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Research article

Time-Varying Tail connectedness between green bonds, US tech equities, and AI/Cybersecurity ETFs: A TVP-FQVAR and machine learning approach

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Appendix A: Results of Neural Networks

A feedforward neural network is developed to capture deep non-linear relationships across explanatory variables. Hidden layers are configured with ReLU activation functions and regularized with dropout to prevent overfitting. The backpropagation algorithm minimizes the mean square error loss function via the Adam optimizer. Grid search determines optimal architecture parameters, including number of layers, neurons per layer, and learning rate. Neural networks' flexible representation learning is proven beneficial to assess the volatility sensitivity of the TCI across quantile regimes and revealed complementarity with more structured methods like SVM and XGBoost.

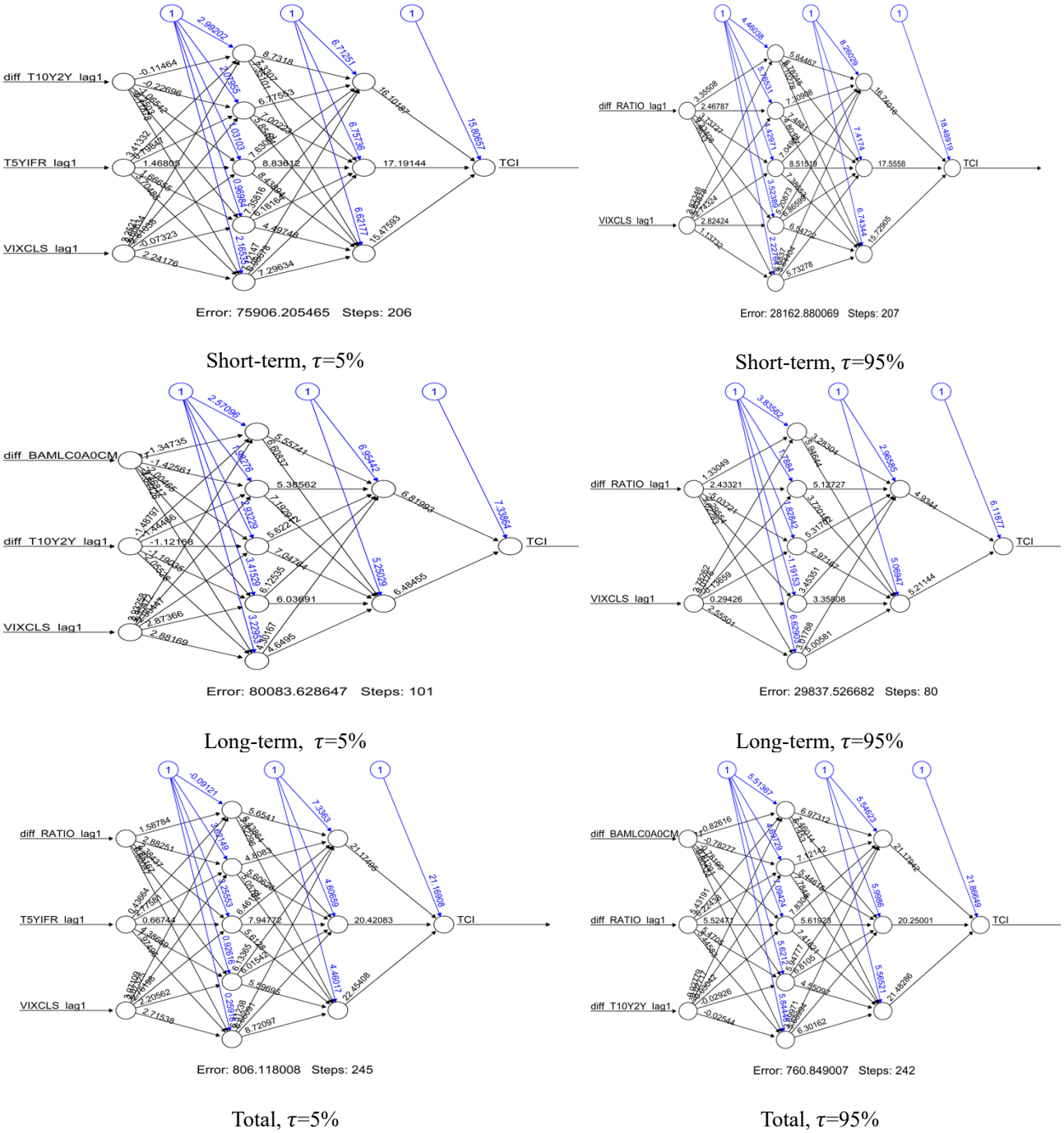


Figure A1. Best fitting neural network architectures.

Appendix B: Uncertainty and Sentiment-based Indicators as Predictors in the ML Models

In addition to these macro-financial predictors, and to assess whether broader uncertainty and sentiment-based indicators improve the out-of-sample predictive performance of the machine learning models in Section 3.2, we construct an expanded predictor set comprising four uncertainty-related variables: the Economic Policy Uncertainty index [EPU; Baker et al. (2016)], the Aruoba-Diebold-Scotti Business Conditions Index [ADS; Aruoba et al. (2009)], the Geopolitical Risk index [GPR; Caldara and Iacoviello (2022)], and the Media Climate Change Concerns Index [MCCC; Ardia et al.

(2023)]. EPU is a news-based index constructed from the frequency of newspaper articles containing terms related to the economy, policy, and uncertainty, and is widely used as a proxy for the level of ambiguity surrounding future economic policy. ADS tracks real business conditions at a daily frequency by combining high-frequency (weekly and monthly) and low-frequency (quarterly) macroeconomic indicators through a dynamic factor model; a reading of zero corresponds to average historical growth conditions, with positive (negative) values indicating above- (below-) average growth. GPR is a text-based index constructed from automated searches of major newspaper archives for terms associated with geopolitical tensions, armed conflict, and terrorism, and is commonly used to proxy the intensity of geopolitical risk perceived by market participants. MCCC quantifies the daily intensity of climate-change-related concern expressed in U.S. media coverage, based on textual sentiment analysis of a broad corpus of newspapers and newswires, and is included given its direct relevance to the green bond component of our connectedness system.

Table B1 gives the descriptive statistics of the four series and Figure B1 provides their time-series plots.

Table B1. Descriptive statistics for the uncertainty and sentiment-based indicators.

	EPU	ADS	MCCC	GPR
Mean	-0.060	-0.277	1.193	0.112
Median	-0.056	-0.078	1.147	0.081
Maximum	3.139	9.627	3.052	2.871
Minimum	-2.635	-26.574	0.000e+00	-1.637
St. Dev	0.544	3.910	0.474	0.497
Skewness	0.220	-4.201	0.457	0.616
Kurtosis	5.723	27.934	3.312	5.550
Jarque-Bera	427.594	38807.401	52.327	450.572
P-value	0.000e+00	0.000e+00	4.338e-12	0.000e+00
N. Observations	1341	1341	1341	1341

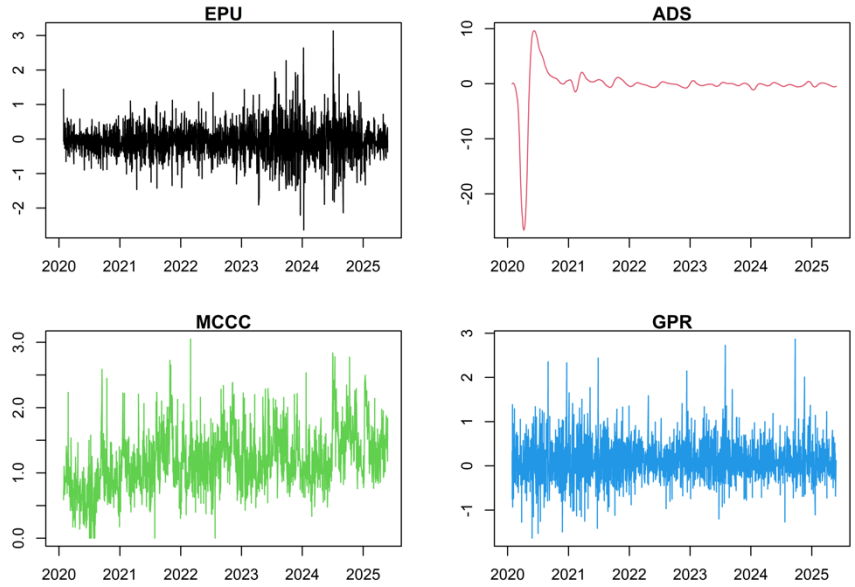


Figure B1. Time Series Plots, uncertainty and sentiment-based indicators.

As with the macro-financial predictors used in Section 5.3, all four variables are used at a one-day lag in the machine learning models of Section 3.2. Tables B2-B7 report the ten best-performing models for each dependent variable and quantile when the uncertainty and sentiment-based indicators of Table B1 replace the macro-financial predictors of Table 1 as explanatory variables.

Table B2. Best performing models, dependent variable TCI, τ =5%.

Method	Features	RMSE	R^2
XGBoost	ADS_lag1, EPU_lag1, GPR_lag1, MCCC_lag1	1.277	-0.043
XGBoost	ADS_lag1, EPU_lag1, MCCC_lag1	1.279	-0.046
XGBoost	ADS_lag1, MCCC_lag1	1.279	-0.046
XGBoost	ADS_lag1, EPU_lag1	1.281	-0.048
XGBoost	ADS_lag1, GPR_lag1	1.281	-0.049
XGBoost	ADS_lag1, EPU_lag1, GPR_lag1	1.283	-0.051
XGBoost	ADS_lag1	1.283	-0.051
XGBoost	ADS_lag1, GPR_lag1, MCCC_lag1	1.288	-0.061
XGBoost	EPU_lag1, GPR_lag1, MCCC_lag1	1.293	-0.069
XGBoost	EPU_lag1	1.295	-0.071

Table B3. Best performing models, dependent variable TCI, τ =95%.

Method	Features	RMSE	R^2
XGBoost	ADS_lag1, EPU_lag1	1.132	0.210
XGBoost	ADS_lag1, EPU_lag1, GPR_lag1	1.146	0.190
XGBoost	ADS_lag1, MCCC_lag1	1.147	0.189
XGBoost	ADS_lag1, EPU_lag1, MCCC_lag1	1.149	0.186
XGBoost	ADS_lag1, GPR_lag1	1.151	0.184
XGBoost	ADS_lag1	1.151	0.183
XGBoost	ADS_lag1, EPU_lag1, GPR_lag1, MCCC_lag1	1.154	0.178
XGBoost	ADS_lag1, GPR_lag1, MCCC_lag1	1.167	0.161
XGBoost	EPU_lag1	1.183	0.136
XGBoost	EPU_lag1, GPR_lag1	1.186	0.132

Table B4. Best performing models, dependent variable Short, τ =5%.

Method	Features	RMSE	R^2
SVM (Radial)	ADS_lag1, EPU_lag1	12.857	-0.030
SVM (Radial)	EPU_lag1	12.860	-0.030
XGBoost	ADS_lag1, GPR_lag1, MCCC_lag1	12.865	-0.031
SVM (Radial)	EPU_lag1, MCCC_lag1	12.866	-0.031
SVM (Radial)	ADS_lag1, EPU_lag1, MCCC_lag1	12.871	-0.032
SVM (Radial)	EPU_lag1, GPR_lag1	12.873	-0.032
SVM (Radial)	ADS_lag1, EPU_lag1, GPR_lag1	12.892	-0.035
SVM (Radial)	EPU_lag1, GPR_lag1, MCCC_lag1	12.900	-0.037
XGBoost	ADS_lag1, EPU_lag1, GPR_lag1, MCCC_lag1	12.905	-0.037
SVM (Radial)	ADS_lag1	12.911	-0.038

Table B5. Best performing models, dependent variable Short, τ =95%.

Method	Features	RMSE	R^2
SVM (Radial)	ADS_lag1	7.335	0.033
SVM (Radial)	ADS_lag1, GPR_lag1	7.381	0.021
SVM (Radial)	ADS_lag1, GPR_lag1, MCCC_lag1	7.404	0.015
XGBoost	ADS_lag1, GPR_lag1	7.407	0.014
SVM (Radial)	ADS_lag1, EPU_lag1, MCCC_lag1	7.427	0.009
SVM (Radial)	ADS_lag1, EPU_lag1	7.431	0.007
XGBoost	ADS_lag1, GPR_lag1, MCCC_lag1	7.432	0.007
SVM (Radial)	ADS_lag1, MCCC_lag1	7.432	0.007
SVM (Radial)	ADS_lag1, EPU_lag1, GPR_lag1, MCCC_lag1	7.433	0.007
SVM (Radial)	ADS_lag1, EPU_lag1, GPR_lag1	7.445	0.004

Table B6. Best performing models, dependent variable Long, τ =5%.

Method	Features	RMSE	R^2
SVM (Radial)	ADS_lag1, EPU_lag1, GPR_lag1	13.124	0.004
SVM (Radial)	ADS_lag1, EPU_lag1	13.132	0.003
SVM (Radial)	ADS_lag1, EPU_lag1, MCCC_lag1	13.156	-0.001
SVM (Radial)	EPU_lag1	13.160	-0.001
SVM (Radial)	EPU_lag1, MCCC_lag1	13.167	-0.003
SVM (Radial)	ADS_lag1, GPR_lag1	13.195	-0.007
SVM (Radial)	ADS_lag1	13.199	-0.007
SVM (Radial)	EPU_lag1, GPR_lag1	13.203	-0.008
SVM (Radial)	ADS_lag1, EPU_lag1, GPR_lag1, MCCC_lag1	13.209	-0.009
SVM (Radial)	EPU_lag1, GPR_lag1, MCCC_lag1	13.215	-0.010

Table B7. Best performing models, dependent variable Long, τ =95%.

Method	Features	RMSE	R^2
XGBoost	ADS_lag1	7.462	0.094
SVM (Radial)	ADS_lag1	7.576	0.066
XGBoost	ADS_lag1, GPR_lag1	7.594	0.062
SVM (Radial)	ADS_lag1, GPR_lag1	7.604	0.059
SVM (Radial)	ADS_lag1, MCCC_lag1	7.618	0.056
SVM (Radial)	ADS_lag1, EPU_lag1, MCCC_lag1	7.630	0.053
SVM (Radial)	ADS_lag1, GPR_lag1, MCCC_lag1	7.632	0.053
SVM (Radial)	ADS_lag1, EPU_lag1, GPR_lag1, MCCC_lag1	7.653	0.047
SVM (Radial)	ADS_lag1, EPU_lag1	7.664	0.045
SVM (Radial)	ADS_lag1, EPU_lag1, GPR_lag1	7.685	0.039

Comparing these results to the corresponding best-performing models of Tables 6-11 in the main text reveals a consistent asymmetry across quantiles. At the lower quantile (τ=5%), the uncertainty-based predictor set underperforms the macro-financial specification for all three dependent variables: for TCI, the best model's RMSE rises from 1.020 to 1.277 and R^2 falls from 0.335 to −0.043 (Table 6 versus Table B2); and for the short-term component, RMSE rises from 12.241 to 12.857 and R^2 falls from 0.067 to −0.030 (Table 8 versus Table B4); and for the long-term component, RMSE rises from 12.753 to 13.124 and R^2 falls from 0.060 to 0.004 (Table 10 versus Table B6). At the upper quantile (τ=95%), the comparison is considerably closer, and in two of the three cases reverses direction: for TCI, the uncertainty-based specification achieves a marginally lower RMSE (1.148 versus 1.132) and higher R^2 (0.187 versus 0.210) than the macro-financial specification (Table 7 versus Table B3), and

the same holds for the long-term component (RMSE 7.577 versus 7.462; R^2 0.066 versus 0.094; Table 11 versus Table B7). Only for the short-term component does the macro-financial specification retain a (marginal) edge at the upper quantile (RMSE 7.305 versus 7.335; R^2 0.041 versus 0.033; Table 9 versus Table B5).

This pattern indicates that the value of expanding the predictor set to include broader uncertainty and sentiment indicators is quantile-dependent rather than uniformly negative. During market distress (τ=5%), connectedness dynamics remain better explained by market-based risk signals–implied volatility, credit spreads, and term-structure differentials–than by policy-uncertainty, business conditions, geopolitical risk, or media-based climate sentiment. Under calmer or more optimistic conditions (τ=95%), however, the uncertainty and sentiment-based indicators capture a comparable, and for the total and long-run measures a marginally larger, share of the out-of-sample variance in connectedness.

A closer look at which of the four new predictors drives this result also reveals a clear pattern: The Aruoba-Diebold-Scotti Business Conditions Index (ADS) is present in the best-performing model in all six tables and appears in at least eight of the ten best-performing specifications reported in Tables B2, B3, B5, and B7. In the two tables where predictive power is weakest overall (Tables B2 and B3, both for TCI), the specifications that exclude ADS altogether, relying only on EPU, GPR, and/or MCCC, occupy the two lowest-ranked positions in the reported top ten, with the most negative (Table B2) or lowest (Table B3) R^2 values in each table. This suggests that among the four new predictors, the daily business conditions signal captured by ADS carries the great majority of whatever incremental predictive content the expanded feature set offers, while the purely text- and sentiment-based indicators (EPU, GPR, and MCCC) contribute comparatively little on their own. This is consistent with the broader finding, here and in Section 5.3, that indicators tied more directly to observable market and real-economy conditions outperform indicators constructed from news-based textual sentiment when forecasting connectedness dynamics, particularly during periods of market stress.



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