4. ENTROPY AS LEADING INDICATOR FOR EXTREME SYSTEMIC RISK EVENTS

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Abstract

Ensuring financial stability is one of the main objectives of authorities supervising financial markets. Analyses of the extent to which critical destabilising events may materialise fuel their actions. Chief among these investigations is the attempt to identify leading indicators that could set forth early warning systems. This paper focuses on extreme systemic risk situations to document their dependence on market action present in the preceding time intervals. We use the N-BEATS model, which proved to be one of the best neural network tools to predict time series, detect anomalies (jumps) in the dynamics of CoVaR measures for the most liquid banks in the European markets, and measure the Shannon entropy of the power spectral density in samples that lead to these events. Employing several logistic regressions, we document the capacity of entropy to explain the realisation of these anomalies.

Keywords: jumps, anomaly detection tools, early warning systems
JEL Classification: G15, G32, C45

1. Introduction

Awareness of financial stability as an essential aspect for supporting the sound development of economy is widely increasing. As financial products have become more sophisticated and adverse effects have spread between countries and institutions, new factors that could generate instability arise. In these situations, the value of financial stability becomes more visible, and governments and institutions pay increasing attention to the financial system's health. An expected outcome is the emergence of new regulations, such as the introduction of capital requirements imposed through stability buffers and fostering responsible behaviour on financial markets.

It became increasingly clear that there was a need to develop systemic risk measures to

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quantify better financial (in)stability, generate monitoring tools, and implement early warning systems. For this endeavour, anomaly detection can constitute a fundamental step. Therefore, the primary aim of this research is to detect anomalies in systemic risk measures by applying artificial intelligence techniques. Specifically, we identify abnormal periods in the dynamics of the main systemic risk measures (CoVaR, Delta CoVaR and MES) performed for financial institutions listed on the European Stock Exchanges and included in the STOXX 600 index. The neural network specification used for the analysis allows the identification of time series patterns, generally known as 'anomaly detection' in artificial intelligence terminology. The measurement of the simultaneity of these anomalies could provide a new kind of systemic risk indicator across financial institutions in our sample. This approach is motivated by the standing of neural networks as time series models that capture the nonlinear nature of time dependence. We consider analysing the European banking sector from January 2010 – February 2022.

Further, the paper is structured as follows. Section 2 presents the relevant literature, identifying the gap in the literature. Section 3 offers the data and the methods involved in this article. Section 4 displays the results, while a short discussion and the main conclusions are presented in Section 5.

2. Literature Review

More than twenty years ago, a study published by the Group of Ten, conducted at the initiatives of finance ministries and central banks, would draw attention to the fact that systemic financial risks had a high probability of being transmitted to the real economy (Group of Ten, 2001). A few years later, systemic risk was associated with information disruption (Mishkin, 2007), imbalances (Caballero, 2010), turbulences (Andrei *et al*., 2019), or interconnectedness (FSB, BIS and IMF, 2009).

Especially after the 2007-08 crisis, systemic risk was defined by various researchers and institutions, certifying its importance in the economic literature. For instance, at the institutional level, systemic risk was described as "the risk of experiencing a strong systemic event. Such an event adversely affects a number of systemically important intermediaries or markets" (European Central Bank, 2009). Similarly, in the economic literature, Billio *et al*. (2012) consider systemic risk "any set of circumstances that threatens the stability of or public confidence in the financial system". On the same note, Acharya *et al*. (2017) construe systemic risk as "the risk of a crisis in the financial sector and its spillover to the economy at large". Financial stability is also considered to rely on financial education (Clichici and Moagar-Poladian, 2022).

To measure financial stability, there were applied different methods such as the random matrix (Li, Kang and Xu, 2022), nonlinear models (Albu *et al*., 2019), quantile approach (Chirilă and Chirilă, 2015), or leverage-based instruments (Adrian, Borowiecki and Tepper, 2022). Some of the most widely accepted and used measures in the literature of measuring systemic risk are CoVaR, Delta CoVaR or marginal expected shortfall (MES) proposed by Adrian and Brunnermeier (2016) and Acharya *et al*. (2017). These measures were previously used in an entropy context (Lupu *et al*., 2020), asymptotic approach (Chen and Liu, 2022), economic sector analysis (Lupu *et al*., 2021) or financial regulation (Cipra and Hendrych, 2017). These three measures will be implemented in our research procedure to capture systemic risk and will be described later in the methodology section.

On the other side, jumps were identified as important for financial decisions, and research in the field has intensified some time ago. A jump-diffusion model was proposed by Merton

(1976); the rare events are embedded in a continuous process. Prices can have two types of conduct: normal and abnormal fluctuations, modelled with geometric Brownian motion, respectively, by Poisson processes.

New jump research methods have appeared in modern financial literature. To obtain real-time identification, Ramchandran and Sangaia (2018) framed an algorithm to detect unsupervised anomalies. For five stocks present on the US market and a period of 18 months, Mäkinen *et al*. (2019) applied a new convolutional long short-term memory with a supplementary attention mechanism. They considered that this approach could better anticipate the shocks. Park and Ryu (2021) used a bidirectional long short-term memory to forecast the stock market. Given the characteristics of high-frequency data, usually used in financial research, Chen, Lai and Sun (2019) proposed a technique for data cleaning; they used an algorithm for adaptive separation iterations through a discrete wavelet transform that identified the jump, drew out the patterns and eliminated marginal disturbances. The jump component was documented to be relevant for total risk, when high-frequency data was considered in context of Chinese stock market (Yu and Zhao, 2021). Another application, a hybrid method for financial series, was developed by Au Yeung *et al.* (2020); their methodology combines an extended short-term memory model with machine learning algorithms.

An interesting concept (”contagious jumps”) for the financial area was introduced by Hawkes (2020), considering the processes discovered by the author in the 1970s (self-exciting or mutually exciting).

Our paper focuses on the analysis of extreme values of systemic risk measures. Under this approach we centre on the most relevant financial institutions listed on European exchanges and estimate their CoVaR measures with respect to the STOXX 600 index. We consider “extreme events” all situations in which these systemic risk measures are “too large” with respect to the rest of the values. We identify these values with the N-BEATS model, which is described in the following section, and we create dummy variables for each company in our sample to reflect situations when we detected these anomalies.

Our objective is to document the extent to which the market action that precedes the jumps contains information that may predict these extreme events. To this end we use the Shannon entropy of the power spectral density estimated for a sample of observations that took place just before each jump.

Our results rely on logistic regression to detect significant dependence of jump realization on these measures of entropy that characterize the recent market dynamics.

3. Data and Methods

Our data consists in daily closing prices for all the companies belonging to the Banks sector that are part of the European STOXX 600 market index, as of February 2022. Analysed companies and their corresponding tickers are displayed in Appendix 1. The data covers the period 2010 – 2022, totalling 3,164 daily observations. Main descriptive statistics for the log-returns of all bank companies and the European STOXX 600 index are presented in Appendix 2.

Under the Machine Learning approach, the methodology of jumps identification is equivalent to “anomaly detection” for the analysis of time series. Parsimonious transformations of this type of random variables render this process suitable for several Machine Learning tools, usually designed with the purpose to identify observations that tend to be situated at a statistically significant distance from the rest. Referred to as “unsupervised learning”, this methodology is notoriously known to employ a large number of features to “learn” in an “unsupervised” manner to which such distances are abnormal enough to be considered an anomaly.

When referring to time series, these features usually are metrics that characterize the distribution for each observation. They could be lags, statistical moments of rolling or expanding windows or metrics that relate to trends and seasonality.

Our approach here is to combine the perspectives of machine learning and financial time series used for anomaly detection and identify abnormal observations.

To this end, we use a methodology that relies on neural networks to forecast values for a systemic risk measure (CoVaR). A comparison of this forecast with the actual realization will help us decide the extent to which the respective value can be considered an outlier.

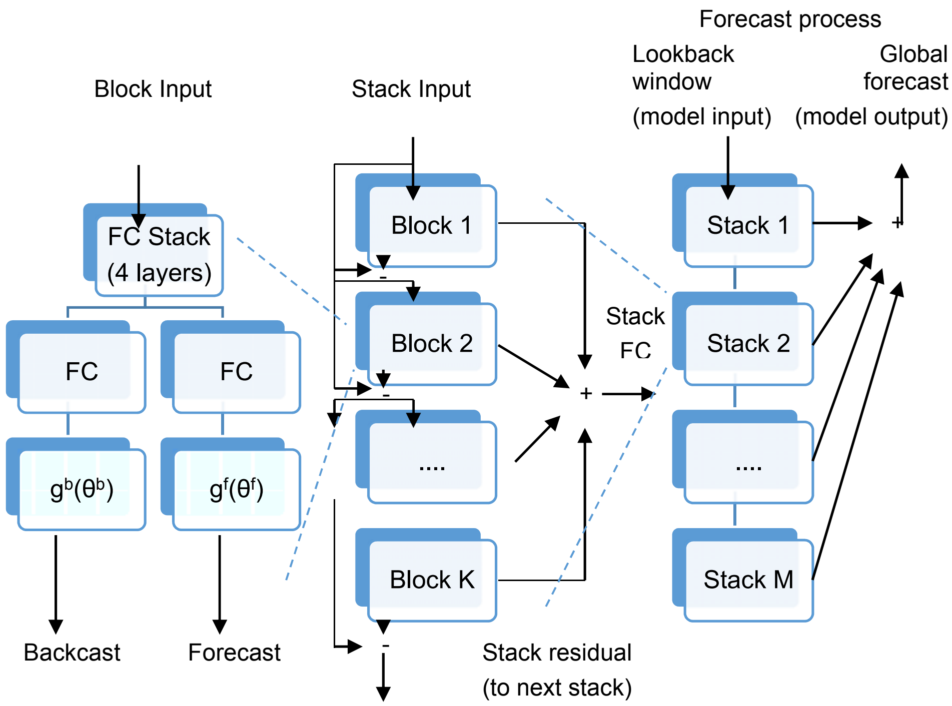
A type of neural network used for deep forecasting is N-BEATS (Neural Basis Expansion Analysis for Time Series), a neural architecture proposed by Oreshkin *et al*. (2020). It is a combination of recurrent neural networks and an exponential smoothing approach that, according to the authors, outperformed the M4 forecast competition held by the International Journal of Forecasting. The goal of this method is to employ pure deep learning for handling the forecast for univariate time series. The model configuration allows for linking backward and forward residuals, permitting a connection of all layers, as is represented in Figure 1.

The basic item is the forecast (FC) network with multilayers, that forms the block. The block receives an input and produces a backcast and a forecast. In their turn, blocks form stacks, by dividing residual stacking into two parts. The hierarchical arrangement of forecasts allows the construction of a deep neural network that allows interpretable results.

The first block in the construction has as input a previous window of information that closes with the last measured observation. The forecast period will be of size H, which will be based on a lookback window generally between 2H and 7H. For the following blocks, the input is the residual products of the previous blocks. Finally, the partial forecasts are incorporated into the final model forecast.

We use the N-BEATS model on rolling windows of 100 observations each, shifting by one day. They are used to produce one-step ahead forecasts for the CoVaR measures for each of the 29 banks in our sample. The combination of methods comes into play by the use of a jump-detection mechanism applied on the differences between the forecasts from the N-BEATS model and the actual values of CoVaR for each company.

Figure 1. Forecast Model Architecture



Source: Authors' representation after Oreshkin et al. (2020)

We compare the values of these errors with the average value of errors in the previous 20 days. We consider as jump (anomaly) all situations when the value of abnormal changes (differences between forecasts and actual values) is larger than 6.77 times this average error. This threshold is obtained from the Lee and Mykland (2008) methodology for jump detection. For a window of 10 observations before each jump we compute the Spectral Entropy, which is the Shannon entropy (Shannon, 1948) of the power spectral density (PSD). This is computes as:

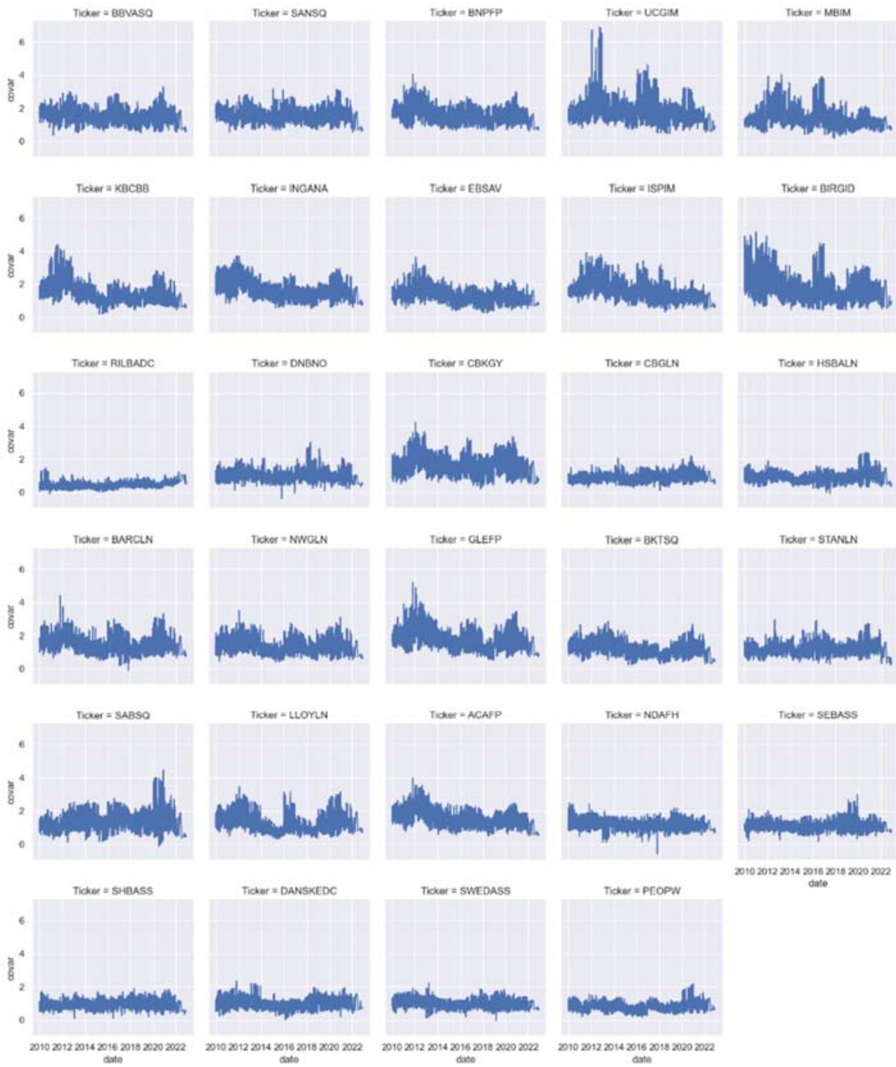
$$H(x, sf) = -\sum_{f=0}^{f_s/2} P(f)\log_2[P(f)],$$

where P stands for the normalised power spectral density, and f_s is the sampling frequency.

4. Results

Our first step consists in computation of CoVaR measures with a daily frequency for all the companies in our sample, the results being graphically presented in Figure 2.

Figure 2. CoVaR Measures for All Banks in Our Sample



We used log-returns for each time series and for the European STOXX 600 index. The first one hundred log-returns were employed for the calibration of the computation of CoVaR. They are the results of estimations of rolling windows of size one hundred observations.

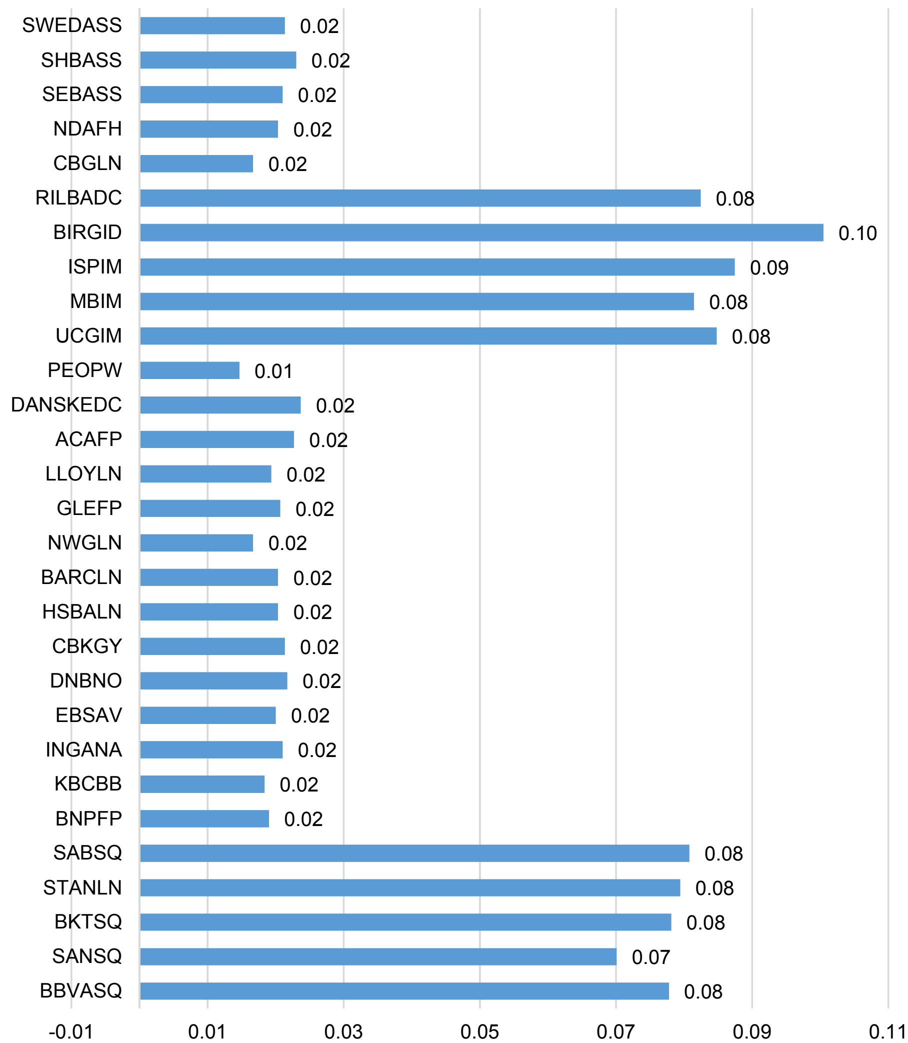
We applied the methodology described above for anomaly detection for each moment of each time series. A presentation of the descriptive statistics of the outliers identified for each time series is presented in Table 1.

Table 1. Descriptive Statistics of Anomalies (Jumps) Identified with N-BEATS Model

	Mean	Stx. Err.	Inter Quart.	MAD	Range	Max	Min	Skew.	Kurt.	Jarque Bera p-val.	Mode	Median
BBVASQ	44.23	0.44	20.27	45.55	1151.72	1158.76	7.04	7.32	70.33	0	7.04	16.75
SANSQ	48.32	0.5	20.57	52.32	852.2	859.3	7.1	4.7	28.65	0	7.1	16.61
BNPFP	35.09	0.19	29.36	29.33	259.16	266.17	7.01	2.72	11.17	0	7.01	17.39
UCGIM	60.7	0.96	26.69	70.01	2824.53	2831.58	7.06	9.56	105.89	0	7.06	18.22
MBIM	41.23	0.43	19.73	42.08	1214.3	1221.41	7.11	7.75	77.12	0	7.11	14.47
KBCBB	11.26	0.08	5.51	3.28	20.19	27.24	7.05	1.58	5.46	0	7.05	9.81
INGANA	11.36	0.1	4.22	3.73	29.3	36.32	7.01	2.61	10.37	0	7.01	9.67
EBSAV	11.49	0.09	5.06	3.92	25.26	32.32	7.06	1.92	6.47	0	7.06	9.58
ISPIM	12.38	0.13	4.37	4.42	52.46	59.51	7.05	4.24	25.89	0	7.05	10.42
BIRGID	11.43	0.09	3.52	4.01	28.04	35.12	7.08	2.23	7.77	0	7.08	9.24
RILBADC	11.85	0.09	5.1	4.22	26.86	33.91	7.05	2	6.81	0	7.05	9.36
DNBNO	11.03	0.07	3.43	2.88	17.99	25.11	7.12	1.87	6.28	0	7.12	9.64
CBKGY	11.61	0.1	5.17	4.16	26.2	33.27	7.06	2.12	7.29	0	7.06	9.5
CBGLN	12.55	0.13	5.48	4.66	26.95	34.05	7.1	1.76	5.43	0	7.1	9.89
HSBALN	11.7	0.09	5.07	4.09	23.27	30.39	7.12	1.94	6.35	0	7.12	9.36
BARCLN	12.3	0.13	4.46	5.26	32.29	39.32	7.03	2.06	6.26	0	7.03	9.47
NWGLN	11.37	0.09	3.89	3.95	32.19	39.22	7.03	2.63	10.18	0	7.03	9.28
GLEFP	11.44	0.09	4.17	3.95	34.48	41.49	7.01	2.82	12.2	0	7.01	9.34
BKTSQ	12.4	0.13	6.37	3.99	27.39	34.9	7.51	2.01	7.9	0	7.51	10.55
STANLN	68.02	0.84	28.47	81.27	2657.44	2664.46	7.02	8.55	94.17	0	7.02	16.25
SABSQ	70.59	0.88	38.33	82.26	2600.29	2607.34	7.05	8.47	89.47	0	7.05	18.1
LLOYLN	64.07	0.73	29.93	74.56	2504.27	2511.29	7.02	8.98	105.99	0	7.02	16.92
ACAFP	114.16	1.78	53.79	145.28	8808.35	8815.36	7.01	14.5	234.13	0	7.01	21.48
NDAFH	57.14	0.73	24.72	64.27	2471.63	2478.66	7.03	10.35	131.98	0	7.03	16.38
SEBASS	9.99	0.07	3.45	2.57	15.39	22.42	7.03	1.78	5.83	0	7.03	8.81
SHBASS	11.22	0.09	3.25	3.57	30.84	37.85	7.02	2.71	12.31	0	7.02	9.5
DANSKEDC	10.87	0.07	3.93	3.4	19.75	26.78	7.03	1.78	5.53	0	7.03	9.22
SWEDASS	10.6	0.06	3.94	2.91	15.33	22.34	7.01	1.51	4.48	0	7.01	9.3
PEOPW	11.36	0.08	5.1	3.92	22.87	29.92	7.04	1.8	5.62	0	7.04	9.19

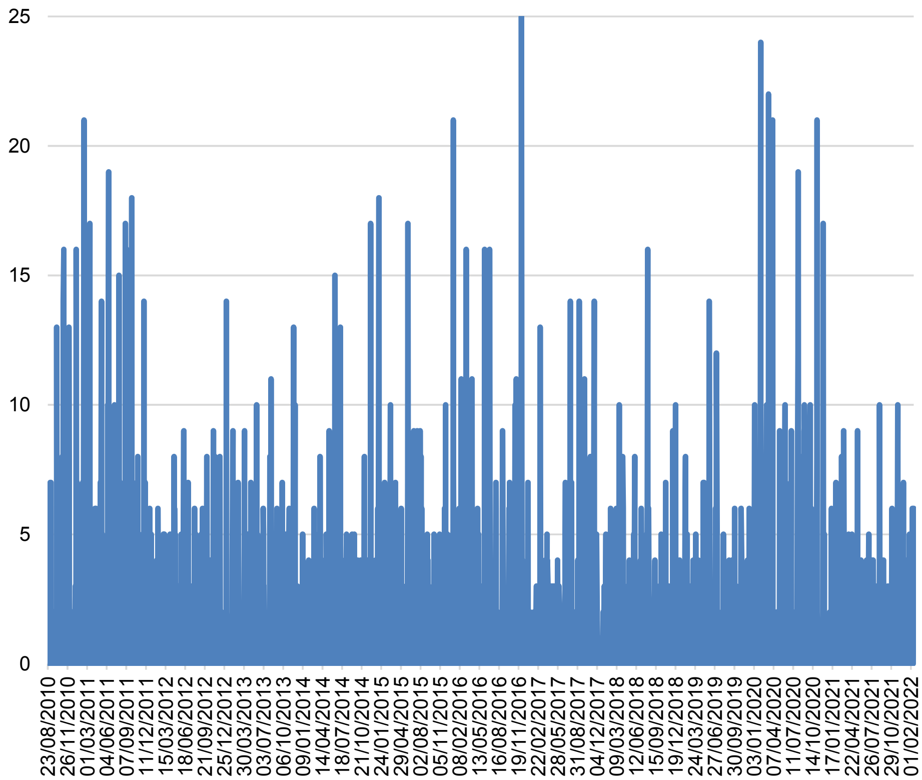
We notice that the number of jumps differs across companies as well as their intensities, the distribution of which is depicted by the moments estimated in the table above. However, their mode tends to be similar, and the median is not very diverse either. The percentage of the number of daily CoVaR measures are displayed in Figure 3.

Figure 3. Number of Jumps as Percentage of Number of Daily CoVaR Measures



The dynamics of jumps is depicted in the Figure 4. We can notice that the vast majority of such events is idiosyncratic. However, we also count several situations when we acknowledge simultaneous jumps across many companies.

Figure 4. Dynamics of the Number of Jumps Across Time



As mentioned, our attempt is to estimate the extent to which the measures of entropy computed in the sample of 10 observations before each jump succeed to explain the manifestation of such anomalies.

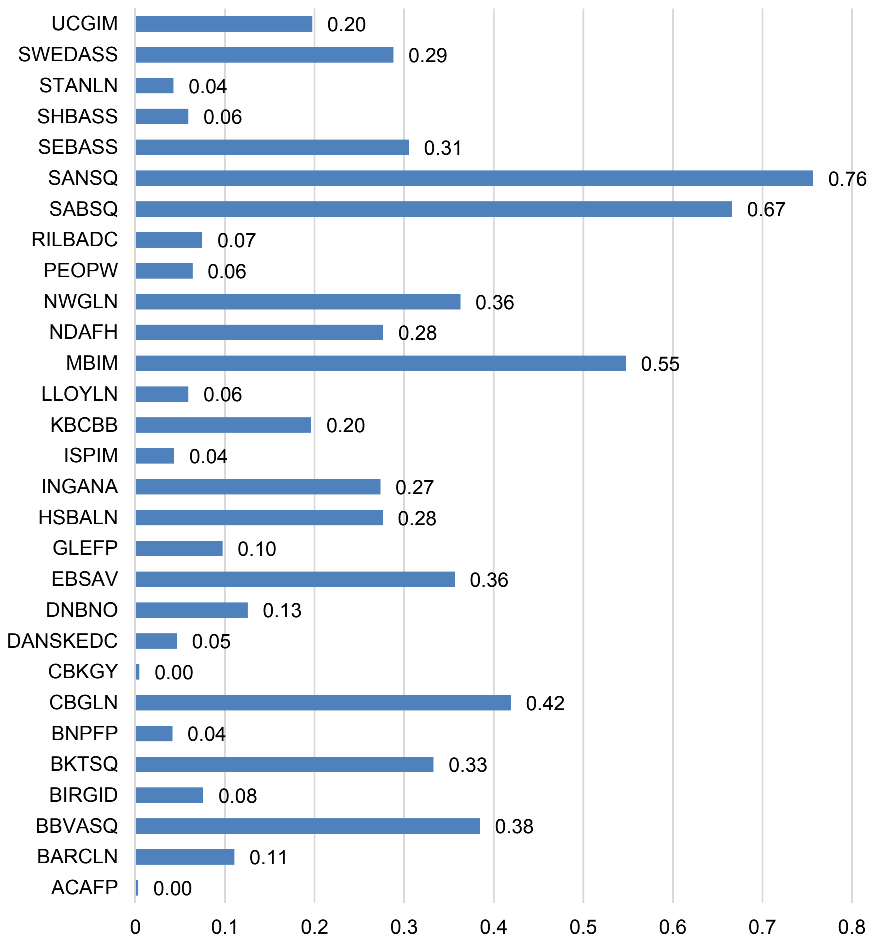
For this purpose, we run logistic regressions of dummy variables for jumps on the values of Shannon entropies computed for the power spectral density in the samples that precede the jumps.

The analysis is driven on the whole sample for each company and results in 29 such regressions. P-values for their coefficients are depicted in Figure 5.

We notice that 12 of these regressions yielded significant coefficients, which provides evidence that, in general, entropies have the power to explain the realization of anomalies (jumps).

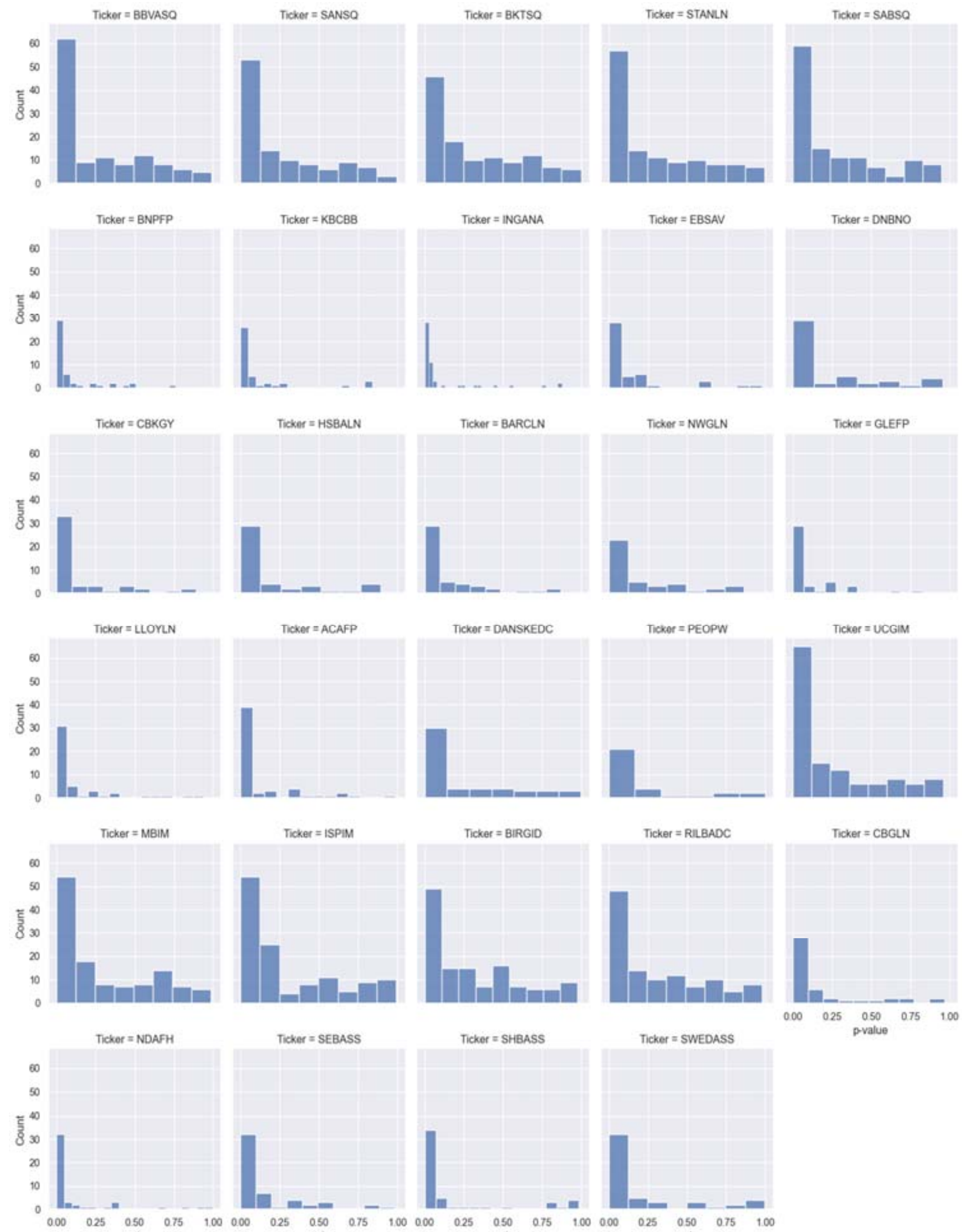
For further investigation we run the same regression for each month and each company in our sample. We leave aside the situations where there were no jumps in a particular month.

Figure 5. P-values of Logistic Regression of Dummy Variables for Jumps on Entropies



P-values for coefficients of these monthly regressions are presented in the Figure 6. We can see that the majority lies with the situations where these values are higher than 10%.

Figure 6. P-values for Monthly Regressions Coefficients



5. Discussions and Conclusions

The aim of the research was to explore the properties of extreme values of systemic risk measures by observing information regarding the most relevant financial institutions listed on European exchanges. For these banks we estimated CoVaR measures with respect to the STOXX 600 index. We identified the extreme events with the N-BEATS model, a neural network architecture relying on recurrent neural networks and exponential smoothing approach respectively.

Our novel approach allows to document the extent to which the jumps included in the previous market dynamics contain information that permit the prediction of these extreme events. The Shannon entropy was employed for the observations that preceded each jump and a logistic regression was used to discover substantial dependency on these entropy values for jump realization. Even if this is not true for the whole sample and in all situations, we can conjecture that entropies have significant impact on the realization of jumps (anomalies) for the time series that represent CoVaR measures.

Our results provide another perspective on the clues delivered by systemic risk measures, and may account for new developments of risk management techniques. Therefore, they can incur new paradigms for early warning systems. The repetitive nature of these occurrences may be the subject for further research directions: the existence of patterns and a possible simultaneity may reflect particular features of a company or a group of companies or of the financial system, which could affect the financial stability measures.

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Appendix 1. Companies and their Corresponding Tickers

Company	Ticker
Banco Bilbao Vizcaya Argentaria SA	BBVASQ
Banco de Sabadell SA	SABSQ
Banco Santander SA	SANSQ
Bank of Ireland Group PLC	BIRGID
Bank Polska Kasa Opieki SA	PEOPW
Bankinter SA	BKTSQ
Barclays PLC	BARCLN
BNP Paribas SA	BNPFP
Close Brothers Group PLC	CBGLN
Commerzbank AG	CBKGY
Credit Agricole SA	ACAFP
Danske Bank A/S	DANSKEDC
DNB ASA	DNBNO
Erste Group Bank AG	EBSAV
HSBC Holdings PLC	HSBALN
ING Groep NV	INGANA
Intesa Sanpaolo SpA	ISPIM
KBC Group NV	KBCBB
Lloyds Banking Group PLC	LLOYLN
Mediobanca Banca di Credito Finanziario	MBIM
NatWest Group PLC	NWGLN
Nordea Bank Abp	NDAFH
Ringkjoebing Landbobank A/S	RILBADC
Skandinaviska Enskilda Banken AB	SEBASS
Societe Generale SA	GLEFP
Standard Chartered PLC	STANLN
Svenska Handelsbanken AB	SHBASS
Swedbank AB	SWEDASS
UniCredit SpA	UCGIM

Appendix 2. Descriptive Statistics for the Logarithmic Returns

	No. Obs.	Mean	Stx. Err.	Inter Quart.	MAD	Range	Max	Min	Skew.	Kurt.	Jarque Bera p-val.	Mode	Median
ACAFP	3163	0.00	0.00	0.02	0.02	0.38	0.20	-0.18	-0.10	10.35	0.00	0.00	0.00
BARCLN	3163	0.00	0.00	0.02	0.02	0.36	0.16	-0.19	-0.40	11.93	0.00	0.00	0.00
BBVASQ	3163	0.00	0.00	0.02	0.02	0.38	0.20	-0.18	0.02	10.68	0.00	0.00	0.00
BIRGID	3163	0.00	0.00	0.03	0.02	0.67	0.35	-0.33	-0.24	14.00	0.00	0.00	0.00
BKTSQ	3163	0.00	0.00	0.02	0.02	0.35	0.18	-0.17	0.26	8.81	0.00	0.00	0.00
BNPFP	3163	0.00	0.00	0.02	0.02	0.38	0.19	-0.19	-0.04	11.41	0.00	0.00	0.00
CBGLN	3163	0.00	0.00	0.01	0.01	0.25	0.09	-0.15	-0.49	11.15	0.00	0.00	0.00
CBKGY	3163	0.00	0.00	0.03	0.02	0.40	0.17	-0.24	-0.14	8.59	0.00	0.00	0.00
DANSKEDC	3163	0.00	0.00	0.02	0.01	0.24	0.12	-0.12	-0.26	7.51	0.00	0.00	0.00
DNBNO	3163	0.00	0.00	0.02	0.01	0.23	0.09	-0.13	-0.32	7.65	0.00	0.00	0.00
EBSAV	3163	0.00	0.00	0.02	0.02	0.32	0.14	-0.18	-0.32	8.38	0.00	0.00	0.00
GLEFP	3163	0.00	0.00	0.02	0.02	0.44	0.21	-0.23	-0.25	12.43	0.00	0.00	0.00
HSBALN	3163	0.00	0.00	0.01	0.01	0.20	0.10	-0.10	-0.04	7.83	0.00	0.00	0.00
INGANA	3163	0.00	0.00	0.02	0.02	0.44	0.22	-0.22	-0.13	12.40	0.00	0.00	0.00
ISPIM	3163	0.00	0.00	0.02	0.02	0.44	0.18	-0.26	-0.64	12.21	0.00	0.00	0.00
KBCBB	3163	0.00	0.00	0.02	0.02	0.42	0.20	-0.21	-0.10	10.76	0.00	0.00	0.00
LLOYLN	3163	0.00	0.00	0.02	0.01	0.37	0.13	-0.24	-0.37	11.40	0.00	0.00	0.00
MBIM	3163	0.00	0.00	0.02	0.02	0.39	0.15	-0.24	-0.69	12.33	0.00	0.00	0.00
NDAFH	3163	0.00	0.00	0.02	0.01	0.27	0.12	-0.15	-0.38	8.97	0.00	0.00	0.00
NWGLN	3163	0.00	0.00	0.02	0.02	0.33	0.13	-0.20	-0.32	8.16	0.00	0.00	0.00
PEOPW	3163	0.00	0.00	0.02	0.01	0.31	0.09	-0.22	-0.73	11.81	0.00	0.00	0.00
RILBADC	3163	0.00	0.00	0.01	0.01	0.18	0.08	-0.10	-0.03	9.23	0.00	0.00	0.00
SABSQ	3163	0.00	0.00	0.02	0.02	0.43	0.22	-0.21	0.02	11.54	0.00	0.00	0.00
SANSQ	3163	0.00	0.00	0.02	0.02	0.43	0.21	-0.22	-0.20	13.60	0.00	0.00	0.00
SEBASS	3163	0.00	0.00	0.02	0.01	0.27	0.12	-0.15	-0.55	10.62	0.00	0.00	0.00
SHBASS	3163	0.00	0.00	0.01	0.01	0.22	0.09	-0.13	-0.57	9.19	0.00	0.00	0.00
STANLN	3163	0.00	0.00	0.02	0.01	0.33	0.15	-0.18	-0.12	9.62	0.00	0.00	0.00
STOXX 600	3163	0.00	0.00	0.01	0.01	0.20	0.08	-0.12	-0.85	13.55	0.00	0.00	0.00
SWEDASS	3163	0.00	0.00	0.02	0.01	0.27	0.12	-0.15	-0.85	11.90	0.00	0.00	0.00
UCGIM	3163	0.00	0.00	0.03	0.02	0.46	0.19	-0.27	-0.34	9.82	0.00	0.00	0.00