DRIVING FACTORS BEHIND GLOBAL SYSTEMIC RISK

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Driving Factors Behind Global Systemic Risk

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1 Introduction

Systemic risk has become a focal point for regulatory institutions and economic research after the last financial crisis. The large negative impact it had, especially in terms of social welfare and confidence on the financial system, made necessary to identify systemic risk in advance in order to prevent it or, at least, mitigate its side-effects. Moreover, although its comprehension has significantly grown last years, it is not yet fully understood and it can be interpreted in many ways due to its multifaceted nature. Regardless, most of the definitions include the instability of the financial system, and the interconnections of its institutions.

Hollo et al. (2012) defined systemic risk as an instability "so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially". Billio et al. (2012) describe it as "any set of circumstances that threatens the stability of or public confidence in the financial system", being the *system* a set of interconnected institutions that have beneficial relationships through which illiquidity, insolvency or losses can quickly propagate. Likewise, Giglio et al. (2016) defend that financial distress not necessarily triggers a crisis but, rather, it is the consequence of simultaneous leading factors. Therefore, systemic risk would be any event simultaneously affecting many market participants by severe losses, triggers a strong propagation of failures among institutions, markets or systems and impacts the real economy.

In the European case, systemic risk has been more widely studied after the financial and sovereign debt crises, especially considering systemic risk spillovers and correlations in the European banking system. Not only the financial system could be a source of systemic risk, but it is usually the first considered and it seems to be the main one. Roncoroni et al. (2019) show evidence of a European bank-bias related to a higher systemic risk and lower economic growth, particularly during times of large drops in asset prices. Acharya et al. (2017) think in systemic risk as the contribution of financial entities to the capital shortfall of the financial system expected in a crisis. Billio et al. (2012) and Allen et al. (2012) agree in the specialness of the banking sector in transmitting shocks to the real economy. According to Brownlees and Engle (2012), negative externalities on the real economy are imposed by financial undercapitalization that cannot be absorbed by any other competitors. Thus, systemic risk ongoing enquiries concern financial entities 'too-big-to-fail' and 'too-interconnected-to-fail'. The nature of individual risks and financial interconnections have been gaining importance up to become regulators' main center of attention.

They focus on how individual institutions can accumulate a distressful quantity of risk and how direct and indirect spillovers can be quantitatively more important than individual failures.

However, Bisias et al. (2012) comment the difficulty of measuring systemic risk since there is still not a global consensus in which factors condition it. We find common points in the economic literature. Considering two of the main classifications, made by Giglio et al. (2016) and Benoit et al. (2017), we can presume the existence of three main sources of systemic risk: *individual risk taking*, when an individual institution assumes large and correlated positions; *contagion*, which occurs when losses spillover among different institutions as a result of being too interconnected; and finally, *amplification mechanisms*, instability factors that make small shocks end up in large impacts. Furthermore, systemic risk as an inherently asymmetric and nonlinear phenomenon is also a commonality in much of the research work. Giglio et al. (2016) show how systemic risk measures are more informative about the left tail of macroeconomic shocks than about their central or right tendency. For Acemoglu et al. (2015), the nonlinear nature of financial interactions is essential to determine the importance of the financial entities due to contagion and spillover effects. Lopez-Espinosa et al. (2015) prove how asymmetric models for measuring systemic risk produce much better fitting. Ignoring tail asymmetries leads to risk underestimation.

Consequently, most of the systemic measures deal with the left-tail of returns' distribution. Adrian and Brunnermeier (2016) develop CoVaR and Δ CoVaR systemic risk measures to highlight the importance of gauging tail co-movements among financial institutions' assets. It also does Acharya et al. (2017) with the Marginal Expected Shortfall for measuring stocks tail-dependencies. In this framework, Ascorbebeitia Bilbatua et al. (2021) demonstrate that multivariate dependencies can be itself considered a risk factor for the financial system, especially with heavy-tailed and non-Gaussian distributions. They show that stronger asset dependence is related to bearish scenarios and prove evidence in favor of causality in the case of the Euros Stoxx market index. Cappiello et al. (2006) also support the existence of asymmetries in correlations since they increase in bearish scenarios and decrease when stocks rebound. Other studies like Pollet and Wilson (2010) and Longin and Solnik (1995) also document asymmetric and dynamic stock correlations which vary over time. The latter illustrates how correlation rises in periods of high volatility as well as some economic variables, like dividend yields or interest rates, contain valuable information about future dependencies. Connections between non-linear correlations and systemic risk allow to analyze non-linear dependencies' effects on low-tail risk.

Interestingly, there is also a recent area of research which goes beyond financial variables and which relates economic policy uncertainty with drops on stock market returns and higher volatility. For some years now, Economic Policy Uncertainty (EPU) indexes, based on policy economic news, have been developed across many countries and they have gained international attention. Baker et al. (2016) find EPU associations with greater stock volatility and reduced investment or employment in some policy-sensitive sectors, like finance. Likewise, EPU innovations foreshadow declines in investment, output or employment in the United States and in other 12 major economies. Liu and Zhang (2015) evidence that higher EPU values leads to significant increases in market volatility and its inclusion in predictive models improves volatility forecast. Similarly, Mei et al. (2018) corroborate EPU usefulness for predicting volatility impacts during recessions, more than during expansions. They also prove stronger impacts of the US EPU on European stock market data than any of the European EPU indexes. Ko and Lee (2015) also find that stock prices decrease after an EPU increase, but only during limited periods and which cannot be diversified away, even in global markets.

Furthermore, evidence of causal relationships between EPU indexes and stock markets have been proved but they differ across countries. Considering the European framework, Wu et al. (2016) demonstrate negative impacts of policy uncertainty on stock returns but only in some countries. It is the case for Spain or Italy, where an optimal policy choice should be made to prevent it. By contrast, Škrinjarić and Orlović (2020) show little evidence of causality from EPU to stock prices in the Eastern European countries. However, it is proved from stock prices to the EPU indexes for the Czech, Slovakian, Estonian and Slovenian markets. Then, shocks of an individual country's risk series could also affect total economic uncertainty in Europe. In the US case, Pástor and Veronesi (2013) find a larger magnitude of the risk premia commanded by the EPU under weak economic conditions, although causality is not evidenced.

The more the macroeconomic environment is uncertain, more difficult is to evaluate asset prices and to make investment decisions. The phenomenon of globalized and highly interconnected economies has been directly linked with a higher uncertainty. We will see whether such uncertainty and multivariate dependencies have any impact on our systemic risk European aggregates by analyzing forecasting abilities and Granger causality relationships. In addition, although many systemic risk measures have been developed for some years now, Giglio et al. (2016) demonstrate how their predictive capacity seem to be still limited while current regulation falls short in capturing and preventing macroeconomic downturns. Benoit et al. (2017) reaffirm the need of improving our macro-prudential tools and policies since, despite the fact of having a better understanding where the risk can lie, we fail in regulating optimally the market deficiencies.

Hence, the need to measure, prevent and discern what is behind European systemic risk is what motivates our study. We focus on 3 principal aspects: what are capturing our systemic risk measures, what could be driving or can be causing them, and whether they have any macroeconomic predictive capability. Concerning the first one, we try to figure out what individual estimates explain and we show how global measures of systemic risk can be constructed from them. We consider that a global measure is more useful than a set of individuals to improve our macroprudential tools and comprehension. Afterwards, a causality fact-finding analysis is implemented to ascertain any causal relationship to our global measures. We analyze the effects of the US Economic Policy Uncertainty (EPU) index and the average pairwise Kendall's τ of Ascorbebeitia Bilbatua et al. (2021) on global systemic risk following the recent literature insights. Lastly, we try to discern whether such global systemic risk measures can forecast macroeconomic downturns and which can have the highest predictive power.

The remainder of the study proceeds as follows. Section 2 describes the methodology applied in our three points of analysis: the nature of the systemic risk measures selected; causality and predictive relationships on global systemic risk and scrutiny of systemic risk measures' predictive power. Section 3 describes the data employed and Section 4 presents the empirical results and new insights obtained for each one of our objectives. Finally, Section 5 concludes. Additional results can be found in the Annex.

2 Methodology Implemented

2.1 Measuring Systemic Risk

Among all the systemic risk measures developed during the last years, Conditional Value-at-Risk (CoVaR) and Δ CoVaR (Adrian and Brunnermeier (2016)), as well as the Marginal Expected Shortfall (Acharya et al. (2017)) have been some of the most widely-accepted and implemented when measuring conditional left-tail risk. All of them are considered individual measures that try to prevent institutions from taking high exposures to risk since their default can lead to the instability of the whole financial system. More precisely, these measures enable us to identify and rank Systemically Important Financial Institutions (SIFI's) which, formerly, were considered 'too-big-to-fail'.

Adrian and Brunnermeier (2016) propose the Conditional Value-at-Risk (CoVaR) to measure the empirical relationship between two series' Value-at-Risk (VaR), i.e. the tail of their joint distribution. There, we use it to estimate the global system CoVaR, conditional on individual financial institutions that are in a state of distress.

In other words, the CoVaR provides the VaR of the whole system when one of the financial institutions is at its lower tail. Following the general risk approach, we estimate system's dynamic CoVaR at a low quantile ($\theta = 0.05$) when each individual firm is at its VaR threshold for the same quantile[1]. We obtain as many CoVaR time series as individual financial institutions and a window of three months (63 days) is considered for each one.

We call $CoVaR_\theta^{S|R^i=VaR_\theta^i}$ to the VaR of the system conditioned to institution i being at its θ-quantile or, implicitly, the θ-quantile of the conditional probability distribution:

$$Pr(R^S \leq CoVaR_\theta^{S|R^i=VaR_\theta^i} | R^i = VaR_\theta^i) = \theta, \tag{1}$$

where S refers to the system, R to the logarithmic returns, θ to the quantile of the logarithmic returns' distribution and VaR_θ^i to the Value-at-Risk of an institution i or, equivalently, the θ-quantile of the institution's return distribution.

Analogously, the above equation can be restated as follows:

$$CoVaR_\theta^{S|R^i=VaR_\theta^i} = VaR_\theta^S | VaR_\theta^i = \alpha_\theta^i + \beta_\theta^i VaR_\theta^i. \tag{2}$$

After estimating firm's Value-at-Risk, VaR_θ^i, we use quantile regression to estimate the CoVaR of the system conditioned to each individual firm.

From the latter approach, Adrian and Brunnermeier (2016) also develop the Δ CoVaR as the contribution of an individual firm to systemic risk when it falls in financial distress. It is measured through the difference between the CoVaR evaluated in a low quantile ($\theta = 0.05$) and the CoVaR evaluated at the median of the distribution. As previously mentioned, we follow a similar approach as for the CoVaR and we estimate individual Δ CoVaR for each individual financial institution using a rolling window of three months daily data.

The Δ CoVaR of the system conditioned to an institution i is defined as the relative difference between its VaR when the institution i is at its θ-quantile and its median:

$$\Delta CoVaR_\theta^{S|i} = CoVaR_\theta^{S|R^i=VaR_\theta^i} - CoVaR_\theta^{S|R^i=Median^i} = \beta_\theta^i (VaR_\theta^i - VaR_{0.5}^i), \tag{3}$$

where $CoVaR_\theta^{S|R^i=VaR_\theta^i}$ represents the Conditional Value-at-Risk when firm i is at its θ-quantile and, $CoVaR_\theta^{S|R^i=Median^i}$, at its median.

The Marginal Expected Shortfall (MES) studied by Acharya et al. (2017) corresponds to the expected firm's equity loss when market falls below a certain threshold over a given horizon. Therefore, MES is defined as the average return of each firm

[1] We consider the profit and loss distribution.

equity during the 5% worst days for the overall market return. However, as it happens to the CoVaR, the MES is directional, i.e. the MES for a firm i conditional on the system is not the same as the MES for the system conditional on the i institution. Then, for the sake of comparison, we propose to estimate the Systemic Marginal Expected Shortfall (SMES), the dynamic average return of the market during the 5% worst days of each financial entity.

The Systemic MES, conditioned to an individual institution i, is defined as:

$$SMES^i = E[R^S | R^i < \theta] = \frac{1}{n_d} \sum_{d:\, R_i < \theta} R_d^S, \tag{4}$$

where S represents the market or system, R are the logarithmic returns, θ is the 0.05 quantile of returns' distribution and n_d is the number of days at which institution i returns are under its threshold, θ. The threshold would be the Value at Risk of an individual institution i under a 5% probability, $VaR^i_{0.05}$. The SMES is estimated using a rolling window of three months daily data.

Finally, we construct aggregated systemic risk measures as an equally-weighted average of the individual ones due to the higher interest that global systemic risk has for policy regulators.

2.2 Causality and Predictive Effects on Systemic Risk Measures

Once we have estimated the aggregated systemic risk measures, we try to ascertain what could be causing them. To do so, we implement the Linear Granger-Causality analysis of Granger (1980) to test whether an explanatory variable X causes global systemic risk. Assuming that the cause is prior to the effect and it has unique information about the future value of its effects, we assess whether such X variable provides statistically significant information to future values of Y. It is said that X Granger-causes Y when predictions of Y based on its own past and X are better than predictions based only on Y's own past values.

Granger causality is statistically tested through the following regression model:

$$Y_t = \sum_{j=1}^{p} A_{1,j} Y_{t-j} + \sum_{j=1}^{p} A_{2,j} X_{t-j} + e_t, \tag{5}$$

where Y is the variable of interest that we want to predict through the information of an individual variable X, p is the number of lags included in the series involved, and A_i for $i = 1, 2$ are the vectors containing the contributions of each lagged observation to the predicted value of Y. Finally, e represents the error term.

The null hypothesis is that $A_{2,j} = 0$ given the assumptions of covariance stationarity on X and Y. In other words, it states that the second time series, X, does not cause the first one, Y. Moreover, we check for a specific level of confidence whether the null hypothesis is rejected considering different number of lags.

After analyzing possible causal relationships on global systemic risk, we try to discern any predictive effects on our measures. First, we implement a pre-whitening process on our predictable variables where we only keep the non-autoregressive part of the series we want to forecast. This way, we avoid their own-predictive effects.

More concretely, we keep the non-own-predictive part of our systemic risk measures like the residuals of an auto-regression of the following form:

$$Y_{ASR,t} = c + \sum_{l=1}^{d} \alpha_l Y_{ASR,t-l} + \varepsilon_{ASR,t} = c_d + \alpha_d(L) Y_{ASR,t} + \varepsilon_{ASR,t}, \tag{6}$$

where Y_{ASR} represents the estimated daily aggregated systemic risk measures at time t and d is the autoregressive order that minimizes the Akaike Information Criterion. Likewise, ε_{ASR} represents the non-auto-predictive part of our measures that we would try to explain. The method is implemented using an expanding window of three months length where the information is updated for every time t.

Thereafter, any predictive effects on the non-auto-predictive part of our measures, i.e. the residuals of Equation (6), are evaluated through a simple linear regression:

$$\hat{\varepsilon}_{ASR,t} = c_t + \boldsymbol{\beta}_t' \mathbf{X}_{t-d} + \epsilon_t, \tag{7}$$

where d is the number of lags in days considered, $\boldsymbol{\beta}_t$ is a vector containing the regression coefficients at time t and $\mathbf{X}_t$ the vector containing the explanatory variables at time t whose predictive power on systemic risk we want to evaluate.

The goodness of fit is examined through the adjusted R^2, which is a modified version of the classical R^2 for linear regression. It penalizes for predictors that are not significant in the model. Consequently, the adjusted R^2 is always lower than the classical R^2 and it can be, even, negative. Unlike the classical R^2, an increase in the adjusted R^2 with the addition of a new exogenous variable implies an improvement in the regression model, and vice versa.

Finally, we should add that, additionally to the exogenous variables considered to forecast the non-explanatory part of the systemic risk, we take into account the pairwise Kendall's τ correlation as a measure of systemic interconnectivity among institutions. The pairwise dependence between two financial institutions' log returns (R^1 and R^2) is estimated through the nonparametric time varying Kendall's

τ estimator proposed by Ascorbebeitia Bilbatua et al. (2021):

$$\hat{\tau}_t = \frac{4}{1 - \sum_{r=1}^{T} w_{b,tr}^2} \sum_{r,s=1}^{T} w_{b,tr} w_{b,ts} \mathbf{I} \left\{ R_r^1 < R_s^1, R_r^2 < R_s^2 \right\} - 1 \tag{8}$$

for $t = 1, \ldots, T$, where $w_{b,tr} = (Tb)^{-1} k \left((t - r) / (Tb) \right)$ is the kernel weight that smooths over the time space, $b > 0$ is the bandwidth that regulates the degree of smoothness, and $\mathbf{I}\left\{\cdot\right\}$ is the indicator function. In all our calculations we consider the Epanechnikov kernel, $k(v) = \frac{3}{4}\left(1 - v^2\right) I\left\{|v| < 1\right\}$, which assigns a higher weight to the closer values in time and the other way round. The smoothing parameter b is selected minimizing the mean squared error of the Kendall's τ estimator in Equation (8) (for more details see Ascorbebeitia Bilbatua et al. (2021)).

2.3 Evaluation of Macroeconomic Predictive Capabilities

Once we have analyzed in depth our individual and aggregated systemic risk measures, we try to capture the forecasting ability of the latter when macroeconomic downturns happen. In other words, whether global systemic risk measures could predict European negative shocks on real economy in advance.

Similarly to the process followed in Section 2.2, we also implement the prewhitening method of Equation (6) to some macroeconomic European variables selected. In this case, we use a dynamic window of three years instead of three months due to the observations' monthly frequency. As previously exposed, this approach purges each macroeconomic variable of their own-predictable variations and the residuals representing the non-auto-predictive part is what we try to explain. Specifically, we try to predict the left-tail distribution of the macroeconomic variables with the daily aggregated systemic risk measures. Then, unlike the previous subsection, the frequency among variables differs since the macroeconomic variables have a lower frequency than the systemic risk estimates. Consequently, we implement a Mixed-data Sampling (MIDAS) quantile regression in our forecasting analysis.

MIDAS quantile regression models, first proposed by Ghysels et al. (2016), have two principal advantages over other methods: they allow to use all the richness of the high-frequency (daily) data as well as to quantify the dependence between variables at various distribution quantiles. Consequently, we can focus on extreme regions of the macroeconomic variables avoiding the need to aggregate high frequency conditioning variables to match the low frequency ones. In short, the use of high-frequency data increases the precision of the quantile estimates, overall, in extreme regions characterized by high variances and few observations.

The MIDAS quantile regression model is expressed as follows:

$$Q_{\theta,t}(Z_{t+h};\delta_{\theta,h}) = \alpha_{\theta,h} + \beta_{\theta,h} W_t(\kappa_{\theta,h}), \tag{9}$$

$$W_t(\kappa_{\theta,h}) = \sum_{d=0}^{D} \lambda_d(\kappa_{\theta,h}) L^d Y_t, \tag{10}$$

where $Q_{\theta,t}(Z_{t+h};\delta_{\theta,h})$ represents the estimation of the low frequency variable θ-quantile at time t for the macroeconomic variable Z_{t+h} that we pretend to predict at a horizon of $h = 21$ days. $\delta_{\theta,h} = (\alpha_{\theta,h}, \beta_{\theta,h}, \kappa_{\theta,h})$ are the unknown parameters to estimate, Y_t the high-frequency conditioning explanatory variable, L^d the lag operator of order d, and $\lambda_d(\kappa_{\theta,h})$ the MIDAS weighting scheme.

Regarding MIDAS weighting scheme $\lambda_d(\kappa_{\theta,h})$, we implement the Exponential Almong lag approach which guarantees positive weights on the high frequency estimates and it is flexible enough to take various shapes like increasing, decreasing or hump-shaped patterns. Its expression considering two parameters is the following one:

$$\lambda_d(\kappa_{\theta,h}) = \frac{exp(\kappa_1 d + \kappa_2 d^2)}{\sum_{d=0}^{D} exp(\kappa_1 d + \kappa_2 d^2)} \ . \tag{11}$$

Finally, we calculate quantile regression's $pseudo - R^2$ to evaluate the predictive power of our aggregated systemic risk measures when forecasting the negative impacts in macroeconomic series. The $pseudo - R^2$ captures the relative loss in forecasting the θ-quantile of the low frequency variable, where $\theta = 0.05$, using conditioning information as in Equation (9), relative to the loss using the historical unconditional quantile estimate, $\hat{\theta}$.

MIDAS $pseudo - R^2$ is expressed as follows:

$$pseudo - R^2_\theta = 1 - \frac{RASW_\theta}{TASW_\theta} \ , \tag{12}$$

where $RASW_\theta$ is the Residual Absolute Sum of Weighted differences and $TASW_\theta$ the Total Absolute Sum of Weighted differences for the θ-quantile.

$RASW_\theta$ and $TASW_\theta$ expressions are:

$$RASW_\theta = \sum_{Z_t \geq \hat{Q}_{\theta,t}(Z_{t+h};\delta_{\theta,h})} \theta \, |Z_t - \hat{Q}_{\theta,t}(Z_{t+h};\delta_{\theta,h})| \qquad +$$

$$\sum_{Z_t < \hat{Q}_{\theta,t}(Z_{t+h};\delta_{\theta,h})} (1-\theta)|Z_t - \hat{Q}_{\theta,t}(Z_{t+h};\delta_{\theta,h})| \tag{13}$$

$$TASW_\theta = \sum_{Z_t \geq \hat{\theta}} \theta \, |Z_t - \hat{\theta}| + \sum_{Z_t < \hat{\theta}} (1-\theta)|Z_t - \hat{\theta}| \tag{14}$$

where $\theta = 0.05$, Z_t our variable of interest whose θ-quantile we want to forecast, $\hat{Q}_{\theta,t}(Z_{t+h}; \delta_{\theta,h})$ the conditioned estimated θ-quantile, and $\hat{\theta}$ its unconditional estimated value.

As we can appreciate in Equation (12), $pseudo - R^2$ ranges between 0 and 1 only in case that the Residual Absolute Sum of Weighted differences is lower than the Total Absolute Sum of Weighted differences. Otherwise, the $pseudo - R^2$ returns a negative value indicating that historical unconditional quantile $\hat{\theta}$ for the low frequency variable offers a better forecast or at least is more informative than conditioning to the high frequency variable estimates. We must stand out that the $pseudo - R^2$ cannot be considered as a measure of goodness of fit for the whole model because it is specific for a given θ-quantile.

3 Data Employed

Financial institutions interconnect all sectors in an economy thanks to its funding and saving functions. Their fall can be transmitted through the whole system and this fact, along with their relative importance in the European economy, are the reasons why we are going to focus our analysis on them. More concretely, we put our attention on publicly traded financial institutions from four financial sectors: commercial banks, security broker-dealers (including the investment banks), insurance companies, and real estate companies. Publicly listed entities' data allows to incorporate the most current available information to our analysis so that market returns reflect new information sooner than any other variables.

Moreover, with the aim of representing a comprehensive sample of the European financial system, we select the 20 most important European financial institutions in terms of market capitalization that are included in the S&P Europe 350 index. Regarding the latter, the S&P index encompasses 363 of the main European companies[2] considering only the 16th most developed European stock markets. It is our benchmark representing the European system. The data employed are the daily closing prices for the sample period between the 1st of January 2010 and the 31st of October 2020. Then, we calculate their respective logarithmic returns and construct the systemic risk measures presented in Section 2.1. All market data has been obtained from *MorningStar*'s database. Table 1 shows the 20 European finan-

[2]The number of components can vary over time.

cial institutions selected. Their descriptive statistics are exhibited in Table 8 of the Annex.

Table 1: Principal financial entities in terms of market capitalization within the S&P Europe 350 Index

	Name	**Ticker**		**Name**	**Ticker**
1	HSBC Holdings PLC	HSBA	**11**	Münchener Rück AG	MUV2
2	Allianz SE	ALV	**12**	London SE Group PLC	LSE
3	BNP Paribas	BNP	**13**	ING Groep NV	ING
4	Zurich Insurance Gr. AG	ZUR	**14**	Nordea Bank Abp	NDA FI
5	AXA SA	CS	**15**	Lloyds Banking Gr.	LLOY
6	Investor AB B	INV B	**16**	Barclays PLC	BARC
7	UBS Group AG	UBSG	**17**	Credit Agricole SA	ACA
8	Banco Santander SA	SAN	**18**	Credit Suisse Group AG	CSGN
9	Prudential PLC	PRU	**19**	Deutsche Boerse AG	DB1
10	Intesa Sanpaolo	ISP	**20**	BBVA	BBVA

Note: Evaluated at the 31st October 2020.

Regarding the data employed to implement Section 2.2, we evaluate two specific causal relationships and predictive effects on our daily systemic risk measures. On the one hand, we try to ascertain how policy uncertainty perception could impact on global systemic risk. Particularly, we evaluate the effect of the daily US news-based Economic Policy Uncertainty (EPU) index. It is obtained from the *Federal Reserve Bank of Saint Louis*'s database. The index is composed by newspaper archives from NewsBank Access World News database that contains archives of thousands of newspapers and other news sources from different countries across the globe. In the US case, there are around 1000 newspapers considered. Regarding the index construction, the primary measure is the number of articles that contain at least one term from each of the three following sets of terms: 'economic' or 'economy'; 'uncertain' or 'uncertainty', and 'legislation', 'deficit', 'regulation', 'congress', 'federal reserve' or 'white house'. As the number of newspapers has drastically increased from 18 in 1985 to over 1800 by 2008, EPU values are normalized by the number of articles.

On the other hand, the other effect taken into account is the interconnectivity of European financial institutions. To evaluate it, we calculate the dynamic pairwise Kendall's τ from Equation (8) for the logarithmic returns of the 20 financial entities showed in Table 1.

Moreover, as described in Section 2.3, we want to test our measures' capability in forecasting macroeconomic negative impacts. In order to do that, two series representing the European economic activity are considered: the monthly Normalized Gross Domestic Product (GDP) and the Total Industry Production excluding construction (IP) for the European countries belonging to the Organization for

Economic Co-operation and Development (OECD)[3]. Both series are seasonally adjusted. The GDP and IP indexes are obtained from the *Federal Reserve Bank of Saint Louis*'s database. Three additional years are included to have the same data length after the implementation of the pre-whitening process in Equation (6).

4 Principal Results and Stylized Facts

4.1 Systemic Risk Measures' Insights

CoVaR, $\varDelta$ CoVaR and SMES measures indicate how the financial system is affected by an individual firm being at distress. One of the main concerns is up to what point are they capturing the same facet of systemic risk or are they interchangeable. It is clear that they are computed in different ways and, although they try to quantify the same risk, we obtain different results for each one of them. Then, they are used to identify SIFI's so that we can rank the companies that contribute the most to the overall risk. We could think that their rankings should be similar, considering that they take the same conditioning direction, but their results are disparate.

Table 2: Systemically Important Financial Institutions' ranking (Jan 2010 - Oct 2020)

CoVaR		$\varDelta$ CoVaR		SMES	
Ticker	Value	Ticker	Value	Ticker	Value
ISP	-0.0263	**INVE B**	-0.0163	**INVE B**	-0.0234
DB1	-0.0259	**ALV**	-0.0152	**ALV**	-0.0218
BBVA	-0.0255	CS	-0.0147	PRU	-0.0217
INVE B	-0.0255	CSGN	-0.0138	BARC	-0.0214
CSGN	-0.0254	HSBA	-0.0136	INGA	-0.0214
LLOY	-0.0254	ISP	-0.0136	CS	-0.0210
ALV	-0.0252	ZURN	-0.0136	BNP	-0.0207
ACA	-0.0252	INGA	-0.0136	LSE	-0.0205
UBSG	-0.0251	BNP	-0.0135	UBSG	-0.0204
MUV2	-0.0252	NDA FI	-0.0135	ZURN	-0.0199

Note: We consider profit and loss distribution. Then, negative signs indicate losses. Financial institutions considered as SIFI's by all the measures are signaled in bold.

Table 2 shows that SIFI's resulting rankings for the three measures are unequal. $\varDelta$ CoVaR and the SMES agree in the two principal firms assuming higher systemic risk, *Investor AB* and *Allianz*, for the sample period studied. Additionally, they are the only ones present in all the rankings. It stands outs the differences between

[3] Countries whose stock markets are included in the S&P Europe 350 index belong to the OECD.

CoVaR and Δ CoVaR. Although the second one is constructed from the first one, Δ CoVaR measures the contribution to systemic risk considering the difference from the median situation. In fact, Δ CoVaR and SMES ranking are more similar among themselves than CoVaR and Δ CoVaR. They coincide in 5 out of 10 of the most risky entities.

Thus, rankings' differences encourage us to think that each measure captures different facets of systemic risk. We implement a Principal Component Analysis (PCA) to individual systemic risk measures to examine the relationships among institutions and general patterns that could be driving systemic risk. Specifically, whether they capture the same nature of systemic risk or a different one. Hence, we implement PCA on the 20 individual series estimated for the three systemic risk measures. Additionally, we also apply PCA to the set of the 60 estimated variables (20 for each of the risk measures). We call such proceeding the 'joint PCA'. In order to do so, we have orthogonalized the correlation matrix instead of the covariance matrix with the aim of discerning possible co-movements[4]. It is also important to highlight that series' stationarity has been verified using the Augmented Dickey Fuller unit root test.

Our main finding has been that for all measures studied (CoVaR, Δ CoVaR and SMES), their first Principal Component is the weighted average of the individual estimates. The same result is found in the 'joint PCA' proceeding where we consider the three measures' estimates. More concretely, the first component explains 92.73 %, 82.99 % and 91.12 % of the total variance for the CoVaR, Δ CoVaR and SMES measures, respectively. Moreover, it explains the 87.08 % in the 'joint PCA' case.

Considering the importance of such component, we construct aggregated measures from the conditioned individual series. These are calculated as an equally-weighted average of the individual variables and we call them aggregated CoVaR, aggregated Δ CoVaR, aggregated SMES and 'Global' (for the weighted average of the 60 'joint PCA' estimates), respectively[5]. Through the aggregation of individual effects, it is expected to capture not only financial entities' interconnections, but also the joint contribution of the European financial system to the global market. Then, such aggregated measures are intended to represent a good benchmark of global systemic risk and the distress suffered by the whole financial system.

The second principal component reduces notably its relative importance when explaining the total variance of the system. It explains 1.36%, 2.96% and 1.35 % of the variance for the CoVaR, Δ CoVaR and SMES . For the 'Global' measure

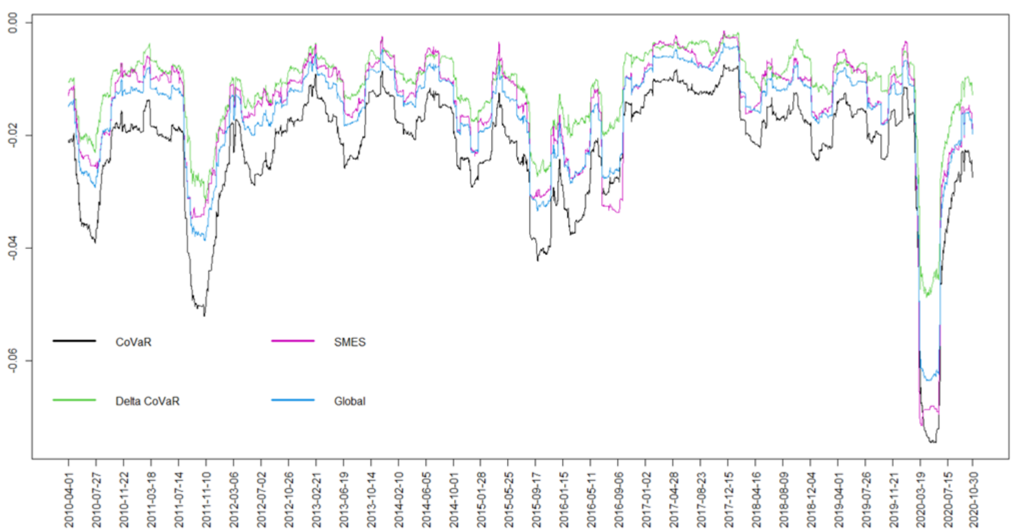
[4]We remind that orthogonalizing the covariance matrix in PCA implies to give higher importance to variables with bigger variance.

[5]We must clarify to the lector that we will also call them CoVaR, Δ CoVaR, SMES and 'Global', indistinctly, without referring to their aggregated nature along the rest of the study.

the second component is the 2.43% of the variance. Although it seems to show a geographical pattern in some measures, robust evidence has not been found in all of them. The other principal components relative importance is not relevant enough.

Thereof, from Principal Component results, we can interpret the importance of the first principal component as a new insight for measuring global systemic risk. The aggregation of the individual financial estimates would allow to evaluate a joint effect of the European financial system in the whole European market. Hence, we are interested in a better understanding of what can be causing and driving global systemic focusing us on such aggregated measures. Their predictive capabilities are also analyzed in next subsections. Aggregated measures' descriptive statistics are exhibited in the Table 9 of the Annex.

Figure 1: Aggregated systemic risk measures comparative (April 2010 - Oct 2020)



As we can see in Figure 1, the four aggregated measures seem to co-move almost during the whole sample period from April 2010 to October 2020. In general, they present similar patterns with the exemption of certain specific moments. In addition, we appreciate that measures' most important falls coincide with critical economic moments like the Flash Crash in May 2010, the European sovereign debt crisis between mid-2011 and February 2012, the Greek debt default in June 2015, an important fall in petroleum prices in January 2016, Brexit outbreak in June 2016, Trump election in November 2016, and the COVID-19 health crisis in March 2020. Consequently, global measures seem to correctly capture systemic risk, i.e. distress in the European financial market transmitted to the real economy.

Regarding each measure individually, we see how the CoVaR stands out for having the most negative values during almost all the sample period while Δ CoVaR presents the highest (less negative) ones. Concerning the other two variables, SMES is usually between CoVaR and Δ CoVaR measures, and oscillates around the 'Global' one. This latter, as an average of CoVaR, Δ CoVaR, and SMES indivual estimates, presents a smoother pattern whose differences with the SMES at some points do not seem to be important enough.

However, we must emphasize the behavior of the SMES measure at two periods. The first period coincides with the distress generated by the Brexit crisis in the United Kingdom and the second one with the outbreak of the COVID-19 health crisis. In both cases, the measure falls exceeding the negative values of the CoVaR. Moreover, during the second period, the SMES overcomes the 'Global' aggregated measure and even the CoVaR at the end of March 2020.

The aggregated CoVaR indicates the VaR_θ^S of the system when the financial sector[6] is in a situation of distress (θ=0.05). Normally, it is not overcome by the SMES because the aggregated CoVaR implies that both, the European market and the financial system are in its 0.05 quantile, while the SMES represents the average of market returns when only the financial sector is at this low quantile. Then, the SMES averages S&P Europe 350 index's profits and losses since the market is not conditioned to be in a situation of distress. When the SMES is more negative than the CoVaR, we can presume that the financial sector affects the European market more intensely than other sectors included in the European index. That is, we can say that the dependence between the financial sector and the European market strengthens. Following this reasoning, it is surprising to note how such dependence has been more affected by Brexit than by other economic crises such as the European sovereign debt. The same appears to happen at the beginning of the COVID-19 crisis when, because of the halt in the economic activity, financial support became essential.

4.2 Causes of and Effects on Global Systemic Risk

Interconnectivity among financial institutions and their returns' lower tail dependencies are considered as intrinsic characteristics of systemic risk so that their correct measurement becomes essential. Thus, any systemic risk measure should ensure, at least, to be capturing such dependencies as well as any reliable connectivity measure should entail systemic risk. In that sense, we prove causality of the pairwise

[6] We consider as the financial sector the conglomerate of the 20 financial European institutions selected.

Kendall's τ developed by Ascorbebeitia Bilbatua et al. (2021) on all our global systemic risk measures.

Furthermore, recent economic literature, like the studies of Baker et al. (2016) and Liu and Zhang (2015), show that economic policy uncertainty has an important effect on stock returns and volatility. We prove that the US EPU index explains and helps to forecast our European global risk measures. Since systemic risk is not fully understood and its nature is unclear, economic policy uncertainty could be an important driving factor. Although it does not seem important enough to trigger a systemic event, it can be understood as an amplifying factor whose effects must be considered in advance.

Table 3 presents empirical evidence of Granger-causality from the US EPU index to all global systemic risk measures. Results for the Granger-causality of the pairwise Kendall's τ are not exhibited since p-value estimates are lower than 1e-3 for all lags and measures studied. We must outline that all our measures and variables accomplish the stationarity causality requirements[7] for the sample period studied. However, we cannot reject the fact that they can be local stationary stochastic processes whose statistical properties change gradually or slowly over time. Despite that, such changes should not alter our results notoriously.

Regarding the results obtained, the dynamic rank correlation measure Granger-causes all our aggregated systemic risk variables, considering even a three-month lag with a significance level of 5%. Actually, we can state that it has an important impact on global risk. With respect to causality of the US EPU index, its effects depend on the autoregressive order and the level of confidence. For a significance level of 5%, only the CoVaR is immediately caused by the US news index. Nonetheless, for a 10% significance level, we find a causality effect over the SMES and the 'Global' measure while the US uncertainty seems to not have statistically significant effects on Δ CoVaR, at least, instantly. However, considering an autoregressive order between 20 and 75 lags, causality is evidenced in all aggregated measures under a 10% significance level. The predictive effects of both variables, the US EPU index and the pairwise Kendall's τ, cease to be important after three months, descending more gradually for the latter.

Consequently, dynamic interconnectivity shows to be an important driver of systemic risk and the economic uncertainty news coming from the United States cannot be either disregarded. While pairwise Kendall's τ causality remains highly significant during a whole quarter, the US EPU index is characterized by its lack of immediate effect. However, it appears after 10 days and lasts up to three months. One plausible explanation is that such news do not impact European returns short

[7] Augmented Dickey-Fuller unit root test has been implemented and the null hypothesis rejected in all cases.

after but that their effects become persistent after some days of assimilation.

Table 3: Linear Granger-causality (Apr 2010 - Oct 2020)

p-value	**EPU Causality on :**			
lags	**Agg. CoVaR**	**Agg. Δ CoVaR**	**Agg. SMES**	**Global**
1	0.0425	0.1909	0.0747	0.0875
5	0.2645	0.4820	0.2308	0.3523
10	0.2669	0.3776	0.2232	0.3056
20	0.0205	0.0288	0.0381	0.0230
30	0.0372	0.0855	0.0488	0.0442
45	0.0889	0.0672	0.1060	0.0847
60	0.0105	0.0178	0.0028	0.0056
75	0.0213	0.0415	0.0156	0.0245
90	0.0808	0.1132	0.0391	0.0835

As mentioned in Section 2.2, we evaluate the average forecasting power of both series, the US EPU index and the pairwise Kendall's τ correlation over the non-auto-predictive part of our global systemic risk measures. First, we consider the effect of both variables jointly and, after, individually.

Following the model in Equation (7), the respective predictive models estimated are:

$$\hat{\varepsilon}_{ASR,t} = c_t + \beta_{E,t} EPU_{t-d} + \beta_{\tau,t}\tau_{t-d} + \epsilon_t \tag{15}$$

$$\hat{\varepsilon}_{ASR,t} = c_t + \beta_{\tau,t}\tau_{t-d} + \epsilon_t \tag{16}$$

$$\hat{\varepsilon}_{ASR,t} = c_t + \beta_{E,t} EPU_{t-d} + \epsilon_t \tag{17}$$

Table 4 shows the results for model in Equation (15). In those, it is observed that the US EPU index and the non-parametric Kendall's τ forecasts the residuals of global systemic risk long in advance. The highest capacity in terms of the adjusted R^2 is found on predicting CoVaR, Δ CoVaR, and 'Global' aggregated measures between 10 and 20 days before. The predictive capacity of the model over the SMES is also notorious during this forecast length. After two months, we see how such capacities start to diminish. In fact, $\beta_{E,t}$ begins to be statistically equal to zero for some measures at $d = 45$.

Comparing individual effects of both explanatory variables, the adjusted R^2 for the individual model with pairwise Kendall's τ are larger than those of the US EPU individual model for all the forecast lengths. Table 5 shows that the pairwise Kendall's τ forecasts systemic risk even 60 days in advance while, as Table 6 presents,

Table 4: Linear regression estimates for model in (15) (July 2010 - Oct 2020)

Adj R^2	$\hat{\varepsilon}_{ASR,t}$ / **US EPU index, pairwise Kendall's** τ			
lags in days(d)	**Agg. CoVaR**	**Agg. Δ CoVaR**	**Agg. SMES**	**Global**
1	0.5437	0.5220	0.4720	0.5440
5	0.5739	0.5549	0.5025	0.5691
10	0.5931	0.5786	0.5185	0.5888
20	0.5854	0.5820	0.5060	0.5845
30	0.5176	0.5263	0.4380	0.5179
45	0.3452	0.3724	$0.2869^{(2)}$	0.3481
60	$0.1591^{(1)}$	$0.1902^{(2)}$	0.1381	$0.1637^{(2)}$
75	$0.0441^{(2)}$	$0.0649^{(1)}$	0.0439	$0.0477^{(1)}$
90	$0.0067^{(1)}$	0.0163	0.0156	0.0098

Note: All the parameters of the regression are statistically different from zero for a confidence level of 95%, except for the following cases: (1) $\beta_{E,t}$ is different from zero for a confidence level of 90%; (2)$\beta_{E,t}$ is statistically equal to zero.

the US EPU index only does it up to 30 days. In addition, pairwise Kendall's τ higher predictive effect is noticed at 20 lags and the US EPU index presents it during the first 10 days. Regarding which European global measure is more influenced by pairwise Kendall's τ, the latter individually explains more about CoVaR and Δ CoVaR measures. In fact, its forecasting ability in the Δ CoVaR seems to be more long-lasting. In the case of the US EPU, it presents the same pattern as the pairwise Kendall's τ in a short-time horizon. However, its effects remain more persistent in the SMES measure. We should add that the 'Global' measure presents the second highest $pseudo - R^2$ values for the three linear models constructed and all the lags considered. As it encompasses CoVaR, Δ CoVaR and SMES effects, it would be creating synergies among the three measures so that it always has a higher predictive ability than two of them. Whether a measure diminishes its predictive ability, it is offset by measures with higher forecasting power.

Furthermore, looking at Tables 4 and 5, the inclusion of the US EPU in the model improves the adjusted R^2 estimates only up to a 45-day prediction. For a higher order lag, it is preferable to consider pairwise dynamic correlation individually. Such result reaffirms the higher importance of the comovements between financial entitites over the US EPU index, although the US EPU effect should not be disregarded.

Finally, above results coincide with the results obtained for causality presented in Table 3. As previously stated, interconnection among financial institutions is once again more important than the US policiy uncertainty when measuring European systemic risk. The major predictive capacity of the joint model in Equation (7) coincides with the range where both explanatory variables Granger-cause more European systemic risk. However, the high R^2 values in the first 10 days for the US

Table 5: Linear regression estimates for model in (16) (July 2010 - Oct 2020)

Adj R^2	$\hat{\varepsilon}_{ASR,t}$ / **pairwise Kendall's** τ			
lags in days (d)	**Agg. CoVaR**	**Agg.** Δ **CoVaR**	**Agg. SMES**	**Global**
1	0.3968	0.3763	0.3497	0.3868
5	0.4319	0.4172	0.3883	0.4267
10	0.4610	0.4539	0.4214	0.4608
20	0.4875	0.4952	0.4502	0.4946
30	0.4568	0.4770	0.4165	0.4660
45	0.3266	0.3603	0.2869	0.3353
60	0.1583	0.1904	0.1272	0.1640
75	0.0443	0.0640	0.0284	0.0468
90	0.0057	0.0128	0.0026	0.0070

Table 6: Linear regression estimates for model in (17) (July 2010 - Oct 2020)

Adj R^2	$\hat{\varepsilon}_{ASR,t}$/ **US EPU index**			
lags in days (d)	**Agg. CoVaR**	**Agg.** Δ **CoVaR**	**Agg. SMES**	**Global**
1	0.2455	0.2410	0.2073	0.2484
5	0.2441	0.2364	0.2021	0.2439
10	0.2350	0.2245	0.1835	0.2297
20	0.1932	0.1786	0.1288	0.1828
30	0.1375	0.1222	0.0714	0.1251
45	0.0597	0.0504	0.0139	0.0499
60	0.0120	0.0088	0.0007	$0.0072^{(1)}$
75	$0.0004^{(2)}$	$-0.0002^{(2)}$	0.0078	$-0.0003^{(2)}$
90	$9.5e\text{-}5^{(2)}$	$0.0012^{(1)}$	0.0104	$0.0012^{(1)}$

Note: $\beta_{E,t}$ is statistically different from zero for a confidence level of 95%, except for the following cases: (1) it is for a 90% level; (2) it is statistically equal to zero.

EPU individual model contrast with its null causality for this period. Although the US news would not Granger-cause global systemic risk in the short-term, an immediate effect should not be rejected. We should remind that the US EPU's effects also remain less over time than the pairwise Kendall's τ one. One hypothesis to evaluate is that only persistent news with high impact could Granger-cause global systemic risk, although they can be helpful to explain short-term risk dynamics.

4.3 Predictive Capacity of the Aggregated Systemic Risk Measures

Giglio et al. (2016) prove that 19 selected individual systemic risk measures have little, if any, macroeconomic predictive power among the three different country regions analyzed: the USA, UK, and Europe[8]. Regarding Europe, they demonstrate that measures like the aggregated CoVaR, Δ CoVaR, and MES[9] are relevant for the lower quantiles of the European GDP distribution. Then, our objective is to develop a similar macroeconomic analysis considering the 16 OECD European countries to construct our European estimates as well as some new aggregated systemic risk measures.

Given the frequencies of the data employed, first, we make an approximation of the predictive power analysis converting our daily systemic measures into monthly data. The reason is that MIDAS quantile regression is a harder process to implement and, this way, we can narrow down the distribution regions where our aggregated systemic measures could forecast the most. Following the methodology explained in Section 2.3, we de-trend our macroeconomic series using the procedure in Equation (6). It is the low-tail distribution of the non-auto-predictive part of the series what we try to predict through quantile regression.

Contrary to Giglio et al. (2016)'s research, we obtain that the European aggregated CoVaR and Δ CoVaR do not predict the lowest quantiles of the European GDP de-trended series. In fact, considering the first two quartiles of the GDP non-autoregressive residuals' distribution, the $pseudo - R^2$ for the CoVaR and Δ CoVaR are nearly zero. On their side, the SMES cannot be rejected for not being significant, regarding 0.02-0.03 quantiles, but its $pseudo - R^2$ are lower than 1%. The results for the 'Global' measure, as a weighted average of the other three measures, are not better than for the CoVaR, Δ CoVaR and SMES. Then, individually, our four aggregated systemic risk measures would lack of a robust statistical association

[8]The European region is constructed considering only some core European economies: Germany, France, Spain, and Italy.

[9]Systemic risk measure described in Acharya et al. (2017) from which we develop our SMES measure.

with macroeconomic downside risk for the European GDP. On the other hand, when we evaluate their predictive ability on the European Production Index, $pseudo-R^2$ values for all measures improve so that they are significant in the lowest part of the index distribution, i.e. in the 0.015 quantile. Such $pseudo-R^2$ values are between 25% and 33%, but we must outline that it is in an extreme region of the distribution where the variance is high and realizations are few, so results must be taken with care (results are shown in Table 10 of the Annex).

Thanks to the previous results, where we have matched data frequencies, we can narrow down the left-tail distribution of the de-trended macroeconomic series to implement our MIDAS quantile regression analysis. In order to compare our results to the ones obtained by Giglio et al. (2016), we also implement the MIDAS quantile regression in the first 20% percentile of both macroeconomic series' distribution.

Table 7: Systemic risk measures' forecasting power for one month length (July 2010 - Oct 2020)

pseudo-R^2	**Prediction on European $\hat{\varepsilon}_{Prod}$**			
Quantile	**Agg. CoVaR**	**Agg. Δ CoVaR**	**Agg. SMES**	**Global**
0.015	0.4375	0.4582	0.5102	0.3539
0.05	0.0744	0.1035	0.1626	0.1268
0.10	0.0194	0.0230	0.0284	0.0054
0.20	0.0034	0.0021	0.0025	0.0029

Note: The methodology implemented has been MIDAS quantile regression. Results for the GDP are not significant (see Table 11 in the Annex).

Table 7 presents the low predictive capacity of our aggregated systemic risk measures for one period ahead macroeconomic data. Regarding the non-auto-predictive part of the European GDP, any of the conditioning variables offers any forecast improvement in comparison with the unconditional quantile. However, all of them are helpful when trying to guess negative shocks in the European Industrial Production (IP) index. Considering the lowest left-tail region of the European IP distribution, aggregated measures present high $pseudo-R^2$ for $\theta = 0.015$ and non-negligible values for $\theta = 0.05$. In fact, it stands out the forecasting ability of the aggregated SMES for the 5% percentile which could be a good predictor but not robust enough. The problem with the most extreme regions, as previously stated, is that such estimates are driven by high variances. For the 10% percentile, all the R^2 are different from zero although we would be barely explaining 2% of the model. For the 0.2 quantile, the one studied by Giglio et al. (2016), we cannot state that our aggregated measures are statistically significant.

Looking at each aggregated measure individually, the SMES results to be the best one for forecasting downside macroeconomic risk in the European Industrial Production Index. The SMES is followed by the 'Global' measure that, similarly to what happened in Section 4.2, offsets the individual forecasting abilities of the other aggregated measures. Consequently, the 'Global' measure predicts better a negative shock in the European IP index than CoVaR or Δ CoVaR did.

Finally, considering MIDAS results and the ones obtained by the monthly approximation of our systemic risk measures, both coincide in indicating a low macroeconomic predictive capacity. Nonetheless, MIDAS $pseudo - R^2$ almost double the ones for the simple quantile regression where we have matched data frequencies. We can guess that better accuracy of the estimations is obtained when using high frequency data instead of matching frequencies. Predictive power for a three-months length analysis has been also tested to contrast the robustness of our results. Measures predictive ability has been notably reduced (for more details see results in Tables 12 and 13 of the Annex).

5 Conclusions

Systemic risk comprehension is still limited. Its multifaceted nature makes it unclear and difficult to identify what exactly is driving it. Therefore, discerning what is behind systemic risk has been the main goal of this study.

First, we have tried to identify what facet individual systemic risk measures capture. In that sense, we have verified that different measures of systemic risk, although conditioning in the same direction, present different SIFI's rankings. Individual estimates of CoVaR, Δ CoVaR, and SMES quantify different aspects of the individual risk contribution to the European market. However, we find that aggregated measures, calculated as weighted averages from the individual measures, can gather almost the same information provided by individual estimates and are more helpful for regulators. Systemic events result from a strong propagation of failures and, less often, from an individual one. Then, although individual risk taking can trigger a crisis and must be controlled, it is the global risk impact on the real economy what must be prevented in advance.

Moreover, our four aggregated measures would represent financial sector risk contribution to the whole European system. Due to financial sector's essential role in the well-functioning of the real economy and other economic sectors, external dependencies with the system would be good predictors of systemic events. In that sense, we have showed that an increase in the negative values of the aggregated SMES measure overcome other global measures in signaling strong influences from the financial sector to the whole system.

Causal and predictive relationships have also been studied to discern driving factors of systemic risk. Internal dependencies among financial institutions are related to possible failures' propagation among individual entities. We have proved that all our aggregated global risk measures are not only Granger-caused but also predicted long in advance by the non-parametric dynamic pairwise Kendall's τ of Ascorbe-beitia Bilbatua et al. (2021). We interpret it as one of the main drivers of global systemic risk that helps to forecast European market distress even three months ahead. Robust evidence is demonstrated. Moreover, its high predictive power elucidates the importance of multivariate dependencies when measuring systemic risk, which has been contrasted in many economic research works, but few emphasis has been given to time varying rank correlations for measuring it. The non-parametric dynamic pairwise Kendall's τ could be a value-added measure for policy regulators.

Interestingly, the results also show that the US Economic Policy Uncertainty index, which it is not constructed from financial or economic data but for news, also Granger-causes and improves the prediction of all our systemic risk measures. The US news gathering the economic uncertainty perception have a significant impact, although only temporarily, in the European systemic risk which cannot be disregarded. Relevant information generated in the United States could not be important enough to trigger a crisis, but it could be an amplification mechanism transforming small shocks in large impacts. What it is clear is that its increase induces financial distress in the European market affecting, this way, systemic risk.

Additionally, it is important to outline that all those effects vary across our aggregated systemic risk measures. Then, the computation of the 'Global' measure, as the average of the 60 individual systemic measure estimates, offsets the differentiated effects while gathering the different facets that CoVaR, Δ CoVaR, and SMES capture.

For preventing and avoiding systemic risk it is not only necessary to measure it correctly, but also to contrast whether our measures capture the real impact on the economy. Consequently, we have tested our aggregated systemic risk measures forecasting power on the European economy. Although the results have not been encouraging, we can appreciate certain predictive ability in the lowest tail of the macroeconomic shocks in the European Industrial Production index for a forecasting horizon of one month. The aggregated SMES performs the best in that sense, followed by the 'Global' measure.

Finally, regarding these findings, further research could be conducted considering expectiles instead of quantiles. Evidence of their better performance in extreme regions has been shown and they consider the whole distribution instead of being only focused on the left-tail. Moreover, it would also be interesting to contrast whether the US EPU index influences in the European system also happen in the domestic country or if it affects more to specific European countries or regions. Last but not least, a sectorial analysis could be also conducted to test sector dependencies and contributions to the European market system.

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6 Annex

6.1 Descriptive Statistics

Table 8: Descriptive statistics of the variables employed

Variables	min	max	mean	θ=0.05	median	θ=0.95	SD	var	skw	kurt
HSBA	-0.0975	0.0937	-0.0003	-0.0239	0.0000	0.0232	0.0152	0.0002	-0.2723	4.2963
ALV	-0.1369	0.1074	0.0002	-0.0249	0.0006	0.0226	0.0162	0.0003	-0.6178	9.0425
BNP	-0.1912	0.1592	-0.0002	-0.036	0.0000	0.0340	0.0233	0.0005	-0.2544	7.2417
ZURN	-0.1472	0.1234	0.0002	-0.0195	0.0004	0.0189	0.0137	0.0002	-1.0999	15.219
CS	-0.1682	0.1618	-0.0001	-0.0333	0.0005	0.0295	0.0210	0.0004	-0.3355	8.9778
INVE B	-0.1410	0.1031	0.0005	-0.0247	0.0008	0.0238	0.0152	0.0002	-0.5294	5.3651
UBSG	-0.1404	0.1160	0.0000	-0.0274	-0.0001	0.0278	0.0183	0.0003	-0.3921	5.7849
SAN	-0.2217	0.2088	-0.0007	-0.0345	0.0000	0.0338	0.0224	0.0005	-0.4064	10.309
PRU	-0.1920	0.1652	0.0002	-0.0295	0.0003	0.0305	0.0210	0.0004	-0.5055	9.4540
ISP	-0.2606	0.1796	-0.0003	-0.0402	0.0000	0.0396	0.0259	0.0007	-0.5838	8.1379
MUV2	-0.1574	0.1566	0.0002	-0.0214	0.0006	0.0201	0.0145	0.0002	-0.2332	15.849
LSE	-0.1520	0.1295	0.0009	-0.0263	0.0008	0.0283	0.0180	0.0003	0.1271	7.3518
INGA	-0.2153	0.2198	-0.0001	-0.0378	0.0000	0.0369	0.0246	0.0006	-0.1749	8.9193
NDA FI	-0.1500	0.1220	0.0000	-0.0285	0.0000	0.0269	0.0184	0.0003	-0.3765	5.8483
LLOY	-0.2979	0.2077	-0.0002	-0.0362	-0.0005	0.0370	0.0252	0.0006	-1.0291	19.670
BARC	-0.2567	0.1556	-0.0003	-0.0358	-0.0003	0.0384	0.0254	0.0006	-0.6968	10.833
ACA	-0.1847	0.1985	-0.0002	-0.0385	0.0000	0.0382	0.0251	0.0006	-0.2335	6.3411
CSGN	-0.1735	0.1372	-0.0005	-0.0316	-0.0002	0.0295	0.0204	0.0004	-0.5034	6.9407
DB1	-0.1242	0.0943	0.0003	-0.0247	0.0002	0.0259	0.0160	0.0003	-0.4169	5.2905
BBVA	-0.1765	0.1991	-0.0006	-0.0358	-0.0005	0.0330	0.0223	0.0005	-0.1817	7.1546
SP EUR 350	-0.1225	0.0817	0.0002	-0.0174	0.0007	0.0163	0.0110	0.0001	-0.8372	10.241
Kendall's τ	0.1734	0.6332	0.3944	0.2550	0.3805	0.5678	0.0934	0.0087	0.3209	-0.3926
US EPU	3.3200	807.66	119.13	36.233	93.805	286.66	86.602	7450.4	2.5024	8.8719
GDP	86.210	100.92	99.641	98.935	100.05	100.86	2.2303	4.9744	-4.3754	19.531
Ind. Prod.	-19.799	12.104	0.1418	-1.2223	0.2350	1.6354	2.5953	6.7357	-2.7026	32.082

Table 9: Descriptive statistics of the systemic risk measures (Apr 2010 - Oct 2020)

Systemic Measures	Min	Max	Mean	Median	SD	Variance	Skewness	Kurtosis
Agg. CoVaR	-0.0746	-0.0074	-0.0225	-0.0194	0.0116	0.0001	-2.0894	5.8247
Agg. Δ CoVaR	-0.0488	-0.0017	-0.0117	-0.0096	0.0079	6.2e-5	-2.1680	6.2584
Agg. SMES	-0.0715	-0.0014	-0.0151	-0.0118	0.0114	0.0001	-2.5754	8.9728
Global	-0.0636	-0.0036	-0.0151	-0.0118	0.0102	0.0001	-2.2964	7.1512

6.2 Other Macroeconomic Results

Table 10: Systemic risk measures forecasting power for one month length (July 2010 - Oct 2020)

$pseudo - R^2$	**Prediction on $\hat{\varepsilon}_{GDP}$**	**Prediction on $\hat{\varepsilon}_{Prod}$**			
Quantile	**Agg. SMES**	**Agg. CoVaR**	**Agg. Δ CoVaR**	**Agg. SMES**	**Global**
0.015	0.0032	0.2718	0.3015	0.3387	0.2718
0.020	0.0027	0.1860	0.2158	0.2672	0.1861
0.025	0.0021				
0.030	0.0016				

Note: $pseudo - R^2$ is only shown for significant variables. Differences between series' frequency have been solved adding daily systemic measures into monthly estimates. $\hat{\varepsilon}_{GDP}$ and $\hat{\varepsilon}_{Prod}$ represent the non-auto-predictive part of the macroeconomic series.

Table 11: Systemic risk measures forecasting power on the European Gross Domestic Product for one month length (July 2010 - Oct 2020)

$pseudo - R^2$	**Prediction on $\hat{\varepsilon}_{GDP}$**			
Quantile	**Agg. CoVaR**	**Agg. Δ CoVaR**	**Agg. SMES**	**Global**
0.015	-0.0219	0.0022	-0.0165	-0.0550
0.05	-2.4e-5	-0.1275	-0.0001	-0.0012
0.10	-3.4e-5	6.6e-5	-0.0557	-0.0001
0.20	0.0002	-0.1932	-0.0015	-0.0040

Note: The methodology implemented has been MIDAS quantile regression.

Table 12: Systemic risk measures forecasting power on European Gross Domestic Product for three months length (July 2010 - Oct 2020)

$pseudo - R^2$	**Prediction on $\hat{\varepsilon}_{GDP}$**			
Quantile	**Agg. CoVaR**	**Agg. Delta CoVaR**	**Agg. SMES**	**Global**
0.015	-0.0045	-0.0038	-0.0049	-0.0044
0.05	0.0008	0.0013	0.0015	0.0013
0.10	8.4e-5	0.0003	0.0003	0.0003
0.20	-0.0021	-0.0006	-0.0022	-0.0001

Note: The methodology implemented has been MIDAS quantile regression.

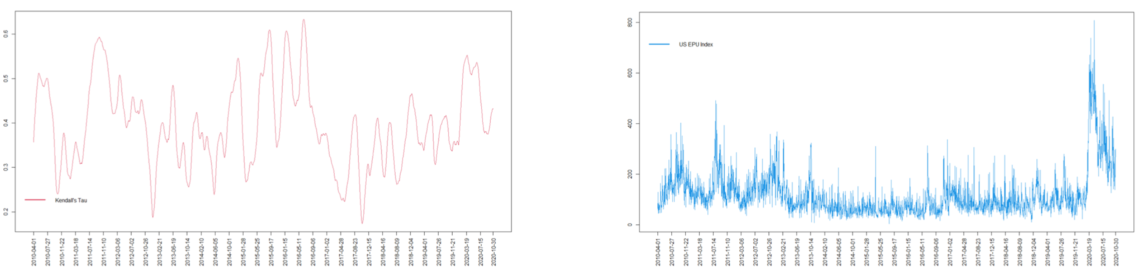
Table 13: Systemic risk measures forecasting power on European Industrial Production for three months length (July 2010 - Oct 2020)

pseudo $-R^2$	**Prediction on $\hat{\varepsilon}_{Prod}$**			
Quantile	**Agg. CoVaR**	**Agg. Delta CoVaR**	**Agg. SMES**	**Global**
0.015	0.1567	0.1360	-0.0918	0.0067
0.05	-0.1369	-0.1616	-0.1785	-0.1531
0.10	-0.1086	-0.0404	-0.0644	-0.0353
0.20	0.0003	0.0002	4.7e-5	0.0002

Note: The methodology implemented has been MIDAS quantile regression.

6.3 Graphs

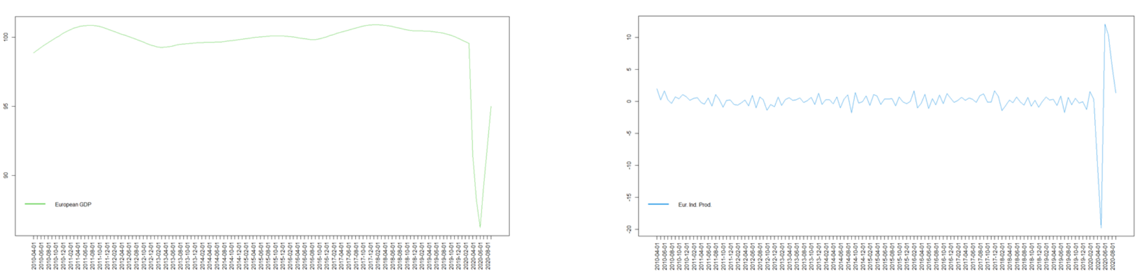
Figure 2: Dynamics of the causality variables (Apr 2010 - Oct 2020)



(a) Pairwise Kendall's τ Aggregated Correlation

(b) US Economic Policy Uncertainty Index

Figure 3: Dynamics of the macroeconomic variables (Apr 2010 - Oct 2020)



(a) OECD European Countries Gross Domestic Product

(b) OECD European Countries Industrial Production (excluding construction) Index