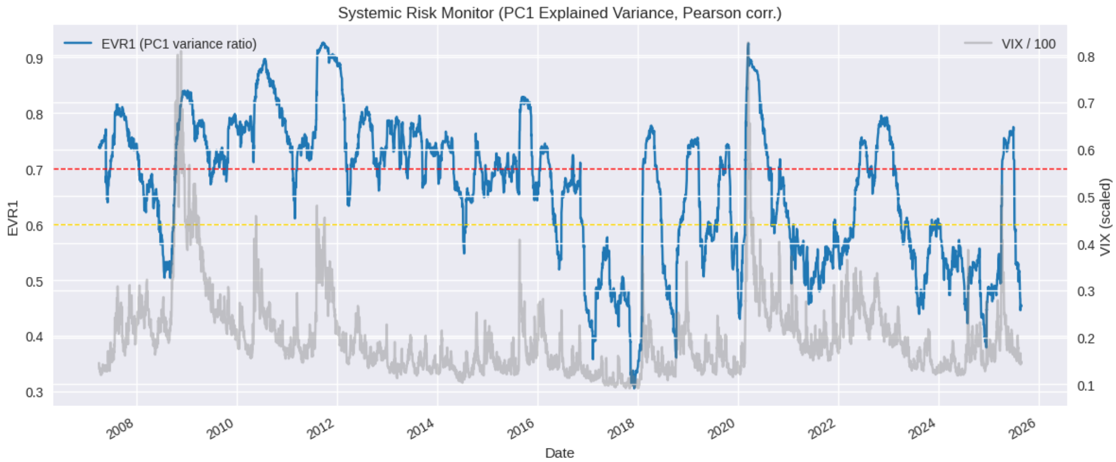
Next, from the rolling 60-days correlations of returns, we compute the EVR for the first eigenvalue (EVR1). We do it for each of the Pearson, Spearman and Kendall correlation matrices.

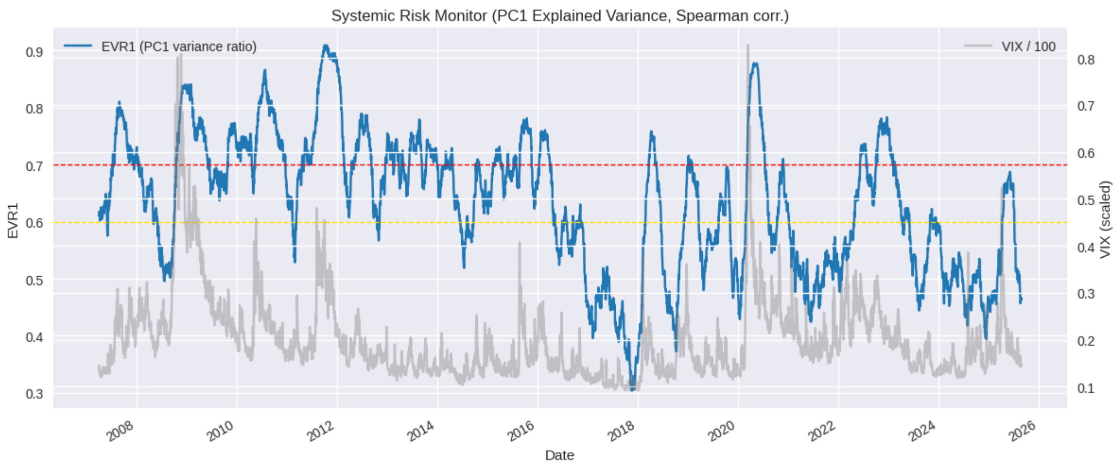
Notice how, on an average home workstation, the computational cost of obtaining the rolling Kendall correlations with Python is 20$\times$ more expensive than with the other methods.

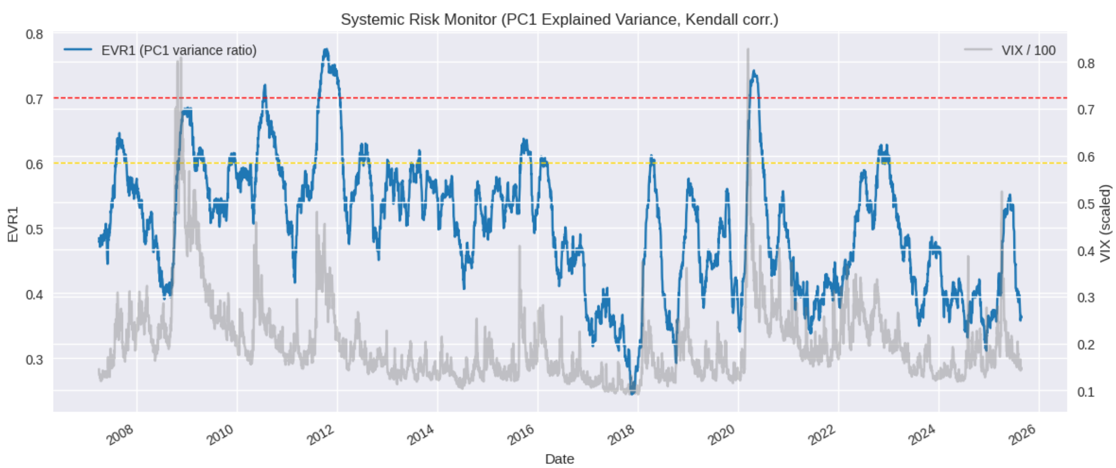
Correlation	Elapsed computation time (s)
Pearson	2.4
Spearman	3.9
Kendall	84.5

From plotting these EVR1s (blue) against time, and in comparison with the ^VIX index (gray), we observe that the EVR1 signal obtained from the Kendall correlation is much more conservative than the previous two. It crosses the highest threshold of correlation (red dotted line) only in three occasions: 2010, 2011-12, and 2020.

It is noticeable that, contrary to the other two correlation methods, the Kendall correlation signal missed the 2007-08 Quant Crash and Great Financial Crisis.







The next step of the analysis consists in checking whether credit spreads and our EVR1 signal are correlated. It would be expected they are as credit spreads widen during systemic crises, just as the proportion of variance explained by the first eigenvalue (EVR1) grows larger.

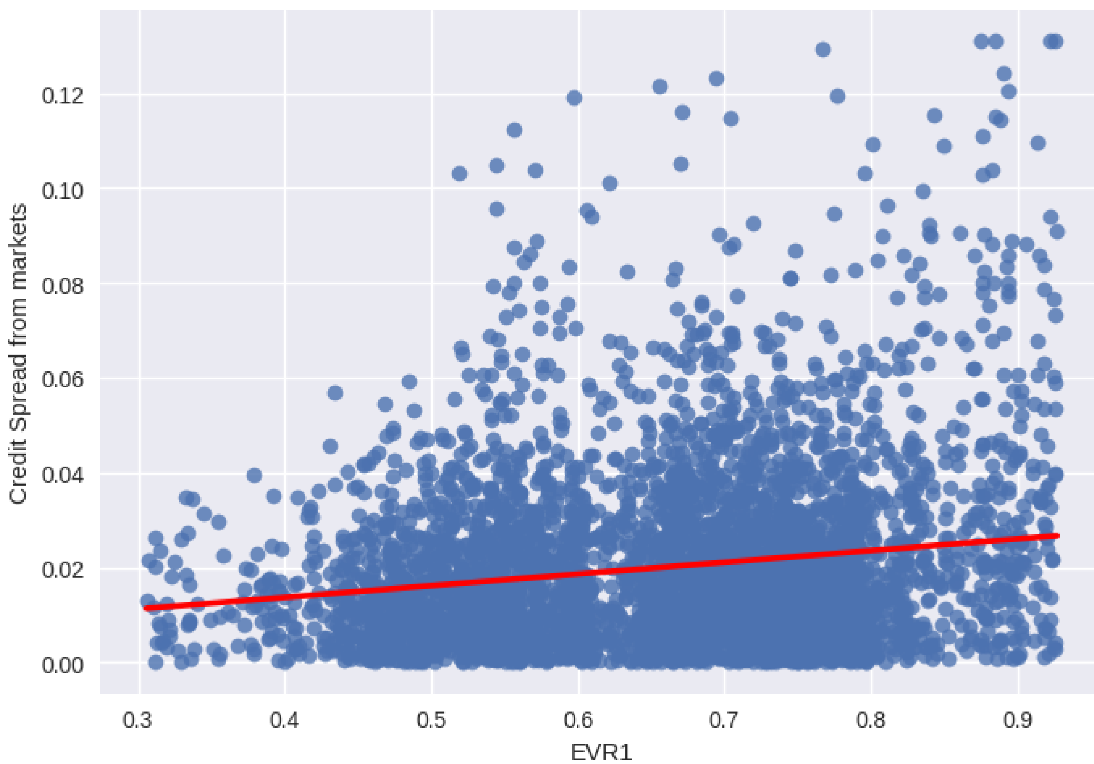
We have two measures of credit spread, one coming from the FRED database and the other downloaded from the markets (LQD ticker as stand-in for corporate bonds), so we have to select the one better attuned to the EVR1 dataset.

For this purpose, we are going to proceed with a linear regression of the Pearson correlation EVR1 data with both the databases of credit spread at our disposal.

```
                                 OLS Regression Results
================================================================================
======
Dep. Variable:     Credit Spread from markets   R-squared:
0.060
Model:                                    OLS   Adj. R-squared:
0.060
Method:                         Least Squares   F-statistic:
99.03
Date:                        Sat, 30 Aug 2025   Prob (F-statistic):
3.98e-62
Time:                                23:39:06   Log-Likelihood:
12074.
No. Observations:                        4629   AIC:
-2.414e+04
Df Residuals:                            4625   BIC:
-2.411e+04
Df Model:                                   3
Covariance Type:                    nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0931      0.008    -11.860      0.000      -0.108      -0.078
EVR1           0.1222      0.008     15.194      0.000       0.106       0.138
EVR2           0.1327      0.013     10.077      0.000       0.107       0.159
EVR3           0.2269      0.022     10.376      0.000       0.184       0.270
==============================================================================
Omnibus:                     1730.517   Durbin-Watson:                   1.628
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             7388.710
Skew:                           1.801   Prob(JB):                         0.00
Kurtosis:                       8.034   Cond. No.                         114.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

```
<AxesSubplot: xlabel='EVR1', ylabel='Credit Spread from markets'>
```



P-values = 0 for the EVR1-2-3 coefficients in the regression are encouraging, however a low value for the R^2 statistic = 0.060 on the contrary signals that a very low proportion of the total variance of the dependent variable, the credit spread, is explained by the EVR coefficients.

Therefore, we record a mixed outcome for this regression.

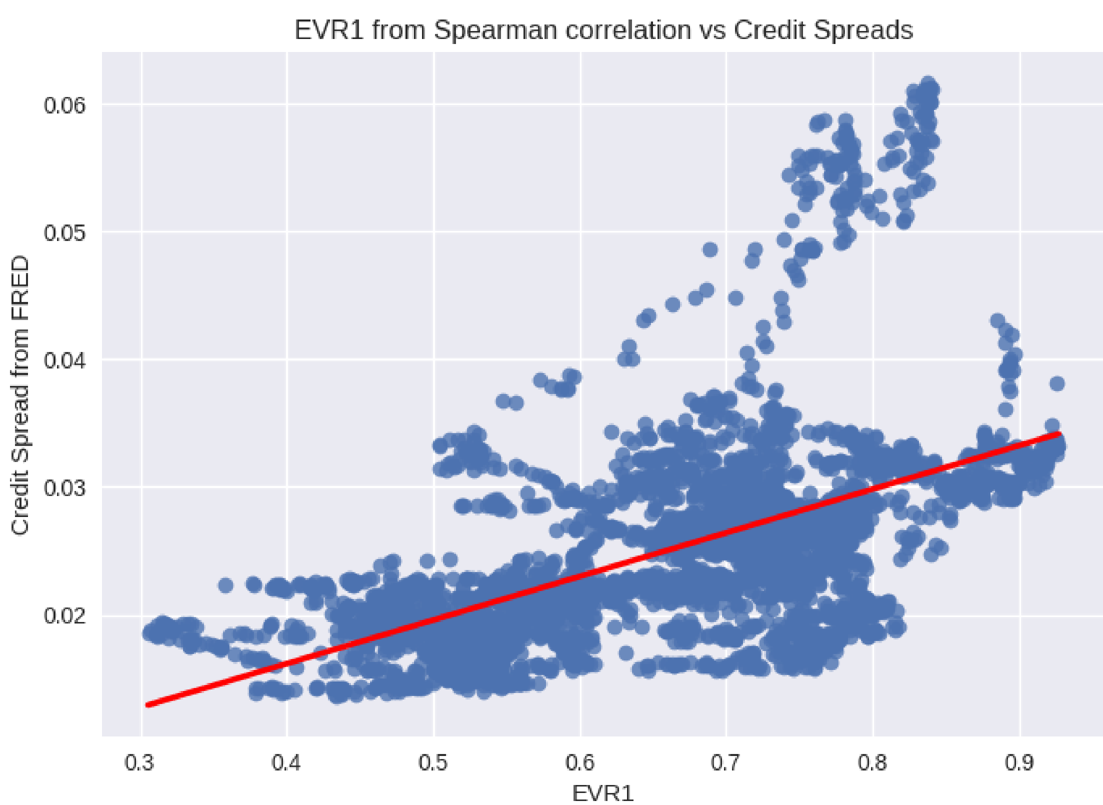
Next, much better results are obtained by regressing the EVR measure against the credit spread series from FRED:

```
                            OLS Regression Results
================================================================================
===
Dep. Variable:     Credit Spread from FRED   R-squared:
0.296
Model:                                 OLS   Adj. R-squared:
0.296
Method:                      Least Squares   F-statistic:
649.5
Date:                     Sat, 30 Aug 2025   Prob (F-statistic):
0.00
Time:                             23:39:06   Log-Likelihood:
16661.
No. Observations:                     4629   AIC:
-3.331e+04
```

```
Df Residuals:                    4625   BIC:
-3.329e+04
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0002      0.003      0.077      0.938      -0.005       0.006
EVR1           0.0364      0.003     12.196      0.000       0.031       0.042
EVR2           0.0093      0.005      1.895      0.058      -0.000       0.019
EVR3          -0.0050      0.008     -0.610      0.542      -0.021       0.011
==============================================================================
Omnibus:                     1889.387   Durbin-Watson:                   0.005
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             9655.221
Skew:                           1.914   Prob(JB):                         0.00
Kurtosis:                       8.950   Cond. No.                         114.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

```
Text(0.5, 1.0, 'EVR1 from Spearman correlation vs Credit Spreads')
```



Now the R^2 statistics is more solid, and at the same time the EVR1 coefficient estimation shows a solid p-stat score.

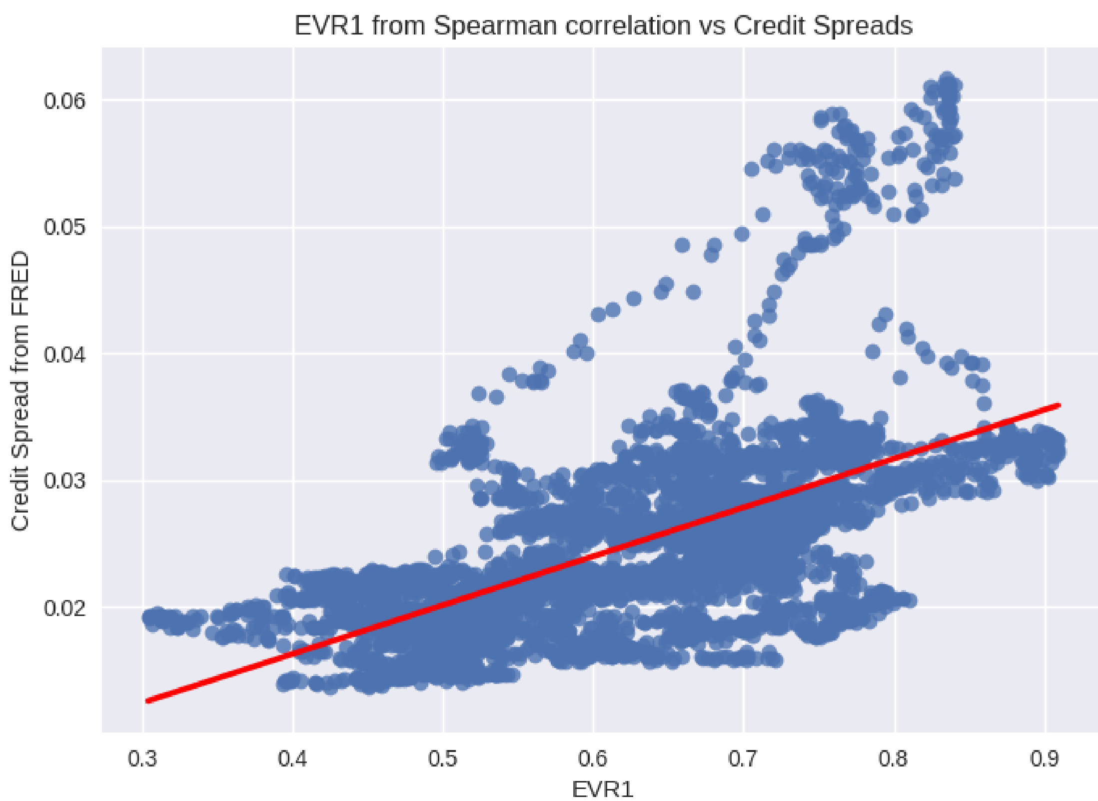
From this information we can infer that credit spreads from Fred are more dependable than their market counterpart, obtained from the LQD ETF.

Proceeding, we complete the picture with the next two regressions which will help selecting the most accurate correlation method for EVR1, in terms of how good it relates to the Fred credit spread.

```
                            OLS Regression Results
===============================================================================
===
Dep. Variable:     Credit Spread from FRED   R-squared:
0.347
Model:                                 OLS   Adj. R-squared:
0.347
Method:                      Least Squares   F-statistic:
819.2
Date:                     Sat, 30 Aug 2025   Prob (F-statistic):
0.00
Time:                             23:39:07   Log-Likelihood:
16833.
No. Observations:                     4629   AIC:
-3.366e+04
Df Residuals:                         4625   BIC:
-3.363e+04
Df Model:                                3
Covariance Type:                 nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0003      0.002      0.137      0.891      -0.004       0.005
EVR1           0.0389      0.002     16.199      0.000       0.034       0.044
EVR2           0.0233      0.005      5.098      0.000       0.014       0.032
EVR3          -0.0353      0.007     -4.887      0.000      -0.049      -0.021
==============================================================================
Omnibus:                     1736.491   Durbin-Watson:                   0.005
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             8054.098
Skew:                           1.773   Prob(JB):                         0.00
Kurtosis:                       8.403   Cond. No.                         98.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

```
Text(0.5, 1.0, 'EVR1 from Spearman correlation vs Credit Spreads')
```

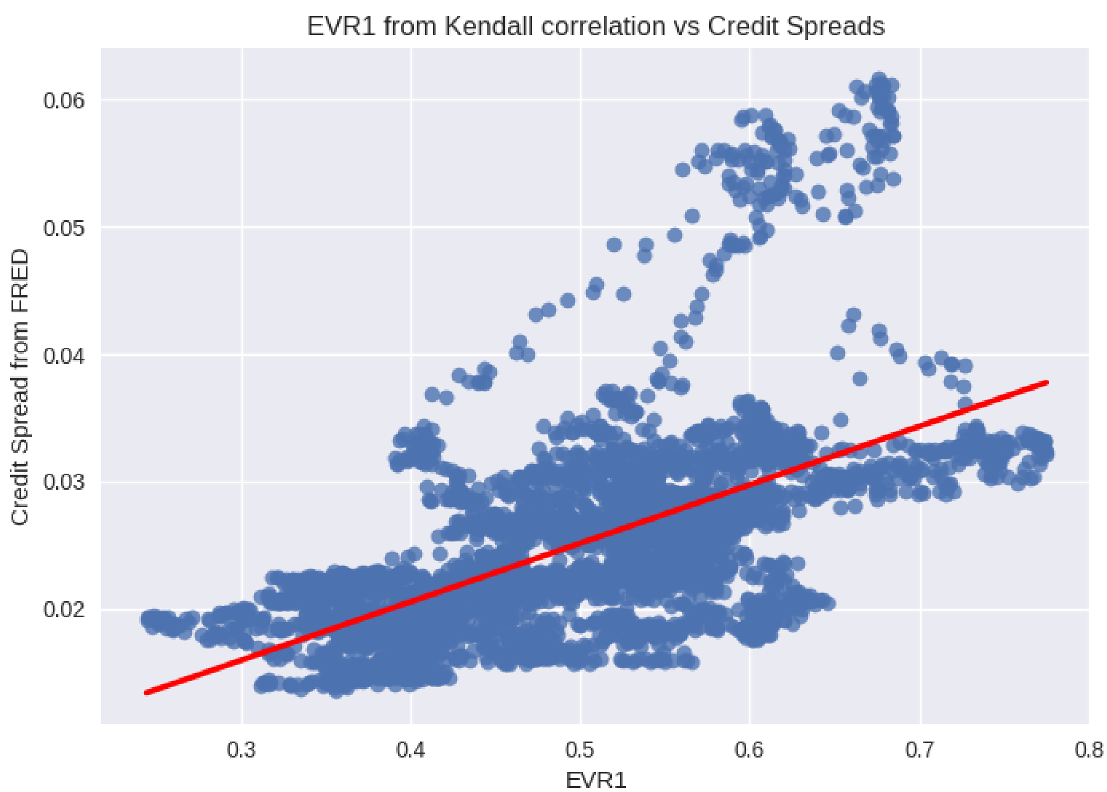



```
                            OLS Regression Results
================================================================================
===
Dep. Variable:     Credit Spread from FRED   R-squared:
0.349
Model:                                 OLS   Adj. R-squared:
0.349
Method:                      Least Squares   F-statistic:
827.1
Date:                     Sat, 30 Aug 2025   Prob (F-statistic):
0.00
Time:                             23:39:07   Log-Likelihood:
16841.
No. Observations:                     4629   AIC:
-3.367e+04
Df Residuals:                         4625   BIC:
-3.365e+04
Df Model:                                3
Covariance Type:                 nonrobust
==============================================================================
```

```
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       6.857e-05      0.002      0.030      0.976      -0.004       0.005
EVR1           0.0481      0.003     19.113      0.000       0.043       0.053
EVR2           0.0348      0.006      6.034      0.000       0.024       0.046
EVR3          -0.0385      0.009     -4.127      0.000      -0.057      -0.020
==============================================================================
Omnibus:                     1753.261   Durbin-Watson:                   0.005
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             8084.434
Skew:                           1.795   Prob(JB):                         0.00
Kurtosis:                       8.388   Cond. No.                         117.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

```
Text(0.5, 1.0, 'EVR1 from Kendall correlation vs Credit Spreads')
```



All three correlation methods, Pearson, Spearman and Kendall, achieve a p-statistic = 0 for the EVR1 coefficient. Values of the R^2 statistic for Spearman and Kendall are better than Pearson's and more or less equal to each other. The standard error of the EVR1 coefficient in Spearman is slightly lower than Kendall's.

Correlation	EVR1 coefficient	R^2	EVR1 p-stat	EVR1 std err
Pearson	0.0364	0.296	0	0.003
Spearman	0.0389	0.346	0	0.002
Kendall	0.0481	0.349	0	0.003

This, and additionally the previous observation that historical data for EVR1 from Kendall correlation is much more conservative and as such detects less false positives (good) due to noise, but also true positives (bad) such as the 2008 financial crisis, leads us to choose the Spearman correlation as our methodology to extract the EVR1 signal.

Generate a Systemic Risk Indicator (SRI) from correlation breakdown and widening credit spreads An obvious observation that can be made of the above procedure that led us to pick the Spearman correlation matrix to generate the EVR1 metric, is that we applied linear regressions over a correlation measure that tracks nonlinearities.

The analysis would greatly benefit from employing Machine Learning in stead of linear regression to track these nonlinearities, at the price of course of more obfuscation in the selection process.

Indeed, the (Spearman EVR1 - credit spread) linear regression coefficient of 0.0389 is quite feeble, but this also might help justifying the construction of a SRI as linear combination of EVR1 and credit spread. The two terms are expected to correlate more heavily during crises, while a linear combination-based SRI would instead suggest EVR1 and credit spread to be independent from each other. However, a weak correlation when markets are placid might make an acceptable proxy for independence, while the linear combination will still cause the SRI to increase at market phase shifts, just more so than if the rising (EVR1-credit spreads) correlation were to be taken into account.

Therefore, we could define the SRI as following

$$\mathrm{SRI}(\text{credit spread}, \mathrm{EVR1}) = \alpha \cdot \text{credit spread} + \beta \cdot \mathrm{EVR1}$$

where coefficients α, β could be selected from a Least Squares minimisation procedure.

The sum of squared residuals Δ to minimise might be the distance of the SRI from the ^VIX index, as volatility increases during crises, and our goal is to generate an indicator of crises.

$$\Delta = \sum_i \|\mathrm{SRI}_i - \mathrm{VIX}_i\|^2$$

For each observation $i \in [2007, 2025]$ inside the selected timeframe.

We use the `curve_fit` method from `scipy` (based on nonlinear least squares) to calibrate the parameters α and β in SRI. The ^VIX index returns have higher order of magnitude, hence we are going to fit against $\frac{\mathrm{VIX}}{100}$.

```
alpha and beta coefficients:  [6.27602895 0.06632101]
```

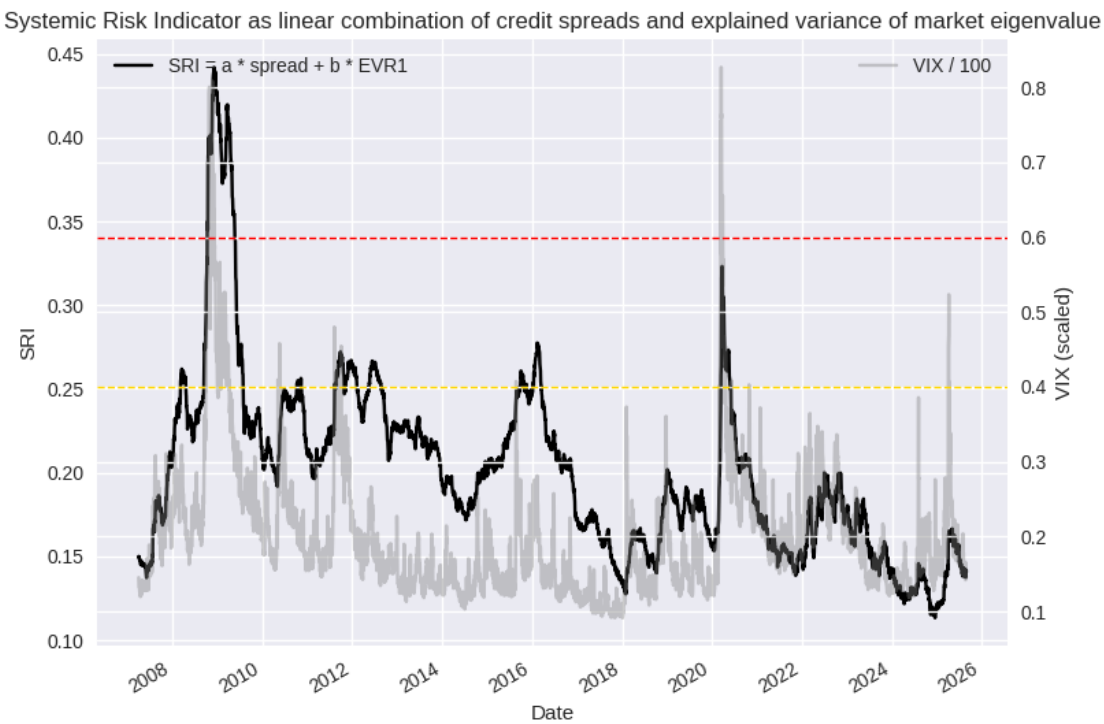
```
stddev of alpha and beta coefficients:  [0.15481731 0.00635234]
```

The procedure yields values of

$$\alpha = 6.276 \pm 0.155$$
$$\beta = 0.066 \pm 0.006$$

This is in line with credit spreads being much smaller in absolute value than the first explained variance of the correlation matrix of returns.

Graphically, the SRI is represented against the ^VIX, below:



Predictably, the SRI mimics well the ^VIX during calm periods.

Outlier values observed during stormy financial periods present a small reaction lag with respect to ^VIX. The financial crisis of 2008 is timely identified by the SRI in the whole of its intensity. Not so much for other periods, like the Covid 2020 crisis, or the increase in US foreign tariff during the first half of 2025. In these cases, the SRI emits tenuous signals when compared to ^VIX. This is why the crisis thresholds were lowered to $0.3 \cdot \text{SRI}$ (red) and $0.25 \cdot \text{SRI}$ (yellow).

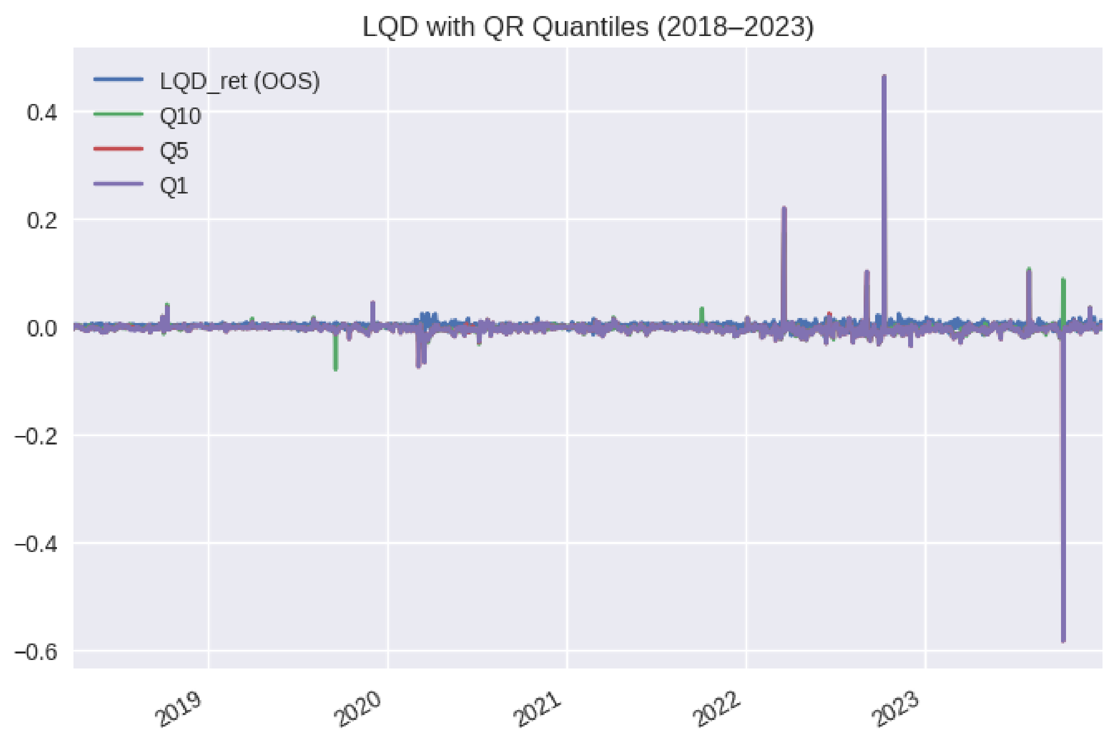
0.2 Student B - Quantile Regression with Time-Varying Correlation

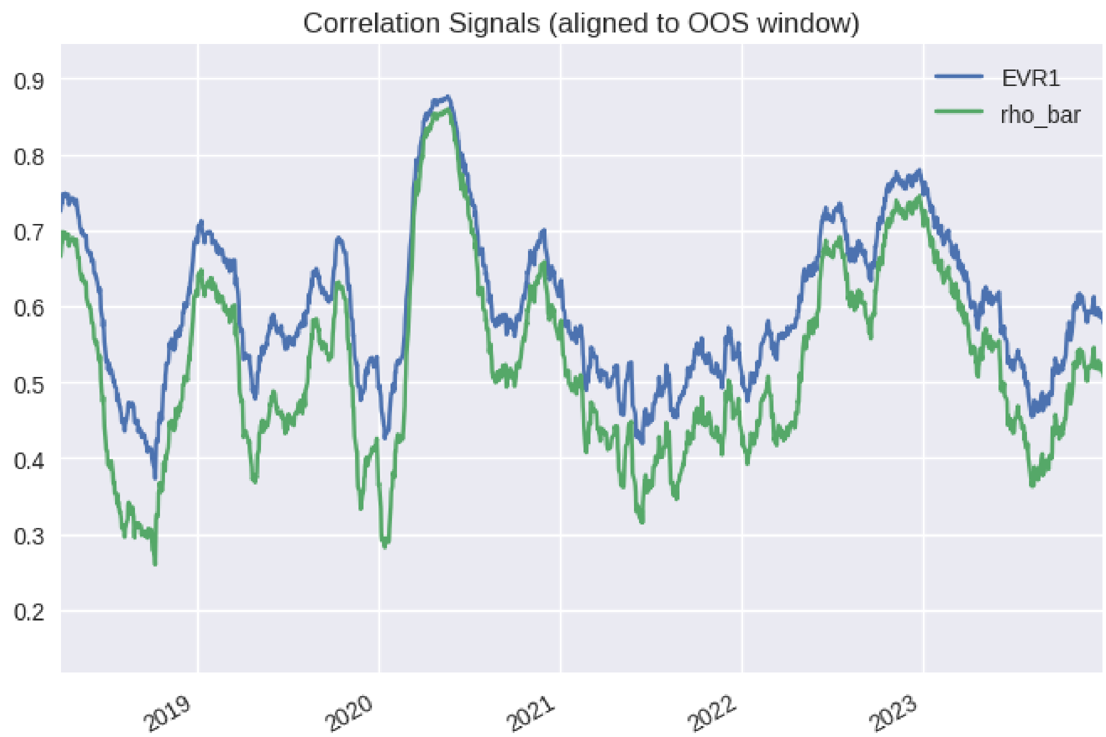
Uses the common loader's variables to fit rolling **Quantile Regression** for $\tau \in \{0.10, 0.05, 0.01\}$ and produce evaluation metrics and figures, all clipped to **2018-04-03 -> 2023-12-31**.

Rolling QR with correlation features adapts, but big regime jumps (like COVID) still cause short-term underestimation. Consider adding a fast-moving volatility proxy (e.g., 21-day realized vol), and include $\frac{\Delta \mathrm{EVR1}}{\Delta \rho}$ to catch rapid correlation shifts.

Higher common-correlation regimes (peaks in 2020, 2023) coincide with periods where left-tail risk is larger, matching the wider/ more negative QR quantiles on the returns chart.

```
[INFO] EVR_WINDOW=63  RHO_WINDOW=63  QR_ROLL_WIN=63
[INFO] EVR1 starts:   2007-04-05 00:00:00 | rho_bar starts: 2007-04-05 00:00:00
[INFO] X starts:      2007-04-10 00:00:00
[INFO] Effective QR window used: 63
[INFO] First OOS pred: 2007-07-11 00:00:00 | OOS points: 4560
tau=0.10  pinball=0.001561  Kupiec(LR,p)=(671.8883132289375,0.0)
Christoffersen(LR,p)=(nan,nan)
tau=0.05  pinball=0.001380  Kupiec(LR,p)=(1630.2841159728705,0.0)
Christoffersen(LR,p)=(nan,nan)
tau=0.01  pinball=0.001169  Kupiec(LR,p)=(4658.390767935948,0.0)
Christoffersen(LR,p)=(nan,nan)
```





The quantile envelopes adjust in size according to market regimes, as anticipated. The COVID shock (March–April 2020) results in the most significant negative outcomes—numerous breaches below the Q5 and Q1 curves—demonstrating the model's short-term underestimation of tail risk during an abrupt regime shift. As conditions stabilize through late 2020 and into 2021, the bands constrict, and realized returns primarily fluctuate between Q10 and Q1, indicating improved calibration during calmer periods. In 2022–2023, characterized by rate shocks and liquidity concerns, the band expands once more, leading to occasional exceedances, though significantly fewer than in 2020—this serves as evidence that the rolling QR adjusts, albeit not immediately, to spikes in volatility and correlation.

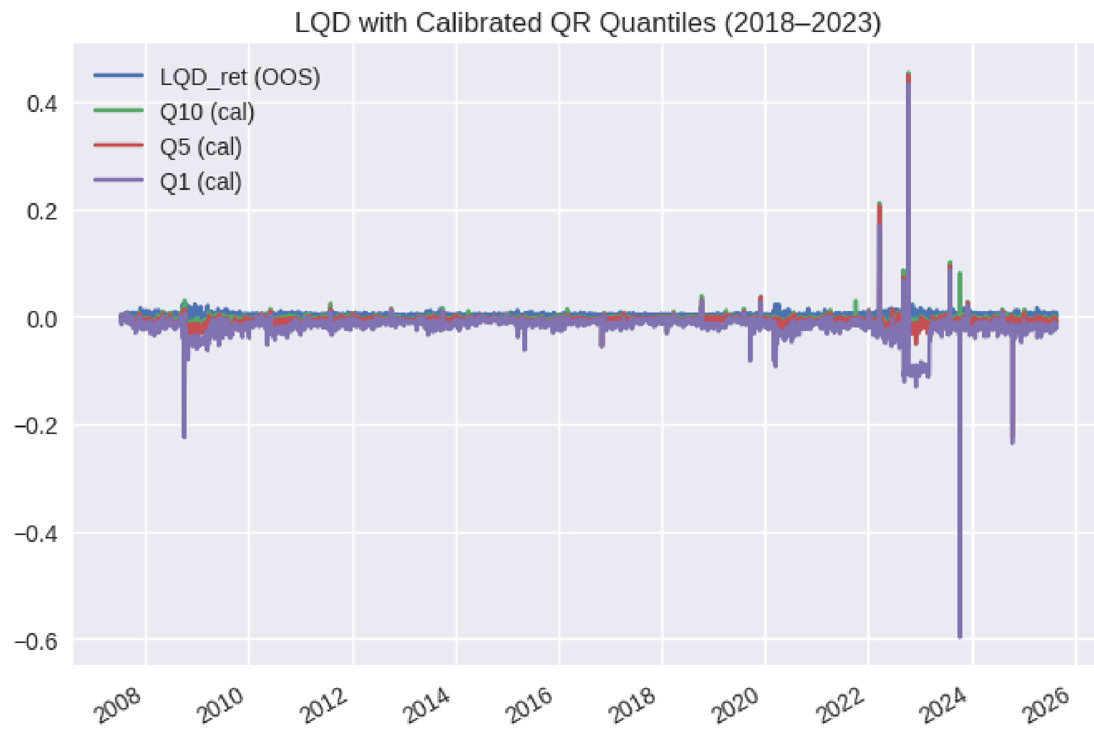
Regarding the levels: the predicted quantiles remain below zero for a substantial portion of the sample, aligning with LQD's sensitivity to left-tail correlation and credit spreads. In instances of local surges (for example, mid-2022 and early 2023), the model preemptively or shortly thereafter reduces the quantile paths, effectively capturing heightened downside risk. For even swifter adaptation during abrupt changes, it may be beneficial to incorporate a short-window realized volatility feature and utilize $\frac{\Delta \mathrm{EVR1}}{\Delta \rho}$ in conjunction with the levels.

EVR1 and rho_bar move in sync, hitting about 0.8+ in early 2020, then going back down before rising again into 2022-2023, and eventually declining. The difference between them (EVR1 being higher than rho_bar) is common: EVR1 looks at how intense the market is ($\frac{\lambda_1}{N}$), which usually is higher than the simple average correlation. The timing matches the returns graph: when the overall correlation goes up, it happens during times when the QR bands drop and spread out (showing more overall movement together, leading to more extreme low values), while a decrease in correlation is linked to tighter bands and less frequent breaks.

```
Q10: hit rate = 23.224% (target 10.0%) | T=4560
Q5: hit rate = 22.390% (target 5.0%) | T=4560
Q1: hit rate = 22.500% (target 1.0%) | T=4560
```

These hit rates mean the model is underestimating downside risk across the board (predicted lower quantiles are too high / not negative enough). To help with this, we add a rolling calibration layer:

```
[Calibration…] Q10: hit rate = 11.338% (target 10.0%) | T=4560
[Calibration…] Q5: hit rate = 5.636% (target 5.0%) | T=4560
[Calibration…] Q1: hit rate = 2.039% (target 1.0%) | T=4560
```



This calibrates each quantile by adding a rolling residual quantile offset so the recent hit rate matches the target.

0.3 Student C - Extension of a DCC-GARCH framework with funding stress indicators acting as regime change detectors

Dynamical Conditional Correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH) is a model capable of estimating large time-varying covariance matrices. It does this by using estimating volatilities individually for each asset using GARCH for each separate time series.

The DCC (Dynamic Conditional Correlation) component is what makes the model "integrated" and powerful. It models how the correlations between these assets change over time. In a stable market, the correlation between stocks and bonds might be low or even negative. But during a market crisis, the correlation between almost all assets tends to spike towards 1 which is usually called a correlation spike.

In our case we will model use market sector tracker ETFs and market stress indicators as data for our correlation modeling, the idea is to be able to infer when the probability of correlation spikes are higher ahead of time. The data we are using are:

Sector tracking ETFs:

- XLY: Consumer Discretionary
- XLP: Consumer Staples
- XLE: Energy
- XLF: Financials
- XLV: Health Care
- XLI: Industrials
- XLB: Materials
- XLK: Technology
- XLU: Utilities

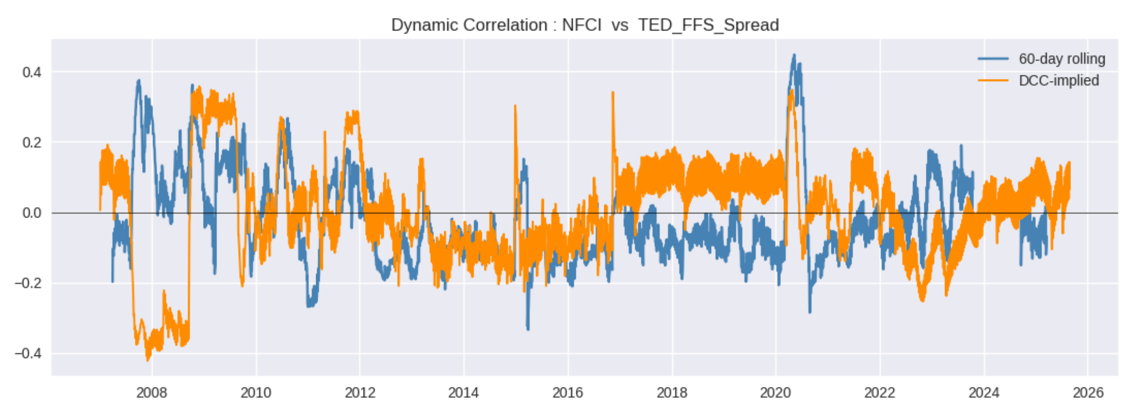
Market stress indicators

- TED: Treasury-Eurodollar spread (This one has been discontinued by FRED in favour of Secured Overnight Financing Rate (SOFR))
- SOFR: Secured Overnight Financing Rate
- DFF: Federal Funds Effective Rate
- NFCI: Chicago Fed National Financial Conditions Index
- STLFSI4: St. Louis Fed Financial Stress Index
- VIX:CBOE Volatility Index

The difference between SOFR and DFF can be taken as a proxy of cross currency basis since it indicates dollar liquidity in the repo market. Adding these market indicators, builds on top of the materials provided by WQU. As SOFR did not exist prior to 2018, we will fill them with 0 to avoid NAN values, for earlier dates we will use TED even though according to the FRED website, the TED indicator should not be used.

After obtaining the data we run a $GARCH(1,1)$ model with a Gaussian error term. then we standardise the residuals,and collect the results in a dataframe.

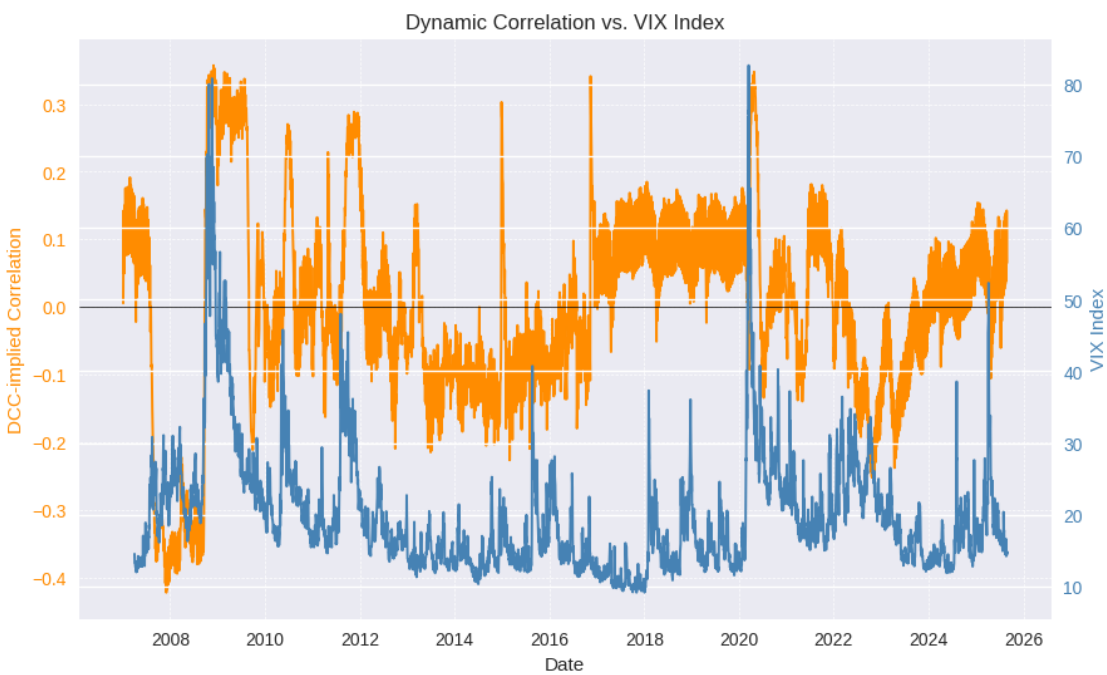
```
DCC alpha=0.050,  beta=0.900,  persistence=0.950
```



A cascade effect in financial markets describes a chain reaction where a shock to one part of the system rapidly spreads to others, creating a self-reinforcing loop of instability. This process often begins with a volatility shock—a sudden, sharp increase in market uncertainty, often triggered by an unexpected event.

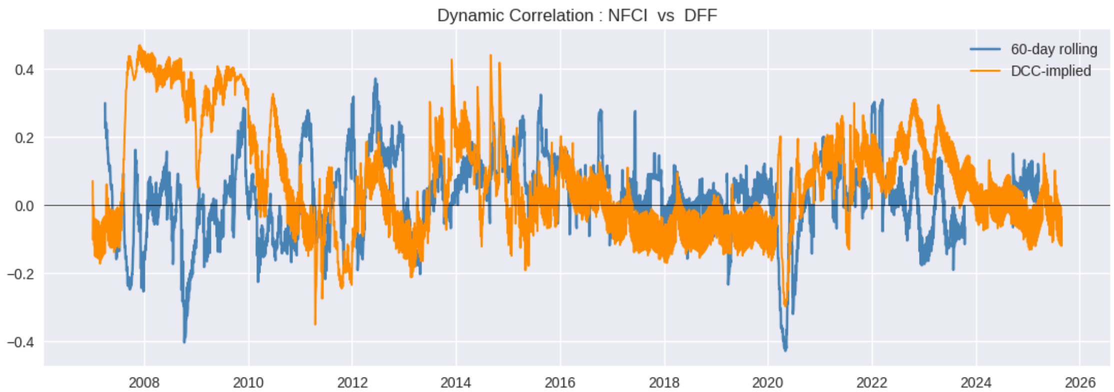
A good proxy for this is the VIX which is a measure of the expected volatility of the market as a whole, when it is big the markets are quite volatile which usually means it is moving as a whole and correlations are close to one. We observe our DCC indicator (which measures the correlation between NFCI and our cross currency proxy) seems to be able to predict ahead of time when spikes in the vix will be present, we see that from 2023 the indicator breaks down, this is most likely due to the Fed changing its economic policies and entering into a high interest rate regime which had not been seen in many years 3, other correlation pairs were considered but this is the one we found gave the best predictions for low interest rates environments.

```
Text(0.5, 1.0, 'Dynamic Correlation vs. VIX Index')
```



As seen in the picture our indicator is often ahead of volatility spikes, since correlations often change in time, Afzan et al. recommend doing the analysis with timeframes in which the macro environment is similar, the volatility spikes induce shocks in the markets. We show the best indicator out of all the different pairs we tried, notice it deviates significantly from the end of 2022, this is because of the huge change in the macro due to interest rate hikes, which drastically changed the correlations, breaking this pair as an indicator. These shocks immediately lead to a correlation spike, as a sudden “risk-off” sentiment causes investors to sell all assets indiscriminately, driving their prices down in unison. Assets that were once uncorrelated or negatively correlated now move together, eliminating the benefits of diversification.

The increased volatility and correlation then trigger a funding freeze. As lenders become hesitant to extend credit due to heightened risk, market liquidity dries up. This forces institutions to sell assets to meet their funding needs, which in turn drives prices down further, causing even more volatility. This completes the feedback loop, as the funding freeze exacerbates the initial volatility shock. This cascade demonstrates how seemingly distinct market dynamics are deeply interconnected, creating a vicious cycle that can lead to a systemic crisis.



Choosing a different pair does not rely on the spread of cross currency pairs yields better results from 2022 on, but is a bit useless as an indicator as shocks in volatility happen after the real ones, perhaps it would serve to do arbitrage in bonds, but not to hedge a stock portfolio. This is why we disregard this pair, others also exhibit similar features, the most promising one being NFCI vs the SOFR spread. Unfortunately, due to the SOFR being non existent prior to 2018 we use the second best NFCI vs the TEDRATE spread, even when it cannot be used in the feature and should be superseeded by the SOFR one.

0.4 Global Systemic Risk Indicator, as combined from individual Indicators of students A, B, C

By integrating the results of the different generalizations we considered, and expanding upon the work of student A, we will create a Global Systemic Risk Indicator (GSRI)

$$\text{GSRI} = (\alpha SRI + \beta DCC + \gamma QR_{10})$$

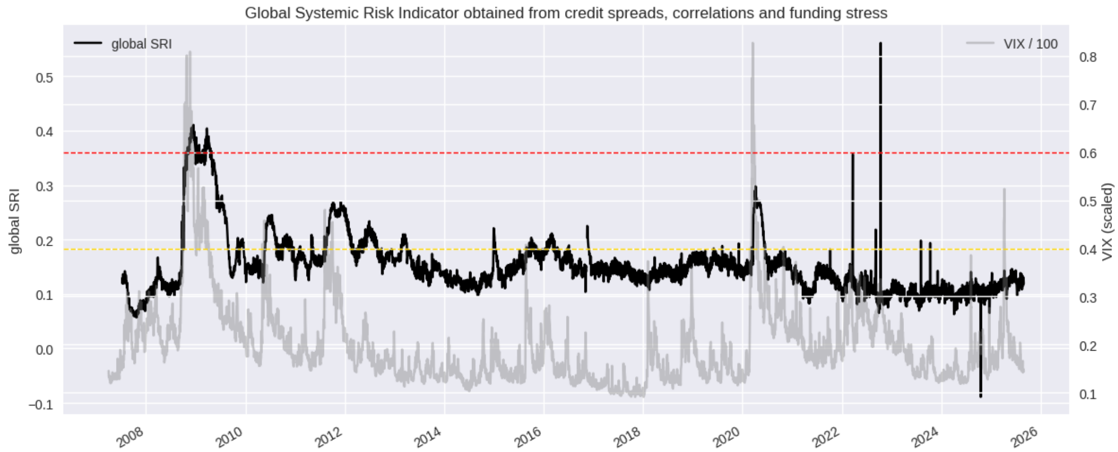
where SRI, DCC and QR_{10}, gave been normalized. We will use scipy's `curve_fit` to produce adequate α, β, γ, in such a way that the indicator becomes apt at predicting possible economic crisis. By going with a simple linear combination of the three different sub-indicators, we are able to produce an easy-to-interpret global risk indicator.

As an aside, it is worth noting that according to Molnar, when it comes to algorithms that can have big repercussions, it's best to have interpretable models so experts can know the particular predicaments in which these models may break down.

```
alpha: 0.8000, beta: 1.0000, gamma: 0.2000
```

The result from the optimization indicate that the most important indicator is the one from student A based on the PCA monitoring framework

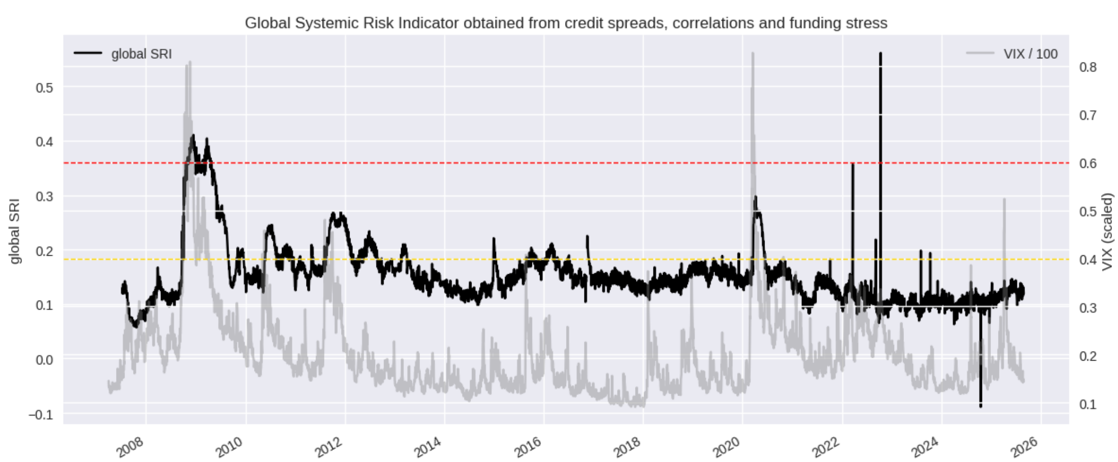
```
std devs of coefficients:
alpha: 0.0071, beta: 0.1171, gamma: 0.0068
```



Our integrated approach is able to signal abrupt movements in market volatility ahead of time, giving us the ability to prevent losses, even though it smooths some of the peaks a bit too much, and it delays many of them as well, so we miss small abrupt movements in the VIX when using our indicator. We can see our indicator breaks down at the end of the 2022.

This is because the contribution of our DCC model based on the SOFR, and Federal interest rate took a massive regime shift, an historical one. This regime shift changed the macro environment into one that had not been seen in decades (see the article by Irvine). As we will see next, allowing our model no lower bound on the importance of this cross-currency indicator based on DCC, gets us better tracking of the VIX. This advantage however comes at the cost of a loss in predictive power, as the spikes are not seen ahead of time.

```
alpha: 0.4413, beta: 0.0000, gamma: 0.0318
```



The change in the macro environment and the fact that a similar macro is not seen in the data gives our indicator some trouble, the good news is that the interest rates cannot be high for a long time, in fact, how long they have been high is what makes the current economical situation so unusual. According to Moore, the possibility of the Federal reserved lowering interest rates next month sits at around 91% , those interest rates will perhaps return the correlation of our indicator into it's normal regime, thus allowing us to use our indicator as the correlations are likely to go back to their usual pattern once interest rates come down.

0.5 Comparison with a VAR model

In this section, we are going to compare our SRI with output prediction for ^VIX from a Vector AutoRegressive (VAR) model.

We are going to focus our attention to the period immediately before the spike in volatility that happened during the Covid crisis from approximately February to April 2020.

The crisis period February - April 2020 (included) will act as our testing period. The training period will cover the two years before, from April 2018 to January 2020.

The VAR model will be composed of

- the ^VIX index itself,
- the credit spreads as obtained from FRED (BBA10Y series),
- the TED spread from FRED,
- the SOFR - FFS spread, from FRED as well.

```
Series included in the VAR model for ^VIX:  Index(['^VIX', 'Credit Spread from
FRED', 'TEDRATE', 'TED_FFS_Spread'], dtype='object')
```

We fit the `VAR` model from the `statsmodels` package in Python.

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Sun, 31, Aug, 2025
Time:                     00:08:33
--------------------------------------------------------------------
No. of Equations:         4.00000    BIC:                   -28.5016
Nobs:                     461.000    HQIC:                  -28.6103
Log likelihood:           4014.43    FPE:                3.49976e-13
AIC:                     -28.6809    Det(Omega_mle):     3.35196e-13
--------------------------------------------------------------------
Results for equation ^VIX
================================================================================
=============
                                coefficient       std. error           t-stat
prob
```

```
--------------------------------------------------------------------------------
-------------
const                         1.265366         0.845710            1.496
0.135
L1.^VIX                       0.919247         0.020181           45.550
0.000
L1.Credit Spread from FRED  -45.704163        45.154989           -1.012
0.311
L1.TEDRATE                    0.498067         0.806943            0.617
0.537
L1.TED_FFS_Spread            -0.463403         0.293508           -1.579
0.114
================================================================================
=============

Results for equation Credit Spread from FRED
================================================================================
=============
                           coefficient       std. error           t-stat
prob
--------------------------------------------------------------------------------
-------------
const                         0.000328         0.000125            2.623
0.009
L1.^VIX                       0.000014         0.000003            4.696
0.000
L1.Credit Spread from FRED    0.977144         0.006673          146.427
0.000
L1.TEDRATE                   -0.000228         0.000119           -1.910
0.056
L1.TED_FFS_Spread            -0.000005         0.000043           -0.108
0.914
================================================================================
=============

Results for equation TEDRATE
================================================================================
=============
                           coefficient       std. error           t-stat
prob
--------------------------------------------------------------------------------
-------------
const                         0.214699         0.045123            4.758
0.000
L1.^VIX                       0.003444         0.001077            3.198
0.001
L1.Credit Spread from FRED   -2.316386         2.409277           -0.961
```

```
0.336
L1.TEDRATE                         0.614910         0.043055           14.282
0.000
L1.TED_FFS_Spread                  0.059665         0.015660            3.810
0.000
================================================================================
=============

Results for equation TED_FFS_Spread
================================================================================
=============
                                coefficient       std. error           t-stat
prob
--------------------------------------------------------------------------------
-------------
const                              0.192962         0.049213            3.921
0.000
L1.^VIX                            0.002873         0.001174            2.446
0.014
L1.Credit Spread from FRED        -1.258901         2.627647           -0.479
0.632
L1.TEDRATE                        -0.375083         0.046957           -7.988
0.000
L1.TED_FFS_Spread                  1.056433         0.017080           61.853
0.000
================================================================================
=============

Correlation matrix of residuals
                               ^VIX  Credit Spread from FRED   TEDRATE
TED_FFS_Spread
^VIX                       1.000000                 0.382682  0.028095
0.032966
Credit Spread from FRED    0.382682                 1.000000 -0.005089
0.007879
TEDRATE                    0.028095                -0.005089  1.000000
0.921368
TED_FFS_Spread             0.032966                 0.007879  0.921368
1.000000
```

Results are statistically acceptable. The model was directed to select autonomously the number of lag terms for the VAR independent variables.

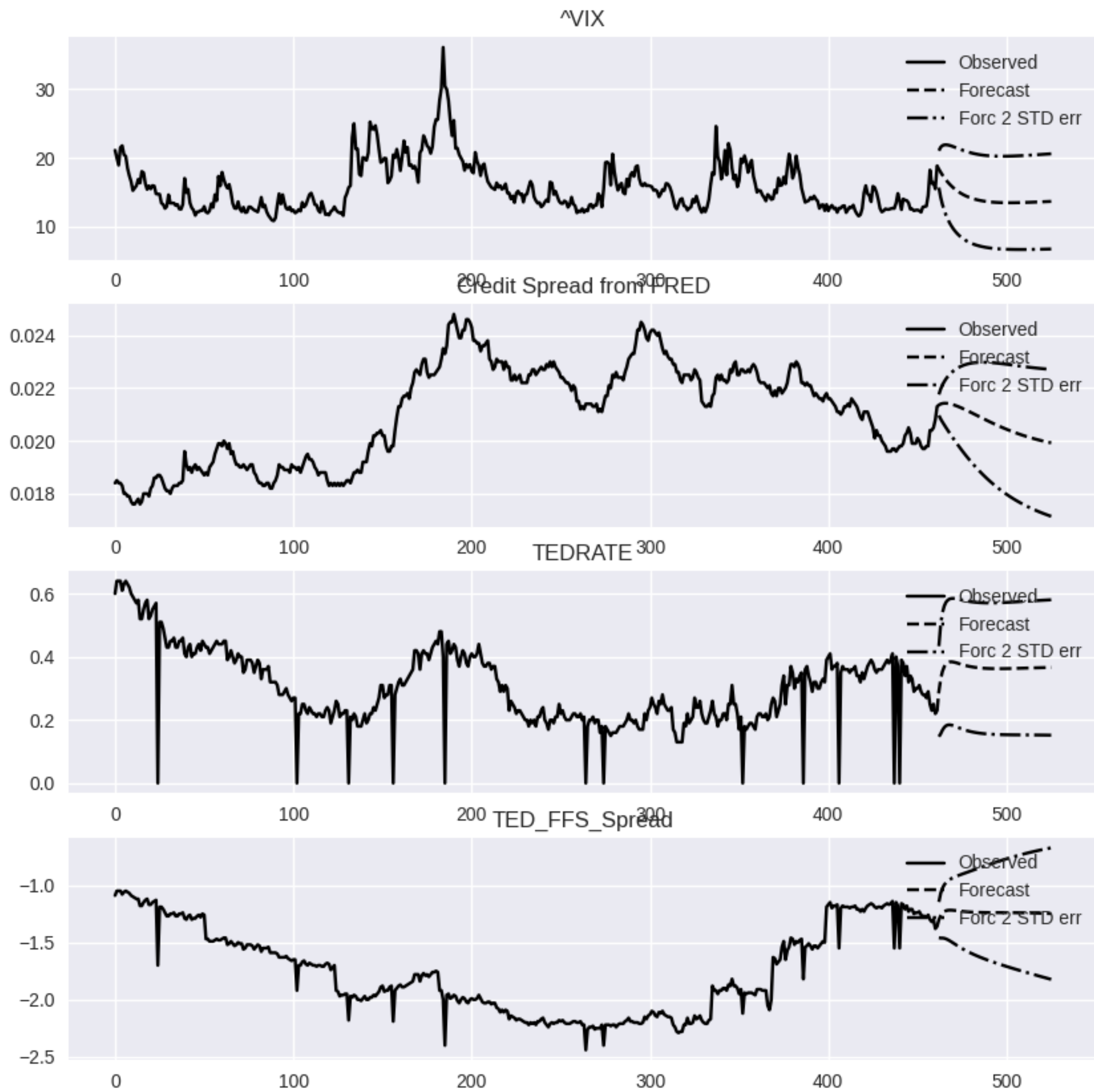
```
VAR model was fitted with 1 lag terms
```

We use below an easy-plotting option in `statsmodels.VAR` for the VAR autoregressions of the four chosen series.

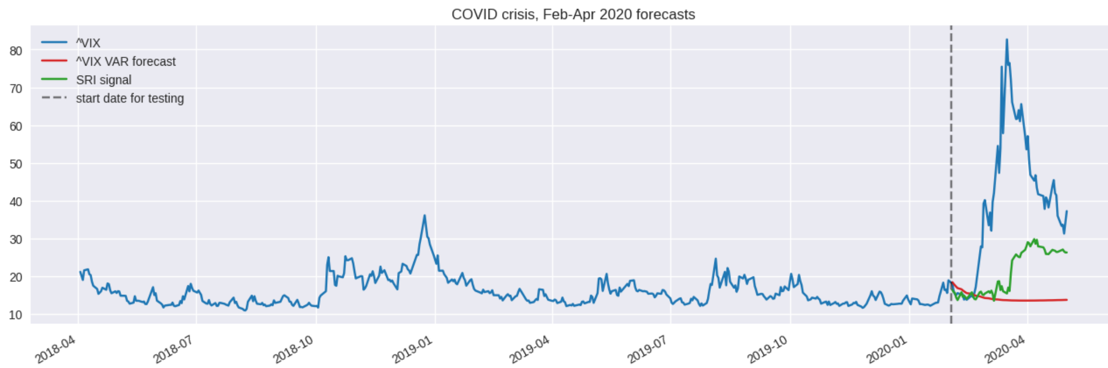
Options for customising the axes are unavailable.

On the x axis there is time expressed in days from the start date, 4th of April 2018.

Dotted plots at the left end of the graph are VAR extrapolations of the testing period (February-April 2020). Central dotted plot is what is given as the most probable forecast, while dotted plots on the sides express a confidence interval set at $2 \cdot$ std dev.



A graphic comparison of the output from the VAR model, the SRI, and the true path taken by ^VIX during the Feb - Apr 2020 testing period is presented below.

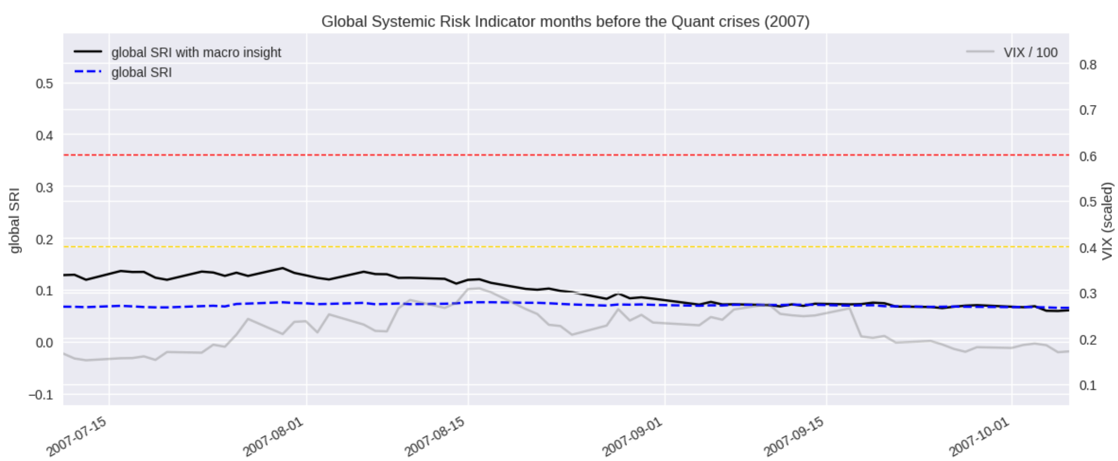


We see that the SRI performs better than the VAR model, although still quite not able of predicting the full intensity of the crisis. However, it manages to predict the overall direction - even if with some lag - thus being an useful indicator.

0.6 Behaviour of the global SRI across different historical crisis

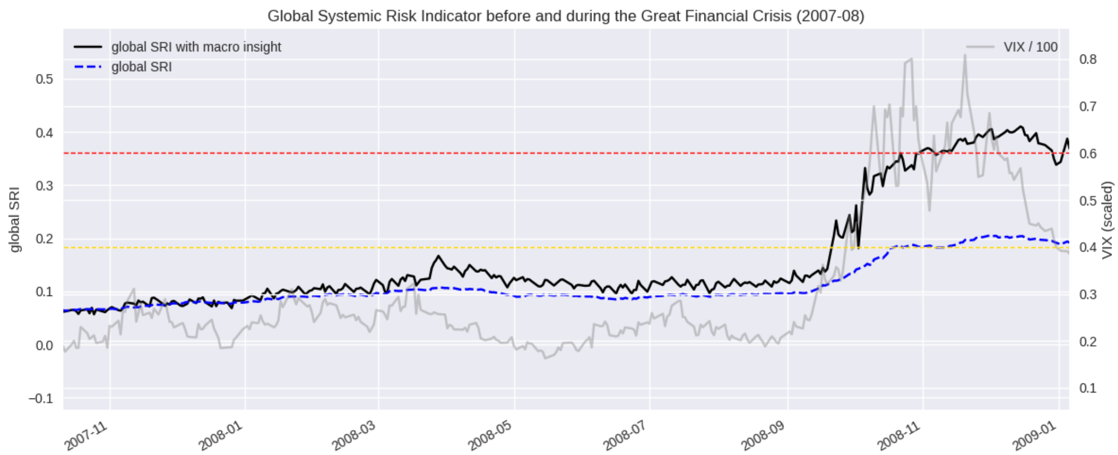
We start with the August 2007 *Quant Crisis*. This was a liquidity crisis due to synchronized deleveraging of positions (enacted by the so-called "quants" at financial institutions), otherwise known as the *avalanche effect*.

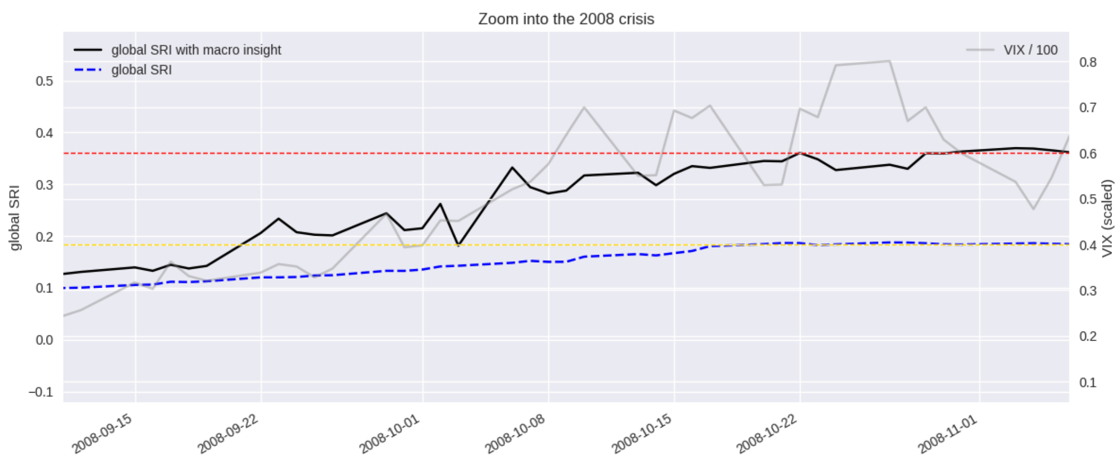
We observe how our indicator behaved in August 2007.



During this crisis, our indicator does not give any sign of distress even if we include our macro insights, but neither does the VIX.

We continue with the 2008 financial crisis, also known as the *Global Financial Crisis* (GFC), ignited by a real estate bubble. Intuition tells us that our global indicator - where we force the correlation to interest rates to have a minimal weight - would be able to reveal to us something ahead of time, as this crisis was caused by the housing bubble. The crisis climaxed in September 2008, and we will zoom in at the behaviour from January 2007 to December 2008:

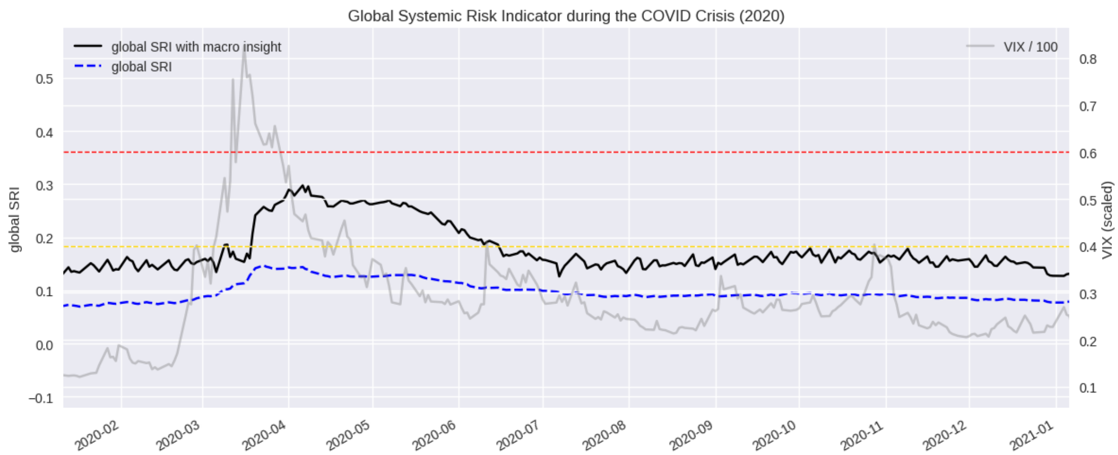




We can observe that the SRI with macro insight predicts the spike in the VIX in September, just a few trading sessions before it happens. Its plot is quite smooth, and gives a good sense than a crisis is incoming, unlike the VIX which proceeds regularly, with ups and downs that were not too uncommon (but had an upward drift) during the crisis.

Though the SRI almost follows the VIX as it is, it would have been a valuable indicator back then. The SRI relying on optimization alone sees the spike in the VIX only a few days after the spike happened, thus not being overly useful. All this highlights the importance of adding your views in the market to your mathematical models.

Next, we continue wih the March 2020 *Covid Crisis*:



Both indicators see the increase in volatility in March, but they signal for it after the VIX does. This tells us that we are lacking some macro measure or correlation. In order to predict this spike, rather than detecting it after-the-fact, we believe the incorporation of macro data related to healthcare expenditure like HLTHSCPCHCSA, might help our indicator predict this sort of spike. After the discussion we have had so far, we would like to highlight some of the advantages of our indicator

1. It is interpretable, meaning we can interpret the signal in terms of macroeconomic factors.
2. It is easily generalizable, we only took a linear combination of our different approaches, but we could retain interpretability and add nonlinear relations via polynomial terms such as $(DCC - QR)^2$.
3. It captures the overall trend of volatilities, as our plots in the global systemic risk indicator show.
4. When it breaks down it signals big changes in the macroeconomic environment, for example in the student C section, we see that as the interest rates increased we expect our DCC model to break down, and we had assigned a big weight to it when we included our macro views.
5. It is customizable, following our opinions of market directions as they change. When the correlation between spreads or the eigenvalue behavior is expected to breakdown, we can decrease their weights inside the global indicator. This would allow us to keep using our SRI in the context of different macroeconomic environments.
6. It smoothens out high frequency peaks, indicating the overall behaviour of the markets, letting go of small quick volatility spikes which are just noise to most hedge funds and patient investors.
7. It allows for easy incorporation of other indicators. In today's world, many things that are not necessarily part of the macro can have huge impact on the markets. For example, one could build another normalized indicator based on market sentiment in social media, and linearly combine it to our indicator, with minimal effort and preserving interpretability.
8. It is based on simple measures that can be updated daily, and computed almost in real time.

Based on the previous advantages, we do believe our indicator outperforms VAR models. However, the latter models should always be taken into consideration, and our indicator should serve to complement them.

0.7 Discussion

The Global Systemic Risk Indicator we propose offers a unique and transparent way to keep tabs on systemic risk, by combining insights from several different analytical approaches. Instead of relying on just one metric, it is built blending together several methods: one of these methods looks at how markets behave during extreme events (that is the Quantile Regression), another tracks how the volatility of different markets changes together (DCC-GARCH), and a third method measures how interconnected the markets are (PCA first eigenvalue monitoring). This combination is key, because it lets us see exactly what is driving the risk - whether it is wild market swings, unexpected correlations, or something else entirely. It is an easy-to-understand signal that tells you not just that something is wrong, but also why.

Practically, you should think about this indicator as a valuable companion to your existing tools, not as a replacement. It will not necessarily predict every tiny, high-frequency jump in the market, but its real power is in signaling a bigger, more fundamental shift across the economic landscape. For example, if it starts to tick up, then that is a sign that the underlying market conditions are changing in a significant way. And since it is so customizable, we can easily tweak the recipe by adjusting the weights of its different parts. This means we can keep using it in different market environments, making it a very adaptable and useful tool for spotting major shifts.

One of the best things about this indicator is that it smooths out the noise. It focuses on the overall behavior of the markets, letting go of small, fleeting volatility spikes that are often just distractions for most investors. This makes it perfect for those who are focused on long-term trends rather than daily overreactions. Plus, it is incredibly flexible. If we wanted to, we could easily plug in a completely new measure - like a sentiment indicator based on social media - and it would still work just fine, adding another layer of insight without sacrificing its interpretability. It is a smart, durable, and transparent way to get a feel for the market's big picture.

0.7.1 References

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