Bearish Vs Bullish risk network: a Eurozone financial system analysis

Abstract

This paper studies the extreme risk spillover between 183 Eurozone financial institutions (such as banks, insurances, diversified financial, real estate firms) over the period 2005–2020. Employing the Granger causality test across quantiles, we are able to investigate the tail risk interdependence between financial firms under extreme (downside and upside) conditions. Thanks to this framework, we can understand and estimate the risk spillover effect, in different propagation mechanisms, during bad and good conditions. Our findings show a heterogeneous effect between risk spillovers depending on the level of risk considered, highlighting how bearish conditions play an important role in the sectoral propagation of risk spillover. We document the presence of "shift-contagion" effect. Finally, we investigate the risk-monetary policy nexus. Our findings provide new insights into the impact of the monetary stance on financial stability, documenting the double strategy played by the European Central Bank, namely the "leaning against the wind" and the "modified Jackson Hole consensus" approach.

JEL Classification: C32; G10; G20; E52

Keywords: Extreme risk spillover; Eurozone financial firms; Financial connectedness; Systemic risk; Monetary policy

1 Introduction

Mapping the interdependencies of financial actors has become a widely studied field of research in recent years. The financial crises (US and Eurozone), the various political events (such as the Brexit), and the COVID-19 pandemic, have shown how the connection between financial institutions plays a fundamental role in shock transmission. In fact, high connectivity among firms contributes to the rapid spread of risks within the system, resulting in financial instability (Battiston et al., 2016; Abad et al., 2017; Daly et al., 2019). High uncertainty in financial markets has highlighted the need to implement measures to accurately assess the systemic importance of institutions, the stability of the financial system and to develop effective macroprudential policies to limit the extent of contagion and systemic risk (Rizwan, 2021). Recently several measurements have been developed to quantify the contagion risk of financial institutions. For example, Adrian and Brunnermeier (2016) proposed the conditional value-at-risk (CoVaR), while Acharya et al. (2012) developed the marginal expected shortfall (MES), also, Brownlees and Engle (2017) designed the conditional capital shortfall index (SRISK).[1]

Nevertheless, a purely quantitative analysis often does not reflect the real complexity of the contagion risk, leading to a partial estimate of the probability of default. A different approach, explicitly oriented towards estimating the interrelationships between all institutions, is based on network models (Nier et al., 2007). A network approach for financial systems is a powerful tool for understanding financial markets (interconnectedness) to assess risks and stability measures. More generally, it is known that market prices are formed by complex mechanisms of interactions that often reflect speculative behaviour rather than by the fundamentals of the companies to which they refer. Models based only on market data may reflect "partial" components that could lead to a biased estimation of systemic risk (Giudici and Parisi, 2018; Brogi et al., 2021). This weakness suggests that models should also be enriched by considering the structure of the financial system as a whole. For this purpose, recent studies have proposed network connectedness frameworks, e.g., the Granger connectedness causality network model of Billio et al. (2012), the connectedness spillover network framework proposed by Diebold and Yılmaz (2012, 2014), the time-varying systemic risk contributions of Betz et al. (2016), and the tail-event driven network (TENET) model of Härdle et al. (2016). More recently, Wang et al. (2017) built, using the Granger causality risk model (Hong et al., 2009), extreme dynamic tail risk networks to investigate the interconnectedness and systemic risk of financial institutions. Chen et al. (2019) extended the TENET to tail event-driven network quantile regression (TENQR) model, which addresses the interdependence, risk propagation and systemic importance of financial institutions. Further, Wang et al. (2021) developed the multilayer information spillover networks, which include return, volatility

[1] See Bongini and Nieri (2014) and Silva et al. (2017) for a review of systemic risk (contagion) measures.

and extreme risk spillover layers in the variance decomposition model.

However, these models allow to understand and estimate the risk spillover effect, but not to deal with the measurement of different propagation mechanisms, during bad and good conditions. Here, different from these works, we investigate the tail risk interdependence between financial firms under extreme (downside and upside) conditions. In this paper, we follow Li et al. (2020) and apply a novel framework to study the (downside and upside) risk spillovers between Eurozone financial firms based on the Granger causality risk model of Candelon and Tokpavi (2016). We aim to measure the risk spillovers between financial institutions in bearish and bullish market conditions, to have a more deeply picture of the potential contagion within the financial actors. Thanks to this model, we can understand and estimate the risk spillover effect, in different propagation mechanisms, during different market conditions.

The contribution of our research is fourfold. First, we develop an approach that constructs different types of spillover networks to estimate the risk spillovers in specific cases. Many studies analyzed the risk spillover between financial institutions (Billio et al., 2012; Diebold and Yılmaz, 2012, 2014; Hautsch et al., 2015; Härdle et al., 2016; Kleinow and Moreira, 2016; Wang et al., 2018; Bongini et al., 2018; Demirer et al., 2018; Barigozzi and Brownlees, 2019; Fang et al., 2019; Foglia and Angelini, 2020), however, a not "market-specific condition" analysis can mask the heterogeneity that can be observed when considering distinct cases. Indeed, we consider two cases, i.e., the left tail (a downturn or crisis period), and the right tail (an upswing period) of the distributions of the institutions' stock returns. This allows us to better understand the dynamics within financial firms depending on the type of market conditions, i.e. bearish or bullish. Second, our dataset is composed of 183 listed financial institutions, located in 10 countries: Austria, Belgium, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain. To the best our knowledge, it is the first research using such a large sample of financial firms in the Eurozone context. Hence, we are able to investigate the risk contagion of a large part of the financial system. Third, we contribute to the small but growing literature on the study of risk spillovers (contagion) among the different operators of the European financial system (Billio et al., 2013; Abad et al., 2017; Foglia and Angelini, 2020; Fong et al., 2021). We contribute to the relevant literature by profoundly examining the risk spillovers between different type of Eurozone financial institutions (such as banks, insurances, diversified financial and real estate firms). This allows us to build a complete picture of risk spillovers in the financial industry. Fourth, we contribute to the literature that investigates the risk-monetary policy nexus (Roache and Rousset, 2013; Altunbasa et al., 2014; Colletaz et al., 2018; Faia and Karau, 2019; Foglia and Angelini, 2019; Kabundi and De Simone, 2020; Jin and De Simone, 2020; Rizwan, 2021). Our findings provide new insights into the impact of the monetary stance on financial stability, documenting the double strategy played by the European Central Bank (ECB), i.e., the "leaning against the wind" and the "modified Jackson Hole consensus" approach.

2 Literature review

The structures of financial networks are a determining factor in the propagation of systemic events. The literature aims to provide answers that make it possible to understand and prevent the various origins of systemic risk. The existing literature can be classified into two broad approaches in measuring systemic risk. The first approach measures the contribution to systemic risk by conditional tail dependence in a uni-variate framework (Acharya et al., 2017; Adrian and Brunnermeier, 2016; Brownlees and Engle, 2017). Hence, these models are unable to consider the network dimension structuring the interconnections between financial institutions (Giudici and Parisi, 2018; Chabot and Bertrand, 2019; Brogi et al., 2021).

To this end, a second steam of literature has focused on interconnections as a potential source of systemic risk and contagion (Billio et al., 2012; Diebold and Yılmaz, 2014; Härdle et al., 2016; Wang et al., 2017; Brunetti et al., 2019; Hué et al., 2019; Torri et al., 2021; Wang et al., 2021). For this purpose, several econometric models have been suggested. For example, Diebold and Yılmaz (2014), Demirer et al. (2018) and Su (2020) proposed the volatility propagation index. These frameworks make it possible to statically and dynamically capture the changes in connectivity reflected by the sensitivity of stock prices to shocks (exogenous or endogenous). Other works, use Granger's causality method. By Granger linear causality tests, Billio et al. (2012) constructed a causal network, which traces the directions of causal relationships between different actors in the financial system.

In particular, some of the literature has focused on tail risk as a measure of systemic risk. The models that have been developed on this topic have focused on extreme movements in the tail distribution. Indeed, these approaches seek to capture systemic interconnections through the simultaneous presence of a tail event (Hong et al., 2009; Hautsch et al., 2015; Härdle et al., 2016; Kleinow and Moreira, 2016; Wang et al., 2017; Nguyen and Lambe, 2021). For example, Hong et al. (2009) suggested a tail Granger causality test. This one focused on tail behavior to detect the effects of the tail. Candelon and Tokpavi (2016) extended the model Hong et al. (2009), proposing a multivariate Granger risk framework. This design allows checking the Granger causality based on the tail events on full distribution (left, center and right). Moreover, in order to maximize the information content resulting from the network structure, many authors have sought to extend or combine the several econometric methods (Härdle et al., 2016; Candelon and Tokpavi, 2016; Brunetti et al., 2019; Su, 2020; Torri et al., 2021; Wang et al., 2021). By considering the network dimension, Härdle et al. (2016) extend the $\text{CoVaR}^{i|j}$ model of Adrian and Brunnermeier (2016). The merit of this model is that it can take into account all the interconnections, which arise as a result of the tail changes of one firm conditioned by the tail changes of the other firms belonging to the same network. Wang et al. (2017) used the Granger causality in risk (Hong et al., 2009) to study the directional risk connectivity of different financial actors and showed that spillover was transmitted from the real estate and banking sector to the insurance and financial services sector. Hué et al. (2019) proposed an approach that combines the pairwise Granger causality approach with the leave-one-out concept to measure systemic risk. In addition, and to measure volatility spillover effects, Su (2020) extended the volatility spillover index suggested by Diebold and Yilmaz (2009) by a quantile decomposition of the variance. By quantile regression of the least absolute selection and shrinkage operator (LASSO), Nguyen and Lambe (2021) constructed a comprehensive network that describes directional tail risk spillovers. Finally, by a multi-layer spillover network, Wang et al. (2021) have highlighted the usefulness of multi-layer networks to study the different spillover channels at the system and individual firms-level.

The literature on the European financial network is increasingly developing. Among the first attempts to study risk spillover effects are Foglia and Angelini (2020), which have shown that risk spillover dynamics become strong during crisis periods in the euro area. Similarly, Torri et al. (2021) have found strong interconnectivity in the structures of the European banking sector's conditional tail risk networks. Brunetti et al. (2019) studied two network structures of European interbank markets. By constructing physical networks based on interbank transactions and correlation networks based on stock returns, they found that the former can only predict liquidity problems. At the same time, the latter can predict systemic risk. Dreassi et al. (2018) analysed the credit risk spillover between the banking and insurance sectors. Their results suggest that the asset-holding and the guarantee are the main risk transmission for the insurance sector, while the additional collateral for the banking sector. Furthermore, Paltalidis et al. (2015) have suggested that the European banking structure is highly interconnected, facilitating financial contagion. Recently, Borri and Di Giorgio (2021) analyzed the systemic risk contribution for large listed European banks. They found that the larger banks contribute more to financial contagion. Moreover, their results showed that during the COVID-19 shock, sovereign default risks influenced the systemic risk of all European banks.

However, these works on financial actors in the euro area did not take into account market conditions separately. Indeed, a global analysis of the propagation of extreme risk without distinguishing the tail level does not allow us to know who influences the directionality of the extreme event more. Stock market returns are jointly influenced by extreme events, suggesting the importance of distinguishing tail levels (Hong et al., 2009). In addition, market conditions can be related to either the left end of the return distribution, which occurs during downturns (left tail) or the right end during economic recoveries (right tail). Including both tail ends in the analysis makes it possible to detect the unobserved heterogeneity that determines the spillovers of extreme risk. In this sense, by distinguishing between the left and right tails of stock return distributions, one could test whether spillover effects are captured primarily by bearish or bullish market conditions. Therefore, our work, catching the tail risk spillover of full distribution, can help predict financial crises as suggested by Brunetti et al. (2019), i.e. stock networks predict systemic risk.

3 Methodology

Our method aims to estimate the risk spillover between Eurozone financial firms in bearish (downside), and bullish (upside) market conditions. For this purpose, we follow the approach of Li et al. (2020). First, we estimate the risk spillover between two institutions by Granger's causality test in risk (Candelon and Tokpavi, 2016). Second, we build the three types of spillover networks and compute the network-based spillover indicators.

3.1 Granger causality in risk

Hong et al. (2009) introduce the concept of Granger causality in risk, i.e., the co-movement between the left quantiles of two distributions. This model is an extension of general Granger causality test (Granger, 1980). More precisely, Hong et al. (2009) use a kernel-based test to verify whether a significant downside risk in one market will cause a significant downside risk in another market. In other words, the ability to predict the future risk of a variable is improved by adding information about the past risk of the other variables. They define downside risk, a situation where asset returns are below value-at-risk (VaR) at a predefined level α. However, considering Granger causality in the downside risk between two markets only at a particular level of risk seems a restrictive hypothesis. For this reason, Candelon and Tokpavi (2016) extend this method to a multivariate framework, which thus permits the identification of Granger Causality in the full distribution between two time series.

Following Peng et al. (2018), we consider a set $T^{\text{up}} = \left\{\theta_1^{\text{up}}, \cdots, \theta_{m+1}^{\text{up}}\right\}$ of $m+1$ quantiles that covers the right-tail regions on the distribution support with $0 \leq \theta_1^{\text{up}} < \ldots < \theta_{m+1}^{\text{up}} \leq 1$. Now, we divide the distribution support of return series r_{it} into m disjoint regions and we specify the upside VaR such as $Q_{it}(\theta_1^{\text{up}}|F_{i,t-1}) < \cdots < Q_{it}(\theta_{m+1}^{\text{up}}|F_{i,t-1})$. Now let $H_{it}^{\text{up}} = (Z_{it,1}^{\text{up}}, \ldots, Z_{it,m}^{\text{up}})'$ be the vector, where

$$Z_{it,k}^{\text{up}} = \begin{cases} 1 & \text{if} \quad Q_{it}(\theta_k^{\text{up}}) \leq r_{it} < Q_{it}(\theta_{k+1}^{\text{up}}) \\ 0 & \text{else} \end{cases} \tag{1}$$

For $k = 1, \ldots, m$, H_{it}^{up} has the information of upside risk. The same steps regard the downside risk. Therefore, we have $H_{it}^{\text{down}} = (Z_{it,1}^{\text{down}}, \ldots, Z_{it,m}^{\text{down}})'$. In order to study the upside and the downside relationship between financial institutions, the null hypothesis of Granger causality in distribution is given by:

$$H_0 : E(H_{i,t}^{\text{up(down)}} | F_{i,t-1}^{\text{up(down)}}, F_{j,t-1}^{\text{up(down)}}) = E(H_{i,t}^{\text{up(down)}} | F_{i,t-1}^{\text{up(down)}}) \tag{2}$$

where $F_{j,t-1}^{\text{up(down)}}$ and $F_{i,t-1}^{\text{up(down)}}$ are the information set available of upside (downside) risk at time $t-1$, for firms i and j. If H_0 is rejected, it means that the upside (downside) risk spillover exists, i.e., the upside (downside) risk of firm j can be used to forecast the upside (downside) risk of firm i. In this paper, we examine two types of causality: i) the down-to-down ($T^{\text{down}} = \{0, 1\%, 5\%, 10\%\}$), and ii) the upside-to-upside ($T^{\text{up}} = \{90\%, 95\%, 99\%, 100\%\}$).

According to Hong et al. (2009), it is particularly important to monitor extreme (downside or upside) risk spillovers between financial institutions when markets are positively correlated and suffer from the same global shock (e.g., the COVID-19 outbreak). Using the Granger causality test in risk, defined as the predictive capacity of one market to forecast other ones, we are able to predict the effects of risk, and we can provide information for capital allocation decisions, investments, and thus regulation, particularly crucial in this sector.

3.2 Bearish-Bullish risk spillover network

Let $G(V, E)$ be a network of extreme risk spillovers (downside-to-downside; upside-to-upside), where $V = \{1, 2, ..., N\}$ is the set of nodes and E is the set of edges. Following Wang et al. (2017), we define a node as a financial institution, and the edge is Granger causality connectivity in risk from one financial institution to another. For example, in the bearish spillover network, a directional edge between two institutions is formed when there is a Granger causality between the downside risk from one institution to the other one. Formally,

$$E_{i\to j} = \begin{cases} 1, & \text{if } i \text{ Granger causes risk to } j \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

By using rolling windows procedure, we build networks that vary over time to investigate the dynamic interconnection between financial institutions. According to Yan et al. (2015) and Wang et al. (2017), we set the time period width L and step size σ to 250 and 20 trading days, respectively.

Following Billio et al. (2012), we build connectivity measures to identify the degree of risk and connectivity between banks. We calculate the total connection spillover (TCS) index as follows:

$$\text{TCS} = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} E_{i \to j} \tag{4}$$

The TCS index indicates the degree level of interconnection of the financial system. Therefore, a higher TCS value suggests that the financial system is highly interconnected.

Moreover, following Wang et al. (2017), we calculate the strength of the cross-sector (SCS) index. This measure is able to capture the cross-sector risk spillover, which is defined as follows:

$$\text{SCS}_{m \to n} = \frac{1}{N_m N_n} \sum_{i=1}^{N_m} \sum_{j=1}^{N_n} E_{i \to j} \tag{5}$$

where N_m and N_n is the number of financial institutions belonging to m and n financial sectors. When $m = n$, this implies $N_n = N_m - 1$.

Following Kenett et al. (2010), we compute the relative influence (RI) of sector m as the ratio between the difference and the sum of out-degree ($k_{\text{out}}(m)$) and in-degree ($k_{\text{in}}(m)$):[2]

$$\text{RI}_{\text{sector}}(m) = \frac{k_{\text{out}}(m) - k_{\text{in}}(m)}{k_{\text{out}}(m) + k_{\text{in}}(m)} \tag{6}$$

where $\text{RI}_{\text{sector}} \in [-1 : 1]$. The index measures the degree of risk spillover from one sector to the other one. A negative value indicates that the sector in question receives more extreme risk than it emits.

4 Data

Our empirical study focuses on Eurozone financial system. Following Wang et al. (2017) and Foglia and Angelini (2020), we divide the financial institutions into three groups according to global industry classification standard (GICS): 40 - Financial. In particular, we select three types of financial institutions, (1) banks, (2) insurance firms, and (3) others financial institutions (which include diversified financial and real estate companies). The sample is composed of 183 financial institutions, grouped as follows: 58 Banks, 19 Insurers

[2] The out-degree of financial institution sector m is the number of outgoing edges from sector m to other sectors. The in-degree of financial institution sector m is the number of incoming edges from other sectors to sector m.

and 106 Others, located in 10 countries: Austria, Belgium, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain. To our knowledge, this is the first research using such a large sample of financial institutions in the Eurozone context. Table 1 shows the list of financial institutions included. We collect the daily stock prices of our sample from Datastream. The period spans from 1 August 2005 to 31 December 2020 (including 4024 observations). Finally, we compute the daily stock returns of each financial firm as $r_{i,t} = \ln P_{i,t} - \ln P_{i,t-1}$, where $P_{i,t}$ is the closing price of firm i at daily t.

5 Empirical results

In this section, we present the results of our empirical analysis. We estimate tail risk spillovers in relation to market conditions. Specifically, we differentiate the tail event across two distinct periods. These are a quiet period (bullish cases) and a crisis period (bearish cases) in the tail distribution of returns. We apply the model of Candelon and Tokpavi (2016), which relies on Granger causality tests between quantiles in the distribution.

The model of Candelon and Tokpavi (2016), estimates causality in the distribution of the tails, which allows us to map the dynamics of contagion in the financial network according to the tail state of the returns. We examine two types of causality: i) the down-to-down, namely $\text{VaR}^{\text{down}} = \{0, 1\%, 5\%, 10\%\}$, and the upside-to-upside, i.e., $\text{VaR}^{\text{up}} = \{90\%, 95\%, 99\%, 100\%\}$). These types of VaRs indicate the risk spillovers in the bearish and bullish conditions.

First, we present the static results of our estimates to highlight the network structure of risk spillover. Then, we illustrate the dynamic evolution of the total connectivity and directional connectivity of risk spillover between the different sectors. Finally, we present the relative risk spillover dynamics. The analysis takes into account the favorable (bullish) market conditions, i.e., the extreme tail high during the recovery period, on the one hand. On the other hand, the analysis also highlights unfavorable (bearish) market conditions, i.e., the extreme bottom of the tail during the recession period.

Our sample includes banks, insurers, and other financial institutions in the euro area. Our results shed light on the topological structure of the risk spillover over a representative time period, which includes both quiet periods and periods of instability including, the 2008 financial crisis, the 2010 Eurozone sovereign-debt crisis and the COVID-19 health crisis.

5.1 Static analysis

Figure 1 shows the static risk spillover results for our entire sample of banks, insurances and other financial institutions. The left-side network reflects the extreme downside-

Table 1. List of sample firms

Number	Firms	Country
	Banks	
1	RAIFFEISEN	Austria
2	OBERBANK	Austria
3	BANK FUR TIROL UND VBG.	Austria
4	BKS BANK	Austria
5	VOLKSBANK VBG.PARTN. (∼U$)	Austria
6	ERSTE GROUP BANK	Austria
7	KBC GROUP	Belgium
8	BANQUE NATIONALE DE BELGIQUE	Belgium
9	CRCAM DE NORMANDIE SEINE CCI PAR	France
10	CREDIT AGRICOLE	France
11	CRCAM ATLANTIQUE VENDEE	France
12	CARDE.CRAG.LRE. HAUTE- LOIRE PAR	France
13	CAISSE REGIONALE CREDIT AGRICOLE MUTUEL	France
14	CAISSE REG CRED AGRIC MUT TOURAIN POITOU	France
15	BNP PARIBAS	France
16	CR.AGRICOLE MORBIHAN	France
17	CRCAM NORD CCI	France
18	CREDIT AGR.TOULOE	France
19	CARDE.CAMU.APR.PAR	France
20	SOCIETE GENERALE	France
21	CREDIT AGR.ILE DE FRANCE	France
22	CARDE.CAMU.SRA.	France
23	CREDIT FONCIER DE MONACO	France
24	NATIXIS	France
25	LOCINDUS SA	France
26	UMWELTBANK	Germany
27	HOEVELRAT H. AG	Germany
28	AAREAL BANK	Germany
29	MERKUR PRIVATBANK	Germany
30	COMMERZBANK	Germany
31	DEUTSCHE BANK	Germany
32	ATTICA BANK	Greece
33	EUROBANK HOLDINGS	Greece
34	PIRAE FINANCIAL HOLDINGS	Greece
35	ALPHA BANK	Greece
36	BANK OF GREECE	Greece
37	NATIONAL BK.OF GREECE	Greece
38	PERMANENT TSB GHG.	Ireland
39	AIB GROUP	Ireland
40	BANK OF IRELAND GROUP	Ireland
41	BANCA PPO.DI SONDRIO	Italy
42	BNC.DI DESIO E DELB.	Italy
43	BCA.PICCOLO CDT.VALTELL	Italy
44	BPER BANCA	Italy
45	BANCA MONTE DEI PASCHI	Italy
46	BANCA PROFILO	Italy
47	BANCO BPM	Italy
48	UNICREDIT	Italy
49	INTESA SANPAOLO	Italy
50	BANCA FINNAT EURAMERICA	Italy
51	CREDITO EMILIANO	Italy
52	ING GROEP	the Netherlands
53	VAN LANSCHOT KEMPEN	the Netherlands
54	BANCO COMR.PORTUGUES 'R'	Portugal
55	BANCO DE SABADELL	Spain
56	BANCO SANTANDER	Spain
57	BANKINTER 'R'	Spain
58	BBV.ARGENTARIA	Spain
	Insurances	
59	VIENNA INSURANCE GROUP A	Austria
60	UNIQA INSU GR AG	Austria
61	AGEAS (EX-FORTIS)	Belgium
62	CNP ASSURANCES	France
63	SCOR SE	France
64	AXA	France
65	CASH LIFE	Germany
66	HANNOVER RUECK	Germany
67	RHEINLAND HOLDING	Germany
68	NUERNBERGER BETS.	Germany
69	ALLIANZ	Germany
70	MUENCHENER RUCK	Germany
71	CATTOLICA ASSICURAZIONI	Italy
72	UNIPOL GRUPPO FINANZIARI	Italy
73	ASSICURAZIONI GENERALI	Italy
74	UNIPOLSAI	Italy
75	AEGON	Spain
76	GRUPO CATALANA OCCIDENTE	Spain
77	MAPFRE	Spain
	Others	
78	FRAUENTHAL HOLDING	Austria
79	UNTERNEHMENS INVEST	Austria
80	WIENER PRIVBK.IM.INVT.	Austria
81	AB EFFECTENBETEILIGUNGEN	Austria
82	ACKERMANS & VAN HAAREN	Belgium
83	GIMV	Belgium
84	SOFINA	Belgium
85	GBL NEW	Belgium
86	COMPAGNIE DU BOIS SAUVAGE	Belgium
87	BELUGA	Belgium
88	PALMBOOMEN CULT. MIJ. MOPOLI PALMERAIES DE	Belgium
89	BREDERODE	Belgium
90	FINANCIERE HOCHE BAINS LIMITED DATA	France
91	PRTE.INDTR.MRE. LIMITED	France
	Others	
92	COURBET	France
93	BOURSE DIRECT	France
94	EUROLAND CORPORATE	France
95	COFIN.DE L AFR.DE L OUEST AFCN.	France
96	SC.FONFNC.ET DE PARTS.	France
97	VERNEUIL FINANCE	France
98	ADVENIS	France
99	ABC ARBITRAGE	France
100	UNION FINC.FRANC.	France
101	IDSUD	France
102	VIEL ET CIE	France
103	ALTAMIR	France
104	FORESTIERE EQUATORIALE	France
105	FIPP	France
106	EURAZEO	France
107	WENDEL	France
108	CAMBODGE (CIE DU)	France
109	GROUPE IRD	France
110	FAUVET-GIREL	France
111	LEBON	France
112	ARTOIS INDFIN.DE L'ARTO	France
113	ROTHSCHILD & CO	France
114	MONCEY FINANCIERE	France
115	KONSORTIUM	Germany
116	DEUTSCHE BOERSE	Germany
117	BAADER BANK	Germany
118	MAIER & PARTNER	Germany
119	SHAREHOLDERS VALUE BET.	Germany
120	DLB-ANLAGESERVICE	Germany
121	MPC MUENCHMEYER CAP.K	Germany
122	HOR	Germany
123	DNI BETEILIGUNGEN	Germany
124	SCHNIGGE CAPITAL MARKETS	Germany
125	CLERE N	Germany
126	OEKOWORLD N PREFERENCE	Germany
127	INSTANT GROUP	Germany
128	FALKENSTEIN NEBENWERTE	Germany
129	GBK BETEILIGUNGEN	Germany
130	SYRAK HOLDING	Germany
131	SCHERZER & CO.	Germany
132	GRENKE N	Germany
133	EUWAX	Germany
134	SINO	Germany
135	HELIAD EQ.PARTNERS	Germany
136	TRADE & VALUE	Germany
137	RM RHEINER MANAGEMENT	Germany
138	NAVIGATOR EQUITY	Germany
139	DEUTSCHE BETEILIGUNGS	Germany
140	MLP	Germany
141	RED ROCK CAPITAL	Germany
142	EFFECTEN-SPIEGEL	Germany
143	VALUE-HOLDINGS	Germany
144	KST BETEILIGUNGS	Germany
145	SPARTA	Germany
146	BET.IM BALTIKUM	Germany
147	FORIS	Germany
148	VALUE MANAGEMENT & RESEARCH	Germany
149	FRITZ NOLS GLB.EQ.SVS.	Germany
150	PEH WERTPAPIER	Germany
151	SM WIRTSCHAFTSBERATUNGS	Germany
152	UCA	Germany
153	MWB FAIRTRADE WPHDLSBANK	Germany
154	SINO GERMAN UNITED K	Germany
155	SLEEPZ	Germany
156	ALLERTHAL-WERKE	Germany
157	ADCAPITAL	Germany
158	HEIDELBERGER BETEILIGUNGSHOLDING	Germany
159	POMM.PRVZ.ZUCKSIE.	Germany
160	GOLD-ZACK	Germany
161	DEUTSCHE BALATON K	Germany
162	BERLINER EFFTG.	Germany
163	VALORA EFFEKTEN HANDEL	Germany
164	WUESTENROT & WUERTT.	Germany
165	DT.EFF.UD.WCH.- BTGU.	Germany
166	HELLENIC EXCHANGES HDG.	Greece
167	MARFIN INV.GP.HDG.	Greece
168	DEA CAPITAL	Italy
169	AZIMUT HOLDING	Italy
170	BANCA IFIS	Italy
171	BANCA INTERMOBILIARE	Italy
172	GEQUITY	Italy
173	LVENTURE GROUP	Italy
174	BANCA MEDIOLANUM	Italy
175	MITTEL	Italy
176	TITANMET	Italy
177	ITALMOBILIARE	Italy
178	MEDIOBANCA BC.FIN	Italy
179	VALUE8	the Netherlands
180	HAL TRT	the Netherlands
181	ALANTRA PARTNERS	Spain
182	MOBILIARIA MONESA	Spain
183	CORPORACION FINCA.ALBA	Spain

downside case while the right-side network reflects the extreme upside-upside case. The following colors: red, purple and yellow refer to banks, insurance companies and other financial institutions, respectively. The network is constructed using Granger causality tests for the tail event in a multivariate framework. Each line in the network confirms a causal relationship between two institutions at 1% significance level. Each line's color reflects the direction of causality for a financial actor in a sector.

Comparing the two networks on the left-side and the right-side, which represent respectively bearish and bullish market conditions, we can see that banks, insurances and other financial institutions are strongly linked in the case where the tails of the return distribution are on the left (bearish). More concretely, the total spillover index in the bearish case amounts to 0.49. In contrast, in the bullish case, this index only reaches 0.12. This suggests that the bearish cases enhance connectivity, and therefore, risk spillovers. This result clarified the reactive behavior of institutions under different market conditions. When the market is under crisis, the risk spillovers between players in different sectors increase, which could threaten the resilience of the entire financial system.

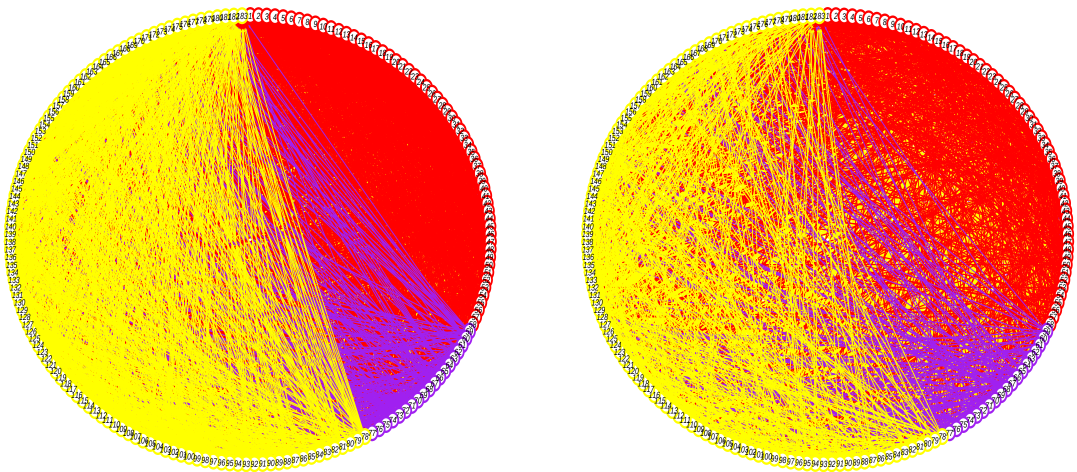

Figure 1. Snapshot of extreme risk spillover networks

Notes: On the left-side is the extreme downside-downside network (Total spillover index = 0.49), and on the right-side is extreme upside-upside network (Total spillover index = 0.12). The color of the node indicates the Bank (red), Insurance (violet) and Others (yellow).

After analyzing the risk spillovers in general, we focus on the directionality of risk spillovers between the three sectors: banking, insurance and other financial institutions. Table 2 specifies the risk spillovers between these three sectors and plots the matrix of total risk spillover directionality indices between sectors (non-diagonal elements) and for the sectors themselves (diagonal elements). We find that the spillover indices in the bearish case, greatly exceed those in the bullish cases. This result shows that bearish conditions play an important role in the sectoral propagation of risk spillover. The different sectors tend to influence each other in a significant and reciprocal way in bearish market conditions than in bullish market conditions. We document evidence to support the asymmetry between negative and positive risk spillovers. In particular, the former is more severe than the case of positive risk spillovers.

Table 2. Risk spillovers across sectors

	TO		
FROM	Banks	Insurances	Others
Bearish case			
Banks	0.587	0.621	0.401
Insurances	0.639	0.667	0.409
Others	0.536	0.627	0.436
Bullish case			
Banks	0.146	0.102	0.088
Insurances	0.098	0.093	0.088
Others	0.125	0.131	0.126

5.2 Dynamic Analysis

Here we analyze the dynamic evolution of total connectivity and directional risk spillover connectivity across sectors. Following Wang et al. (2017), we estimate the directional spillovers using 250-day rolling windows, when $M = 20$ (one trading month). Figure 2 represents the dynamic evolution of the total connectivity spillover (TCS) index under bearish (left-side) and bullish (right-side) market conditions. We observe that the dynamic risk spillover is significantly volatile and peaks during crisis periods in bearish market conditions. We notice peaks of 0.45, 0.30 and 0.50 during the financial crisis (2008), sovereign debt crisis (2010-13) and COVID-19 era (2020-to date), respectively. The behaviour is coherent with the analysis of Claeys and Vasicek (2015), Foglia and Angelini (2020) and Borri and Di Giorgio (2021), which found similar dynamics of risk spillovers. Turning our attention to upside-upside risk spillovers, we see that the connections are fairly stable, with the highest peak in the COVID-19 period. This means that positive risk spillover is less severe than negative risk spillovers.

The findings document that the financial system becomes highly interconnected in bearish conditions and especially during periods of instability. In other words, the results imply that the co-movement effect is more likely to occur under negative extreme risk conditions. This result is fully consistent with the "shift-contagion" theory of Caporin et al. (2018). The authors argue that we can note the "shift-contagion" when the intensity of relationship (between financial firms) changes across different quantiles. Their findings suggest that the degree is higher for lower quantiles, as well as in our case.

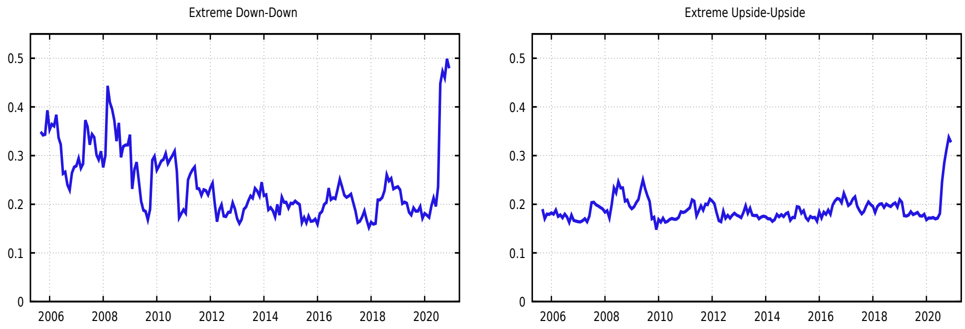

Figure 2. Total connectivity spillover (TCS) index
Notes: On the left-side is the TCS index of the extreme downside-downside network, and on the right-side is that of the extreme upside-upside network.

Now, we examine the dynamic sector spillover, from one sector to another and to itself. Figure 3 exhibits the risk spillover connectivity across sectors, at downside-downside (left-side) and upside-upside (right-side) risk levels, respectively. At first look, we can note, also in this case, the asymmetric pattern between the two types of risk. The dynamics of the bearish condition are more volatile and reaches peaks of high values. On the other hand, the bullish dynamics are more stable with low peaks value. Focusing on sector spillovers, the findings document the key role played by the bank sector and the insurance sector in the transmission of risk. As we can note, these sectors spread major risk in the Eurozone financial system. In the contrast to the "others" sector, which emits less risk spillovers.

To further investigate directional information, in Figure 4, we plot the relative influence (RI) index of each sector. Analyzing the RI index, we can see whether a sector is a net transmitter or a net receiver of extreme risk spillovers. On the basis of the value of the index, we can distinguish sectors that emit on extreme risk (positive value), and sectors that receive tail risk (negative value). The banking sector, on average, acts as a net-sender of risk spillovers under bearish market conditions. This dynamic is consistent with the events that have most affected the Eurozone financial system. In fact, we can see that the banking system is the net sender of extreme risk particularly during the sovereign debt crisis, the Brexit, the Non-Performing-Loans issues, and finally the COVID-19 pandemic. One possible explanation is that the European financial system is bank-centred (ECB, 2017; Borri and Di Giorgio, 2021). For the upside-upside risk, the dynamics are quite interspersed. However, the impact of the COVID-19 outbreak is clear. In this period the banking sector played a significant role on spread tail risk on the financial system (Akhtaruzzaman et al., 2021; Rizwan et al., 2020). The RI index of the insurance sector, on bearish market conditions, changes over time. We can note positive and negative values. On the other hand, on bullish market conditions, the insurance sector, on average, assumes the role of net-sender. Finally, we can see how the "others" sector is a net-receiver of tail risk, especially on upside-upside condition. Our

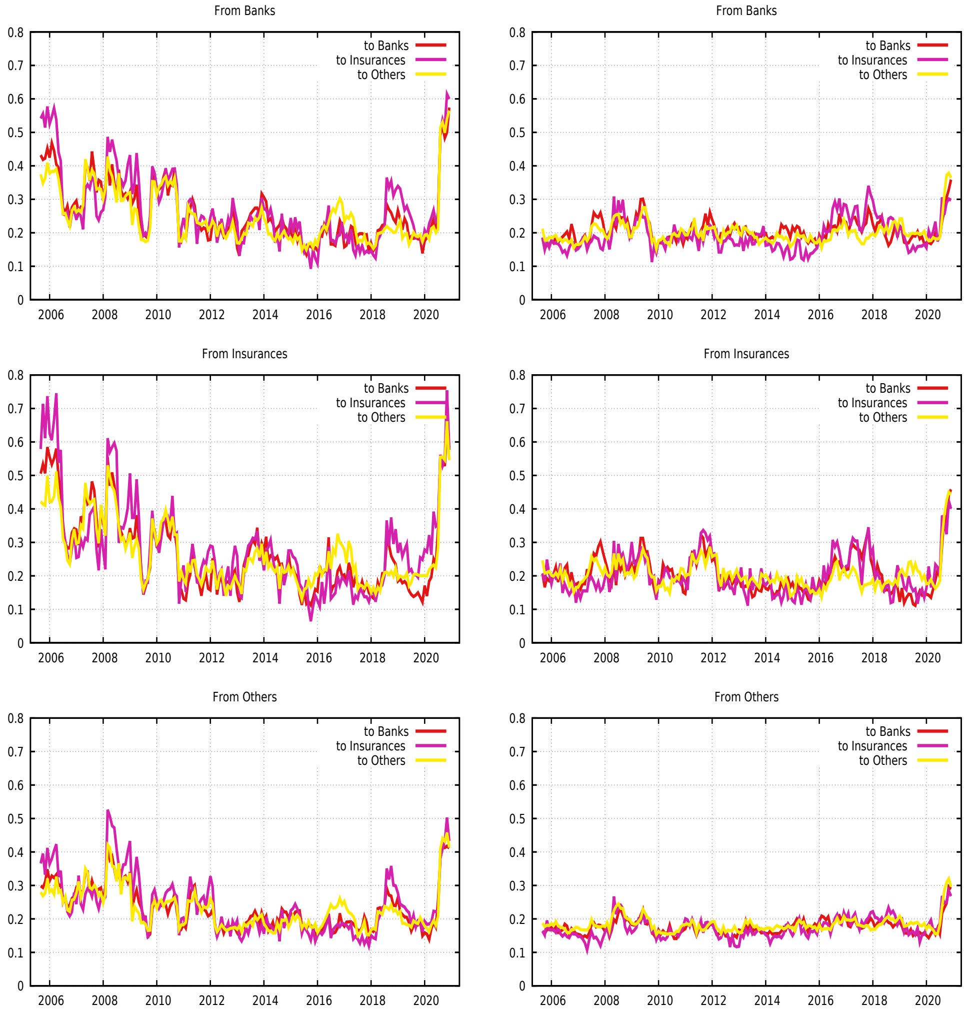

Figure 3. Dynamic risk spillovers across sectors

Notes: Here shows dynamic risk spillovers from one sector to another or itself. On the left-side is the extreme downside-downside network, and on the right-side is extreme upside-upside network.

investigation of risk spillover reveals that there is heterogeneity in tail risk transmission. This result is informative enough for the policymaker to take specific policy measures depending on the role assumed by a given sector in a given time period.

5.3 Extreme connectedness and monetary policy

In this section, we evaluate the monetary policy impact on contagion in the Eurozone financial system. The aim is to analyze the ability of the European Central Bank (ECB) to intervene in the reduction of risk spillover.

We investigate the causality relationship between monetary stance and our two measures of connectedness: bearish and bullish risk networks. Therefore, we examine if this relationship is homogeneous between the two connectedness measures, i.e., whether there are asymmetrical effects. In particular, we attempt to answer two questions: does the

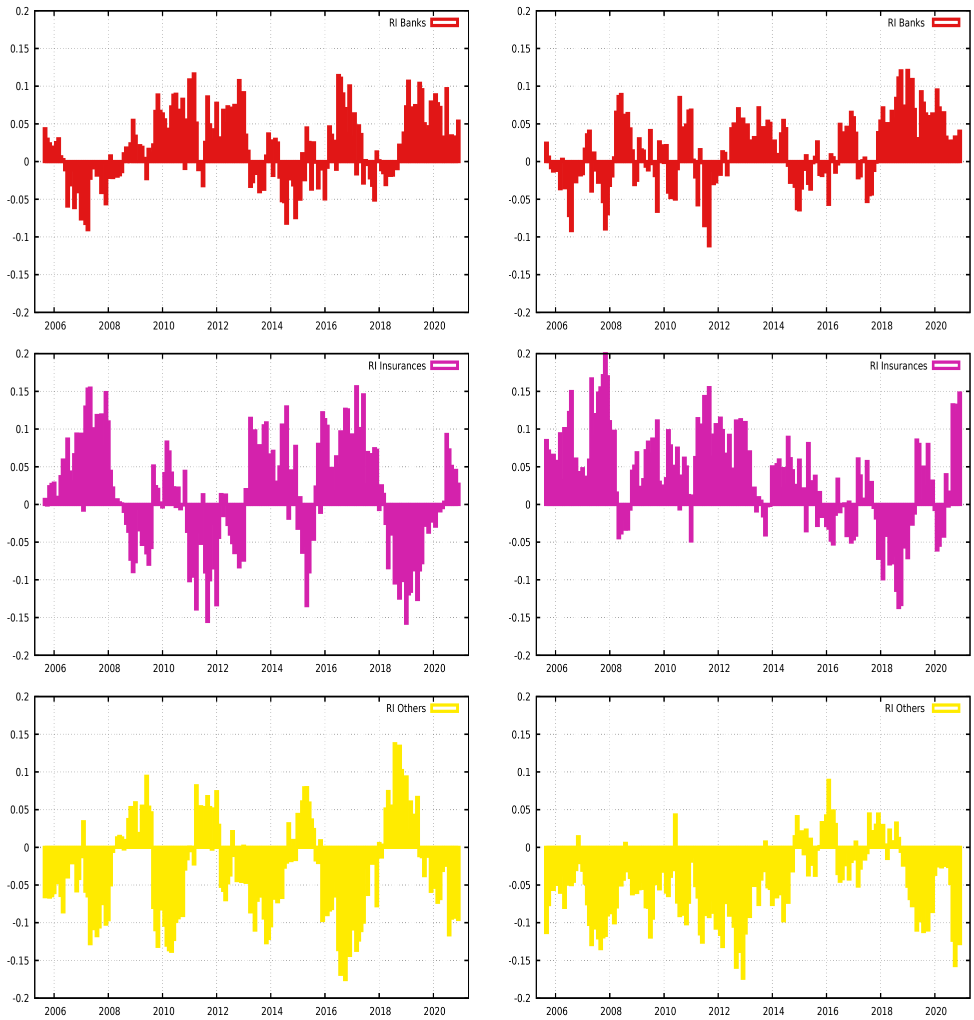

Figure 4. Dynamic relative influence index of each sector
Notes: On the left-side is the extreme downside-downside network, and on the right-side is extreme upside-upside network.

monetary policy affect risk, i.e., does the connection imply monetary policy intervention? Are the asymmetric effects impacting upside and downside risks? Answering these questions, in our view, provides an important and innovative contribution to this recent literature.

For this purpose, we use the Shi et al. (2020) model. This framework is a useful method to investigate the time-varying causality. In particular, the model computes three time-varying causality algorithms: the forward-recursive causality, rolling causality, and recursive evolving causality.[3]

To capture the monetary policy stance, we use a unique index of monetary policy, namely the "shadow rate" (Wu and Xia, 2016; Pattipeilohy et al., 2017; Lombardi and Zhu, 2018). We use a factor analysis to compute the "shadow rate" index from the yield curve provided by ECB, following the approach of Pattipeilohy et al. (2017).[4]

[3]Please see Shi et al. (2020) for the methodological aspect of the model.
[4]For the sake of brevity, we do not report the methodological aspects of shadow-rate estimation.

Figures 5–6 plot the causality results between the total connection spillover TCS (for bearish and bullish networks, respectively) and monetary policy. We plot the three causality tests: (i) the forward-recursive causality, (ii) the rolling causality, and (iii) the recursive evolving causality. The red line represents Wald's statistical sequence. If it exceeds its corresponding critical value (blue dashed line), then the causality is significant. The left side of Figure 5, shows the causal relationship of risk $\longrightarrow$ shadow rate (monetary stance), while the right side shows the shadow rate $\longrightarrow$ risk causality. Looking at the left side, we can see that the bearish connectedness does not exert any causal effect on monetary policy over the entire period. The non-relation between risk and policy can be attributed to the fact that financial stability is not an objective of the ECB. Indeed, financial stability is not among the ECB's objectives as set out in the first paragraph of Article 127 (Mersch, 2018). Focusing on the right-hand side, we can instead identify periods where instead monetary policy Granger causes risk. That is, ECB monetary policies in response to the U.S. financial crisis, such as the cut of the main refinancing rate, the LTROs, and the covered bond purchase programme during 2009, the creation of Single Supervisory Mechanism (SSM, November 2014), the announced (January 2015) and application (March 2015) of the ABS purchase programme (QE), have had an effect on risk. These results confirm the analyses of Colletaz et al. (2018) and Foglia and Angelini (2019) who document the same results. They, find, on the one hand, a significant casual relationship from policy to risk, on the other hand an insignificant causality from risk to policy.

Turning our attention on Figure 6, we can observe a different picture of the relationship. In this case, we find, on one hand, that the risk causes the monetary stance. On the other hand, we find that the monetary stance causes the risk. This means that the contagion risk induces an intervention of the ECB, and the policy of the ECB also has an effect on the risk. The results document the existence of bi-directional causality. We observe that positive risk spillover causes monetary policy stance during 2009 and 2012, i.e., during the most acute phases of the two crises that affected the Eurozone financial system. Indeed, these feedback effects coincide with periods of high volatility in European financial markets (Samarakoon, 2017; MacDonald et al., 2018; Bratis et al., 2020). Focusing on the right side of the figure, we note, again, how monetary policies had an effect on positive risk spillover. The forward and recursive rolling estimates show how from 2014 onwards, the relationship is significant until 2020 (pre-COVID-19 period).

These results add new information to the evidence of time-varying dependence between risk and ECB monetary policy reported by Colletaz et al. (2018) and Foglia and Angelini (2019). In fact, for the first time, we find that positive risk Granger causes monetary policy, i.e., there are asymmetric effects between the two types of risk. This

However, they are available on request. The ECB yield curve is extracted from ECB Statistical Data Warehouse.

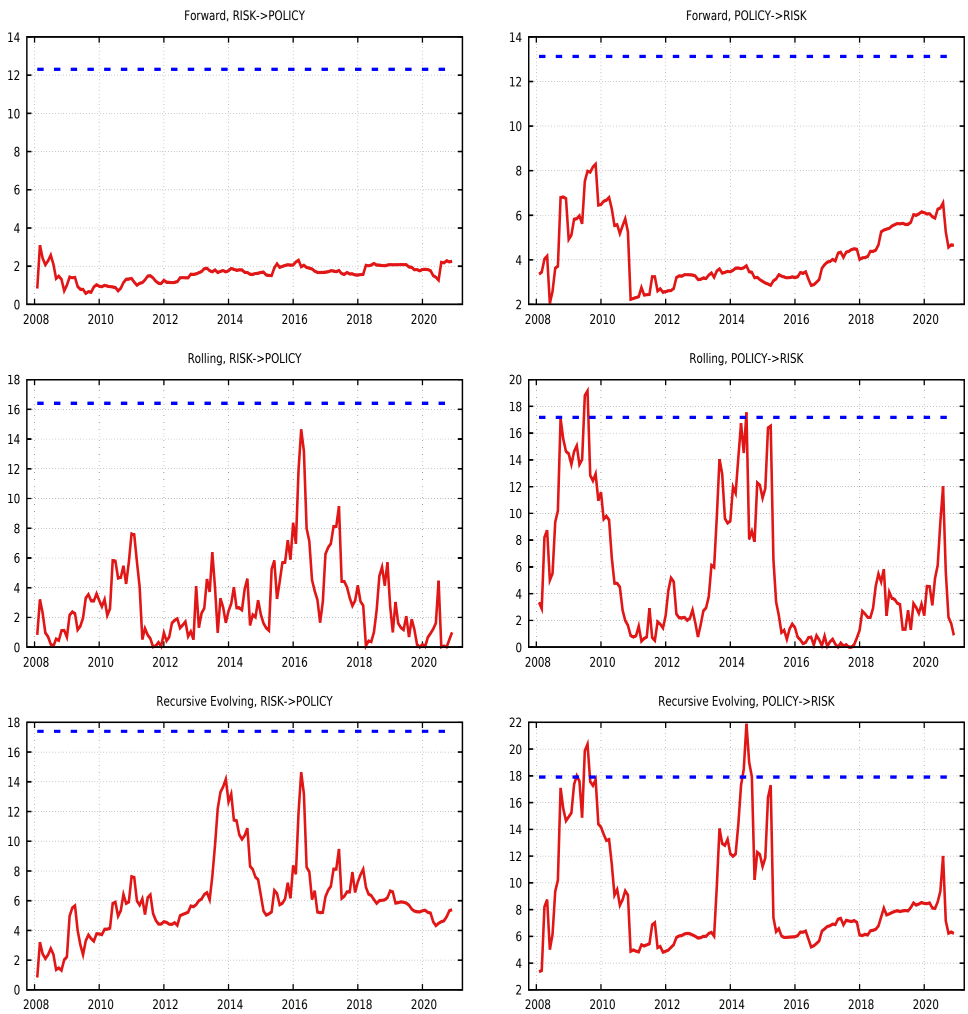

Figure 5. Time-varying causality between downside-downside extreme connectedness and shadow rate.

Notes: The left-side shows risk $\longrightarrow$ shadow rate causality, while the right-side shows the shadow rate $\longrightarrow$ risk causality. The blue dashed line is the 5% critical value, while the red solid line is the Granger test sequence.

result sheds new light on the nature of the relationship between monetary policy and financial stability. For example, if we focus on the left-side of Figure 6, we can observe a significant causality relationship from monetary to risk during 2009. In this period, the ECB intervened on upside risk by cutting interest rates. This effect was also spread on downside risk (see the right-side of Figure 5). As can be seen from the graphs, first, there is the intervention (effect) on upside risk and then at downside level. Hence, the paper provides new evidence on the debate between monetary policy intervention and non-intervention. In fact, our results show that the ECB follows both the "leaning against the wind" approach, i.e., central banks should also use monetary guidance to manage financial imbalances (in the case of upside risk) and the "modified Jackson Hole consensus" approach, i.e., central banks should only focus on price stability (in the case of downside risk).

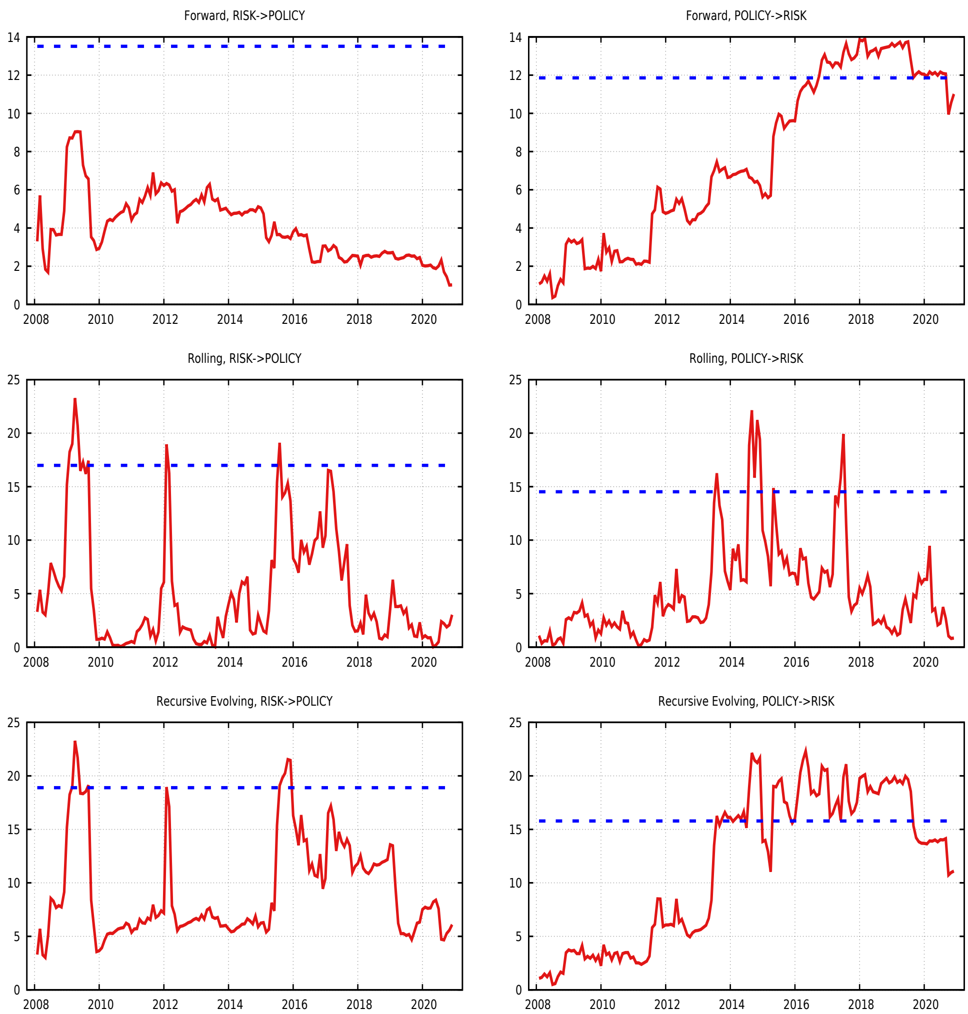

Figure 6. Time-varying causality between upside-upside extreme connectedness and shadow rate.
Notes: The left-side shows risk $\longrightarrow$ shadow rate causality, while the right-side shows the shadow rate $\longrightarrow$ risk causality. The blue dashed line is the 5% critical value, while the red solid line is the Granger test sequence.

5.4 Discussion of results

We developed this research with the following objectives: (i) to develop an approach to identify the downside and upside tail extreme risk between financial institutions, (ii) to analyze the dynamics of contagion, highlighting the co-movement within financial sectors in bearish and bullish market conditions, and (iii) to study the ability of ECB monetary policy to manage the contagion risk.

In terms of implications, our study focused on several key points to better conceptualizing the extreme risk spillover effect and understanding regulatory policies to maintain financial stability. Distinguishing the influence of extreme level events, whether positive or negative, on interconnections allowed us to visibly capture the hidden heterogeneity in interconnection changes. Indeed, an analysis without differentiating the level of the tail risk (left or right) could lead to biased research, and consequently, to an inadequacy of the regulators' interventions. Furthermore, looking at the entire financial system allows for a better understanding of the dynamics between different sectors, which is crucial for effective financial stability policies. The framework that we have suggested enable us to visualize changes in the structure of interconnections in response to externalities to know which sector influences more the extreme behaviors of contagion.

Our results suggest that negative externalities intensify interconnections more than positive ones, i.e., asymmetric effect. In times of crisis, extreme connections between institutions increased dramatically, both within the same sector and between different sectors. This has made it possible to identify sectors that contribute most to the spread of systemic risk. It is also worth noting the role assumed by alternative financial intermediation ("others"). In recent years, investors have shifted their focus to these activities for higher returns encouraged to exploit regulatory gaps in the industry. However, although the growth of non-bank financial intermediaries could bring benefits in terms of financial development, it also requires special prudential attention (ECB, 2020). In fact, in the pre-COVID-19 period (2018–19), our analysis suggests that this sector issued the most risk.

Second, the non-causal relationship between downside risk and monetary policy suggests that the changes in interconnections could be due to idiosyncratic risks, which could systematically affect systemic risk and therefore lead to cascading bankruptcies (Fiordelisi and Marques-Ibanez, 2013). Indeed, the individual default risk can directly impact the behavior of systemic risk, which leads to the reinforcement of conditional dependence due to interconnections. This is what happened during the COVID-19 outbreak. The coronavirus dramatically increased the connections between financial institutions (highest peak), showing how the COVID-19 pandemic is both an economic and financial crisis. Given its twin-crisis nature, the coronavirus crisis could lead to a re-emergence of asymmetries within the Eurozone financial system, both at the country and sector levels. Hence, policies aimed at strengthening financial stability and financial market integration would be welcome. The objective of financial stability should be incorporated into a framework of main policies to avoid self-fulfilling crisis, i.e., to overcome the domino effect of contagion, which is not essentially the cause of the structural conditions of the banks (such as the COVID-19 pandemic). A key message of this study is that the ECB response of contagion risk is not symmetric. An ideal policy would be to follow the "leaning against the wind" approach even under bearish market conditions.

Overall, our findings can be helpful, both in portfolio investment strategies (taking into account systemic risk) and in designing regulatory policies. Analyzing the risk contribution for each sector, we help investors in their investment strategies to include sectors depending on their level of tail risk in that particular period and allow managers to mitigate the risks arising from all financial system. Furthermore, the information can enable policymakers to clearly comprehend the relationship between the Eurozone financial sector depending on market conditions.

6 Conclusion

In this study, we analyze the risk spillover effects among a sample of 183 financial institutions (such as banks, insurances, diversified financials, and real estate firms) in the Eurozone financial system. Following Li et al. (2020)'s approach, we are able to provide an in-depth picture of interactions in the financial system. In fact, thanks to Candelon and Tokpavi (2016)'s model, we have analyzed the Eurozone financial system both from a downside risk perspective and an upside risk perspective. This allowed us to better understand the dynamics within sectors depending on the type of market conditions. The results reveal a heterogeneous effect depending on the level of risk considered, highlighting how bearish conditions play an important role in the sectoral propagation of risk spillover. Different sectors tend to influence each other significantly and reciprocally in bearish conditions than in bullish market conditions. This result documents the presence of "shift-contagion" effect (Caporin et al., 2018). Moreover, as the relative index suggests, we find that banks play a key role in transmitting contagion risk. Finally, we studied, by time-varying Granger causality (Shi et al., 2020), the nexus between monetary policy and risk. Our results show heterogeneity in the relationship depending on the risk considered. We find fresh evidence of ECB monetary policy-risk nexus. In particular, our findings document that the ECB follows the "leaning against the wind" monetary stance in case of upside risk, and the "modified Jackson Hole consensus" approach in case of downside risk.

Future research directions could include further development of the quantile Granger causality in risk models by including firms balance sheet variables in the computation. This new multivariate approach would be able to assess the causal connection by taking into account the fundamental variables of financial firms and the inherent tail risk of the financial market. Thus, mixing two types of risk: "too-big-to-fail" and "too-interconnected-to-fail", respectively. Besides, in this research, we focused on Eurozone financial firms. Future study may involve other geographical areas and other economic sectors.

References

Abad, J., D'Errico, M., Killeen, N., Luz, V., Peltonen, T., Portes, R., and Urbano, T. (2017). Mapping the interconnectedness between eu banks and shadow banking entities. Working Paper w23280, National Bureau of Economic Research.

Acharya, V., Engle, R., and Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review*, 102(3):59–64.

Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. (2017). Measuring systemic risk. *The Review of Financial Studies*, 30(1):2–47.

Adrian, T. and Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, 106(7):1705.

Akhtaruzzaman, M., Boubaker, S., and Sensoy, A. (2021). Financial contagion during COVID–19 crisis. *Finance Research Letters*, 38:101604.

Altunbasa, Y., Gambacortab, L., and Marques-Ibanezc, D. (2014). Does monetary policy affect bank risk? *International Journal of Central Banking*, 10(1):95–135.

Barigozzi, M. and Brownlees, C. (2019). NETS: Network estimation for time series. *Journal of Applied Econometrics*, 34(3):347–364.

Battiston, S., Caldarelli, G., and D'Errico, M. (2016). The financial system as a nexus of interconnected networks. In *Interconnected networks*, pages 195–229. Springer.

Betz, F., Hautsch, N., Peltonen, T. A., and Schienle, M. (2016). Systemic risk spillovers in the european banking and sovereign network. *Journal of Financial Stability*, 25:206–224.

Billio, M., Getmansky, M., Gray, D., Lo, A., Merton, R. C., and Pelizzon, L. (2013). Sovereign, bank and insurance credit spreads: Connectedness and system networks. Working Paper 1, Sloan School of Management, MIT.

Billio, M., Getmansky, M., Lo, A. W., and Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, 104(3):535–559.

Bongini, P., Clemente, G. P., and Grassi, R. (2018). Interconnectedness, G-SIBs and network dynamics of global banking. *Finance Research Letters*, 27:185–192.

Bongini, P. and Nieri, L. (2014). Identifying and regulating systemically important financial institutions. *Economic Notes: Review of Banking, Finance and Monetary Economics*, 43(1):39–62.

Borri, N. and Di Giorgio, G. (2021). Systemic risk and the COVID challenge in the european banking sector. *Journal of Banking & Finance*, page 106073.

Bratis, T., Laopodis, N. T., and Kouretas, G. P. (2020). Systemic risk and financial stability dynamics during the eurozone debt crisis. *Journal of Financial Stability*, 47:100723.

Brogi, M., Lagasio, V., and Riccetti, L. (2021). Systemic risk measurement: bucketing global systemically important banks. *Annals of Finance*, pages 1–33.

Brownlees, C. and Engle, R. F. (2017). SRISK: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies*, 30(1):48–79.

Brunetti, C., Harris, J. H., Mankad, S., and Michailidis, G. (2019). Interconnectedness in the interbank market. *Journal of Financial Economics*, 133(2):520–538.

Candelon, B. and Tokpavi, S. (2016). A nonparametric test for Granger causality in distribution with application to financial contagion. *Journal of Business & Economic Statistics*, 34(2):240–253.

Caporin, M., Pelizzon, L., Ravazzolo, F., and Rigobon, R. (2018). Measuring sovereign contagion in Europe. *Journal of Financial Stability*, 34:150–181.

Chabot, M. and Bertrand, J.-L. (2019). Complexity, interconnectedness and stability: New perspectives applied to the european banking system. *Journal of Business Research*.

Chen, C. Y.-H., Härdle, W. K., and Okhrin, Y. (2019). Tail event driven networks of SIFIs. *Journal of Econometrics*, 208(1):282–298.

Claeys, P. and Vasicek, B. (2015). Systemic risk and the sovereign-bank default nexus: A network vector autoregression approach. *Journal of Network Theory in Finance*, 1(4):27–72.

Colletaz, G., Levieuge, G., and Popescu, A. (2018). Monetary policy and long-run systemic risk-taking. *Journal of Economic Dynamics and Control*, 86:165–184.

Daly, K., Batten, J. A., Mishra, A. V., and Choudhury, T. (2019). Contagion risk in global banking sector. *Journal of International Financial Markets, Institutions and Money*, 63:101136.

Demirer, M., Diebold, F. X., Liu, L., and Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics*, 33(1):1–15.

Diebold, F. X. and Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534):158–171.

Diebold, F. X. and Yılmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1):57–66.

Diebold, F. X. and Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, 182(1):119–134.

Dreassi, A., Miani, S., Paltrinieri, A., and Sclip, A. (2018). Bank-insurance risk spillovers: Evidence from Europe. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 43(1):72–96.

ECB (2017). Report on financial structures. Technical report, European Central Bank.

ECB (2020). Financial integration and structure in the euro area. Technical report, European Central Bank.

Faia, E. and Karau, S. (2019). *Banks' Systemic Risk and Monetary Policy*. Centre for Economic Policy Research.

Fang, L., Cheng, J., and Su, F. (2019). Interconnectedness and systemic risk: A comparative study based on systemically important regions. *Pacific-Basin Finance Journal*, 54:147–158.

Fiordelisi, F. and Marques-Ibanez, D. (2013). Is bank default risk systematic? *Journal of Banking & Finance*, 37(6):2000–2010.

Foglia, M. and Angelini, E. (2019). The time-spatial dimension of eurozone banking systemic risk. *Risks*, 7(3):75.

Foglia, M. and Angelini, E. (2020). From me to you: Measuring connectedness between eurozone financial institutions. *Research in International Business and Finance*, 54:101238.

Fong, T. P. W., Sze, A. K. W., and Ho, E. H. C. (2021). Assessing cross-border interconnectedness between shadow banking systems. *Journal of International Money and Finance*, 110:102278.

Giudici, P. and Parisi, L. (2018). Corisk: Credit risk contagion with correlation network models. *Risks*, 6(3):95.

Granger, C. W. (1980). Testing for causality: A personal viewpoint. *Journal of Economic Dynamics and Control*, 2:329–352.

Härdle, W. K., Wang, W., and Yu, L. (2016). TENET: Tail-event driven network risk. *Journal of Econometrics*, 192(2):499–513.

Hautsch, N., Schaumburg, J., and Schienle, M. (2015). Financial network systemic risk contributions. *Review of Finance*, 19(2):685–738.

Hong, Y., Liu, Y., and Wang, S. (2009). Granger causality in risk and detection of extreme risk spillover between financial markets. *Journal of Econometrics*, 150(2):271–287.

Hué, S., Lucotte, Y., and Tokpavi, S. (2019). Measuring network systemic risk contributions: A leave-one-out approach. *Journal of Economic Dynamics and Control*, 100:86–114.

Jin, X. and De Simone, F. N. (2020). Monetary policy and systemic risk-taking in the Euro area investment fund industry: A structural factor-augmented vector autoregression analysis. *Journal of Financial Stability*, 49:100749.

Kabundi, A. and De Simone, F. N. (2020). Monetary policy and systemic risk-taking in the euro area banking sector. *Economic Modelling*, 91:736–758.

Kenett, D. Y., Tumminello, M., Madi, A., Gur-Gershgoren, G., Mantegna, R. N., and Ben-Jacob, E. (2010). Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market. *PloS ONE*, 5(12):e15032.

Kleinow, J. and Moreira, F. (2016). Systemic risk among european banks: A copula approach. *Journal of International Financial Markets, Institutions and Money*, 42:27–42.

Li, J., Li, J., Zhu, X., Yao, Y., and Casu, B. (2020). Risk spillovers between FinTech and traditional financial institutions: Evidence from the US. *International Review of Financial Analysis*, 71:101544.

Lombardi, M. J. and Zhu, F. (2018). A shadow policy rate to calibrate us monetary policy at the zero lower bound. *International Journal of Central Banking*, 14(5):305–346.

MacDonald, R., Sogiakas, V., and Tsopanakis, A. (2018). Volatility co-movements and spillover effects within the eurozone economies: A multivariate garch approach using the financial stress index. *Journal of International Financial Markets, Institutions and Money*, 52:17–36.

Mersch, Y. (2018). Financial stability and the ECB. *Keynote Speech Financial Stability and the ECB*, page 11.

Nguyen, L. H. and Lambe, B. J. (2021). International tail risk connectedness: Network and determinants. *Journal of International Financial Markets, Institutions and Money*, 72:101332.

Nier, E., Yang, J., Yorulmazer, T., and Alentorn, A. (2007). Network models and financial stability. *Journal of Economic Dynamics and Control*, 31(6):2033–2060.

Paltalidis, N., Gounopoulos, D., Kizys, R., and Koutelidakis, Y. (2015). Transmission channels of systemic risk and contagion in the european financial network. *Journal of Banking & Finance*, 61:S36–S52.

Pattipeilohy, C., Bräuning, C., van den End, J. W., and Maas, R. (2017). Assessing the effective stance of monetary policy: A factor-based approach. *De Nederlandsche Bank Working Paper*.

Peng, C., Zhu, H., Guo, Y., and Chen, X. (2018). Risk spillover of international crude oil to China's firms: Evidence from granger causality across quantile. *Energy Economics*, 72:188–199.

Rizwan, M. S. (2021). Macroprudential regulations and systemic risk: Does the one-size-fits-all approach work? *Journal of International Financial Markets, Institutions and Money*, 74:101409.

Rizwan, M. S., Ahmad, G., and Ashraf, D. (2020). Systemic risk: The impact of COVID-19. *Finance Research Letters*, 36:101682.

Roache, M. S. K. and Rousset, M. M. V. (2013). *Unconventional monetary policy and asset price risk*. International Monetary Fund.

Samarakoon, L. P. (2017). Contagion of the eurozone debt crisis. *Journal of International Financial Markets, Institutions and Money*, 49:115–128.

Shi, S., Hurn, S., and Phillips, P. C. (2020). Causal change detection in possibly integrated systems: Revisiting the money–income relationship. *Journal of Financial Econometrics*, 18(1):158–180.

Silva, W., Kimura, H., and Sobreiro, V. A. (2017). An analysis of the literature on systemic financial risk: A survey. *Journal of Financial Stability*, 28:91–114.

Su, X. (2020). Measuring extreme risk spillovers across international stock markets: A quantile variance decomposition analysis. *The North American Journal of Economics and Finance*, 51:101098.

Torri, G., Giacometti, R., and Tichỳ, T. (2021). Network tail risk estimation in the european banking system. *Journal of Economic Dynamics and Control*, page 104125.

Wang, G.-J., Chen, Y.-Y., Si, H.-B., Xie, C., and Chevallier, J. (2021). Multilayer information spillover networks analysis of China's financial institutions based on variance decompositions. *International Review of Economics & Finance*, 73:325–347.

Wang, G.-J., Jiang, Z.-Q., Lin, M., Xie, C., and Stanley, H. E. (2018). Interconnectedness and systemic risk of China's financial institutions. *Emerging Markets Review*, 35:1–18.

Wang, G.-J., Xie, C., He, K., and Stanley, H. E. (2017). Extreme risk spillover network: Application to financial institutions. *Quantitative Finance*, 17(9):1417–1433.

Wu, J. C. and Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291.

Yan, X.-G., Xie, C., and Wang, G.-J. (2015). Stock market network's topological stability: evidence from planar maximally filtered graph and minimal spanning tree. *International Journal of Modern Physics B*, 29(22):1550161.