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Navigating Turbulence: Unveiling the Spillover Effects Between Non-Financial Risks and Banks

Abstract. *The international context, shaped by (de)globalisation, crises and regulatory recalibration, determined significant transformations in multiple business areas, including banking. As the scientific literature hardly considers the holistic approach of interacting non-financial risk factors, this study raises the awareness over the importance and complexity of the new risk framework. The analysis is based on the dynamics of the shock transmission in stock price and risk channels between geopolitical, economic policy, world uncertainty, climate and volatility risk factors. In the first part of the paper, which represents the estimation of the multivariate DCC GARCH model, we analyse the volatility persistence of the variables over time, while in the second part, representing the spillover analysis, we present the directional connections across total and net spillover indices. The results indicate different reactions of banking sectors to emerging risks, highlighting regional weaknesses and the need for a re-examination of the policy design and risk management practices toward the new stress factors. The paper delves into the new risk framework and provides a better understanding on how non-financial risks factors affect the extended area of banking operations around the world.*

Keywords: *banks, non-financial risks, spillover, volatility, crisis, GARCH model.*

JEL Classification: G21, G32.

1. Introduction

The 21st century banking sector is challenged by the amplification and awareness of non-financial risks, that influence the organisational ecosystem and, if not properly managed, can affect the quality of banking services. These risks do not have a direct impact on financial statements, but trigger multiple and profound

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implications on the reputational, strategic, or operational perspectives of banking organisations.

Although they might seem a separate category, the non-financial risks are critical to risk managers, as they are interconnected with financial risks. The heterogeneity of risk landscape in banking sector requires a holistic approach of risk management that integrates both the financial and non-financial dimensions of risks.

This paper analyses the impact of non-financial risks on banks` investors in different regions, identifies which risks are the most influential and proposes future research directions in the non-financial risk landscape.

Researchers like Li et al. (2020) have examined the spillover path from various points of view, per region, but not in a comprehensive manner. Most studies analyse the spillover effects using time series techniques.

This paper brings a new perspective on the spillover effects between non-financial risks and banks. To establish an inclusive approach, to create comparisons with other sectors of activity related to banking and cross-regional connections, the scientific literature from different industries was analysed and revised, but the focus remained banking.

Our study enriches the current literature by evaluating directional connections across total and net spillover indices using forecast error variance decomposition in a Generalised VAR framework. This research is among the first studies in which a comprehensive set of non-financial risk indicators is analysed in relation to the banking sector. Therefore, it substantially contributes to the development of literature and policy design in this complex area. Our findings could be used as a support for risk management and governance strategies, as well as for other extended policy analyses that aim at creating a framework for a better understanding and quantification of non-financial risks in the banking ecosystem.

2. Literature review

Regardless of the relevance of comprehending the connection between banking risks, the existing literature has primarily focused on examining these risks separately rather than jointly. Furthermore, researchers have focused on analysing the spillover dynamics within a single region (Wang et al., 2018) or a specific type of institution (Liow & Huang, 2018), rather than taking a holistic view of the financial system. As a result, there is a gap in the literature regarding understanding the interconnectedness and transmission mechanisms of banking risks across different markets and institutions in the financial system.

Most scholarly works in this area have examined the co-movement between banking sectors in adjacent areas, but not globally. For instance, Maghyereh & Awartani (2012) use bootstrap measures to study the integration of the banking sector in the Gulf Cooperation Council and demonstrate convergence effects throughout the 2003-2009 transition period, while Jokipii et al. (2007) found a spillover effect in the Central and Eastern European banking sector. Using GARCH models, Alexandrou et al. (2011) underlined that the expansion of the European Union has strengthened the integration of the European banking industry.

The strongest growth in research on the spillover effect occurred after the foreign exchange crisis in East Asian countries and Latin America in the early 1990s (Calvo et al., 1996). For example, some studies (Batuo et al., 2018) pointed to three transmission channels of financial market instability: commercial, business cycle, and behavioural inconsistency of monetary policy. The majority of research on the factors that contribute to bank instability has examined how much a given country (Athanasoglou et al., 2008) or a group of countries is affected by these factors in terms of bank characteristics like efficiency, leverage, and liquidity (de Abreu et al., 2019). Certain studies focus on the role that institutional and regulatory factors play in explaining bank efficiency (Arnold et al., 2018).

One of the fundamental frameworks for examining spillover effects on banking stability is Markowitz's diversification theory (Goldstein & Pauzner, 2004). According to this theory, the demand for an asset depends on the correlation between that asset's returns and the returns of other assets in the same portfolio. To hedge risk through global diversification, financial investors need to understand the interconnectedness of financial markets and the sensitivity of markets to financial external shocks. From the standpoint of global investors, they should consider the problem of increasing the integration of the financial markets, which reduces the positive effects of portfolio diversification and strengthens the spillovers.

Fan et al. (2022) show that the systemic component can be structured as a function of highly correlated common factors that simultaneously affect banks` stock prices using sparse regressions. Therefore, since the common factors reflect the incidence of any observable control variable, we can purposefully omit it from the principal components used to estimate the common unobservable dynamic factors.

The amplification of unfavourable events pertaining to war, terrorism, tensions between states, and political elements that affect the peace process in international relations are all considered geopolitical risks (GPR) (Caldara & Iacoviello, 2022).

Due to its impact on investor sentiment and financial liquidity, the GPR creates extraordinary volatility in the world's financial markets. Gong et al. (2023) focused on the risk spillover mechanism between the international crude oil market and the GPR and found that geopolitical conflicts exacerbate the risk spillover between international energy markets and that the short-term risk spillover effect is more pronounced.

Climate risks can be categorised into physical risks and transition risks. Physical risks primarily involve direct damages and losses resulting from extreme weather events. Transition risks encompass adverse effects on business operations stemming from changes in climate policies, shifts in consumer perceptions, and advancements in green technologies, leading to changes in financial conditions (Colenbrander et al., 2023).

Climate policy uncertainty or news indices are generally considered as proxies of climate, overlooking the physical risks of climate change, which makes it difficult to assess the impact of climate change on market risk spillover.

Uncertainties about future economic policies and political stability are unavoidable and their influence profoundly on macroeconomic developments (Baker et al., 2016). Although uncertainty about policies and national peace is inherent in any country, sudden changes can have profound effects on macroeconomic conditions.

Wang et al. (2023) studied uncertainty indices and commodity market fluctuations, revealing dynamic relationships in the energy, crude oil and carbon markets. They identified varying positive and negative changes over time, with structural shifts caused by random events. The research noted that economic policy uncertainty asymmetrically and positively influences interconnections.

Scientific discussions have focused on cross-border banking interactions. For example, Demirer et al. (2018) estimated the network connectivity of the world's largest banks and discovered that during the Global Financial Crisis and the European Sovereign Debt Crisis, there was a rise in cross-border interactions.

3. Data and methodology

The research aims at presenting cross-continental comparisons between the banking sectors from USA, Europe, and China in terms of the influence non-financial dimension of risk pose to the stock market investors of banks in these regions. The variables used in this study are presented in Table 1.

Based on the 2023 S&P ranking *The world's 100 largest banks*, the sample used was developed considering the country where the headquarter is located (for geographical dimension) and the total assets (for performance dimension). Accordingly, to maintain the comparability between the regions and emphasise strategic differences, only the top 10 publicly listed banks for USA, Europe, and China were selected.

Since the topic of this research arises the interest of both the academic and banking community, to increase its relevance, the entire period starting from the global financial crisis in 2008 until the end of 2023 was considered for the analysis. During this extended period there are turning point moments with various influences that are relevant in the transformational process the banking sector experienced (financial crisis, pandemic, wars, climate crisis and digitalisation of finance).

The methodology in this study is based on Diebold & Yilmaz (2012) and Engle (2002), which analyse directional connections across total and net spillover indices using forecast error variance decomposition in a Generalised VAR framework.

The multivariate GARCH (Generalised Autoregressive Conditional Heteroskedasticity) models represent extend univariate GARCH models which capture correlations between multiple variables, focusing on volatility analysis. The DCC-GARCH (Dynamic Conditional Correlation) model specifically analyses time-varying correlations between variables, combining the flexibility of univariate GARCH models with parsimonious parametric models for correlations.

This model involves three steps. The first step represents estimating a generalised VAR model, then the resulting residuals are standardised using a univariate GARCH model which is suitable for capturing asymmetries in volatility and shock transmission, as well as time-varying cross-correlations between variables, while the last step is the estimation of the model.

In this study we included five univariate models – GARCH, IGARCH, GJR-GARCH, TGARCH, and EGARCH – to determine the optimal model for standardising residuals. The best univariate model identified was EGARCH.

$VAR_{(1)}: X_{1,t} = \alpha_1 + \beta_{11,1} X_{1t-1} + \beta_{12,1} X_{2,t-1} + \varepsilon_t$

$\varepsilon_t \approx Dist\ (0, H_t)$

$H_t = D_t P_t D_t$

$D_t = diag\ \{\sqrt{\ } h^2_t$

- H_t is the conditional variance matrix of the DCC model
- D_t is the diagonal matrix of h_t of univariate GARCH models
- P_t is the correlation matrix that contains expressions from univariate GARCH models

$P_t = Q^*_{t-1}\, Q_t\, Q^*_{t-1}$

$Q_t = (1 - \alpha_{DCC} - \beta_{DCC})\ Q^*_t) + \alpha_{DCC}\ \varphi_{\ t-1} + \beta_{DCC}\ Q_{t-1}$

- Q_t is the conditional covariance matrix
- Q^*_t is the unconditioned covariance matrix
- φ_{t-1} is the matrix of standardised residues
- α_{DCC} and β_{DCC} involve the persistence of shocks. Their amount, which measures the persistence of volatility and must be less than 1.

The second part of the analysis is represented by the directional spillover effects of returns and volatilities of interest variables using the framework developed by Diebold & Yilmaz (2012), which uses variance decompositions of predicted errors and a framework of generalised impulse response functions.

As a first step in this calculation, a VAR with p lags and then the decompositions of the variance allow the evaluation of variation portion of the forecast error xi that is due to the shocks at xj, ∀j ≠ i, for each i. The variance decomposition matrix of the prediction error is calculated by the method developed by Pesaran & Shin (1998), which produces variance decompositions that do not consider the order of introduction of the variables:

$$\theta^g_{ij}(\mathrm{H}) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_j' A_h\, \Sigma e_j'\right)^2}{\sum_{h=0}^{H-1} \left(e_j' A_h\, \Sigma A'_h\, e_i\right)}$$

In order to use the information available in the variance decomposition matrix in calculating the spillover index, each entry of the variance decomposition matrix was normalised by the sum of the rows (number of variables):

$$\tilde{\theta}^g_{ij}(\mathrm{H}) = \frac{\theta^g_{ij}(\mathrm{H})}{\mathrm{N}}$$

Using the volatility contributions from the variance decomposition, Diebold & Yilmaz constructed the total volatility spread index as:

$$S^g(\mathrm{H}) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}^g_{ij}(\mathrm{H})}{\mathrm{N}} . 100$$

The spillover index is based on the "General Forecast Error Variance Decomposition" introduced by Pesaran & Shin (1998). This technique calculates the spillover effect table that has as input the variables ij and measures the contribution of return/volatility shocks to the variations of the forecast error. In addition to the spillover index, Diebold & Yilmaz (2012) also built the directional spillover towards different asset classes. Two directional spillovers have been introduced and are known as: from (to) and to (to).

Directional spillovers allow us to know how much shock is transmitted to and from markets.

The directional spillovers received by market i from all other markets j are:

$$S_{i.}^{g}(\mathrm{H}) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(\mathrm{H})}{\mathrm{N}} . 100$$

The directional spillovers transmitted by market i to all other markets j are:

$$S_{.i}^{g}(\mathrm{H}) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(\mathrm{H})}{\mathrm{N}} . 100$$

The net spillover can be calculated as the difference between the gross return/volatility shocks transmitted and received from all other exchange rate returns:

$$S_{i}^{g}(\mathrm{H}) = S_{.i}^{g}(\mathrm{H}) - S_{i.}^{g}(\mathrm{H})$$

With a monthly frequency and using the above descripted methodology, the stock price is utilised as dependent variable, along with representative indices for non-financial risks – independent variables, encompassing a wide range of aspects, as follows:

Table 1. Description of the variables

Variables	Description	Source
Stock price	Monthly price of a bank`s shares	Refinitiv database
GPR	Geopolitical Risk Index (GPR) developed by Caldara & Iacoviello (2022) was constructed to measure the adverse geopolitical events and their associated risks, highlighting the geopolitical risks on investments, stock prices, employment and the global economic position.	Dario Caldara and Matteo Iacoviello. Data available on www.matteoiacoviello.com
PRI **TRI**	Physical Risk Index (PRI) and Transition Risk Index (TRI) developed by Bua et al. (2024) measures the unexpected discussions on climate physical and transition risks.	Giovanna Bua, Daniel Kapp, Federico Ramella and Lavinia Rognone. Data available on www.policyuncertainty.com
EPU	Economic Policy Uncertainty Index (EPU) developed by Baker et al. (2016) reflects the frequency of newspapers that contain the EPU (economy, policy, uncertainty) trio.	Scott R. Baker, Nicholas Bloom, and Steven J. Davis. Data available on www.policyuncertainty.com
VIX	CBOE Volatility Index (VIX) reflects market risk and investors` fear.	CBOE Global Markets. Data available on www.investing.com

Variables	Description	Source
WUI	Developed by Ahir et al. (2022), the World Uncertainty Index (WUI) reflects global political and economic developments.	Hites Ahir, Nicholas Bloom and Davide Furceri. Data available on www.worlduncertaintyindex.com

Source: Own research.

As it was proven by the stationarity tests Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) the data required the first order difference of the logarithms.

According to the descriptive statistics for the variables, it was observed that a number of 191 monthly observations were introduced and the mean and median are different for all the variables, which means that the data sample used is not symmetrical. The average of the monthly distributions is close to zero and the asymmetry is positive for most of the indices (during the analysed period, the variables had increasing tendencies).

The Kurtosis coefficient has values greater than 3, which means that the distributions of the variables are leptokurtotic, suggesting a higher probability of occurrence of extreme events (large oscillations of indices) than in the case of a normal distribution. The null hypothesis of the Jarque-Bera test that analyses the normality of time series distribution is rejected at a significance level of 1% for all variables in the analysis.

4. DCC GARCH Model

4.1 DCC GARCH Table

The first step of the study involved creating a VAR (1) model, with the number of lags chosen based on the Schwartz information criteria. The next step was to select the optimal univariate GARCH model to standardise the VAR residuals.

Both the information criteria and the Log-Likelihood function indicated that EGARCH (1,1) was the most suitable model for standardising the VAR (1) residuals.

Table 2. DCC-EGARCH European banks

	ω	α1	β1	γ	ν	α+ β
HSBC	-0.2762	-0.1533	0.9519	0.112981	0.872872	0.7987
BNP	-0.4871	-0.3643	0.9045	0.2095	0.951864	0.5403
ACA	-0.0939	-0.1590	0.9793	0.148241	0.965903	0.8203
SAN	-0.2274	-0.2531	0.9557	0.08538	0.935002	0.7025
BARC	-0.1779	-0.3540	0.9679	0.219789	0.799465	0.6138
UBS	-0.0539	-0.0554	0.9872	0.193464	0.963819	0.9318
BRD	-0.0892	-0.1646	0.9808	0.058613	1.055705	0.8162
DBK	-0.1735	-0.1435	0.9622	0.101491	1.06776	0.8187
LLOY	-0.2411	-0.0754	0.9465	0.290705	0.955545	0.8711
ISP	-0.1169	-0.1251	0.9763	0.021399	1.243968	0.8512
GPR	-0.5119	0.2188	0.8552	0.125832	1.013447	1.0740
PRI	-3.7821	0.0898	0.6289	0.414238	1.142619	0.7187
TRI	-0.9082	0.0020	0.7775	0.107459	1.146959	0.7795
EPU	-0.2209	-0.1160	0.9422	-0.2243	0.810392	0.8263
VIX	-0.2144	0.1877	0.9350	-0.25125	0.832906	1.1226
WUI	-0.1037	0.1118	0.9602	0.044804	1.117902	1.0720
α DCC	0.0006					
β DCC	0.9724					

Source: Authors' computations.

Table 3. DCC-EGARCH US banks

	ω	α1	β1	γ	ν	α+ β
JPM	-1.3191	-0.2919	0.7319	0.2473	1.4103	0.4400
BAC	-0.9327	-0.2824	0.7776	0.5116	1.1591	0.4952
CGI	-0.5858	-0.2215	0.8630	0.4249	1.1905	0.6415
WFC	-1.8497	-0.2806	0.6020	0.2957	1.2663	0.3214
GSG	-2.0705	-0.2472	0.5857	0.1910	1.3863	0.3384
MSB	-0.4422	-0.2680	0.8987	0.2462	1.4092	0.6307
USB	-0.4377	-0.1696	0.9141	0.2747	1.6469	0.7445
PNC	-1.2541	-0.2612	0.7492	0.2841	1.4071	0.4880
TFC	-0.4085	-0.1394	0.9137	0.2061	1.3145	0.7742
COF	-0.9576	-0.3040	0.7835	0.4506	1.4198	0.4795
GPR	-0.6075	0.2203	0.8256	0.1893	1.0159	1.0459
PRI	-2.8249	-0.1161	0.7257	0.2482	1.0049	0.6096
TRI	-1.4757	-0.2062	0.6421	-0.0532	1.1691	0.4359
EPU	-0.3320	-0.0222	0.9091	-0.3283	0.9843	0.8869
VIX	-0.4222	0.4330	0.8827	0.1859	1.1305	1.3157
WUI	-0.0193	0.1999	0.9989	-0.1254	1.2149	1.1988
α DCC	0.0162					
β DCC	0.5826					

Source: Authors' computations.

Table 4. DCC-EGARCH Chinese banks

	ω	α1	β1	γ	ν	α+ β
ICBC	-0.6745	0.1100	0.8842	0.2833	1.1779	0.9942
CCB	-1.5410	0.1348	0.7080	0.1114	1.1867	0.8428
BOC	-0.3056	0.0601	0.9464	0.3550	1.4115	1.0065
BOCOM	-0.1911	0.0158	0.9617	0.3659	1.3161	0.9775
IB	-1.0962	-0.1741	0.7677	0.6773	1.1599	0.5936
CITIC	-0.1936	0.0976	0.9594	0.2529	1.1014	1.0570
SPD	-0.3693	-0.1951	0.9270	0.4926	1.1360	0.7320
CMBC	-0.0322	0.0474	0.9900	0.3250	1.1413	1.0374
PAB	-0.5750	-0.0780	0.8658	0.3341	1.1982	0.7878
HXB	-0.0380	-0.0260	0.9896	0.2671	1.1580	0.9636
GPR	-0.1854	0.2992	0.9538	0.1153	1.0299	1.2530
PRI	-1.1099	0.0602	0.8922	-0.3638	1.1539	0.9524
TRI	-0.0853	-0.0366	0.9795	0.0196	1.1420	0.9429
EPU	-0.0441	0.0686	0.9898	-0.0969	0.9362	1.0585
VIX	-0.1189	0.0850	0.9634	-0.1723	0.7462	1.0484
WUI	0.0021	0.1093	0.9999	-0.0964	1.0759	1.1092
α DCC	0.0023					
β DCC	0.9654					

Source: Authors' computations.

In all of the tables above, the ARCH and GARCH coefficients, namely α and β, respectively, are statistically significant, indicating that volatility reacts strongly to market movements and that shocks to conditional variation take time to disappear.

High values of the β coefficient for all variables highlight a long-term persistence of the volatility spillover between the variables. In the first table, the results indicate that European variables have the highest β coefficient, which suggest a stronger long-term persistence of the volatility compared to USA or China. The α coefficient is negative for most of the variables for Europe and the USA and positive for China. The negative values indicate that the variables have a negative reaction to the market shocks and the high values indicate a short-term volatility persistence of the spillover.

The asymmetry term γ is significant in terms of all variables, indicating evidence of the asymmetric impact of bad and good news on conditional volatility. A positive γ means that good news (positive shocks) generates less volatility than bad news. Most of the variables for all three regions have positive values for γ, indicating an asymmetry in volatility, where negative shocks tend to increase volatility more than positive ones.

The negative and statistically significant values of the αDCC and βDCC coefficients suggest that volatilities are highly persistent during market shocks (events). Additionally, the βDCC coefficient being higher than the αDCC coefficient indicates that past variations have a greater influence than current variations, and that conditional correlations vary over time.

4.2 DCC GARCH Conditional Correlations

The DCC GARCH conditional correlations are utilised to present the fluctuations of the indices selected and banks\` stock prices during the entire analysed period. These correlations can highlight whether the relationships are closely related and in which direction.

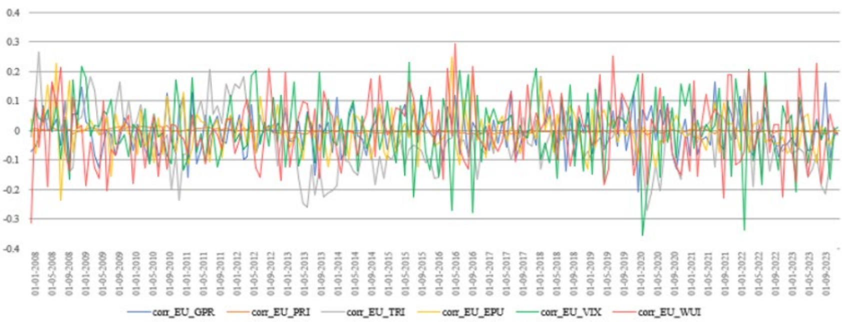
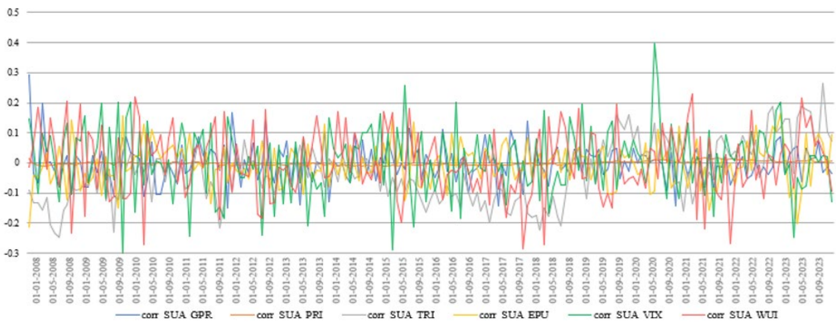
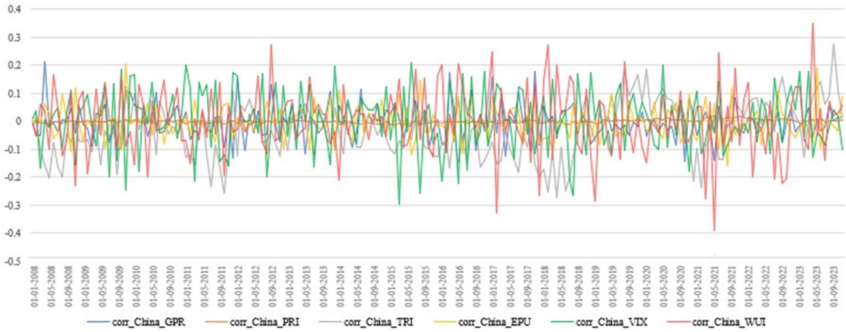


Figure 1. Conditional correlations for European banks
Source: Authors' own creation.



[1]

Figure 2. Conditional correlations for US banks
Source: Authors' own creation.



[2]

Figure 3. Conditional correlations for Chinese banks
Source: Authors' own creation.

The graphical evidence representing conditional correlations between non-financial risk factors and stock prices highlights heterogeneous correlations, intensified during major events. For all the three regions there are periods of positive and negative correlations among all the pairs analysed. US banks tend to be more stable than Chinese and European banks, which have more significant fluctuations. This may be the result of a more resilient and integrated perspective in managing non-financial risks factors, with less vulnerability to sudden fluctuations in the external environment.

For European banks, the most extreme fluctuations come from VIX and TRI pairs, while for US and Chinese banks, the highest spikes are determined by VIX-WUI and WUI-VIX pairs, respectively. This reflects a less global perspective for European banks and a diverse global banking landscape, generated by different behaviours and regulatory environments. The graphs also reveal that Chinese banks are less sensitive to GPR than their US and European peers.

The less significant impact for all regions is generated by PRI, suggesting that banks` investors still do not pay attention to physical implications of climate change.

The results emphasise the importance of regional context, which emerges as an additional factor influencing the management of non-financial risks factors, besides the exposures/lending limits for foreign banks in accordance with their internal strategy and approaches of other banks. The regional differences emphasise the diverse influence non-financial risks have in designing the banking sectors across the world, depending on the local factors like economy, global impact, and regulatory framework.

5. Spillover model

5.1 Spillover table

The spillover tables provide an extended understanding of risk transmission channels and interconnections within the banking system. The results quantify the transmission of shocks from one bank or risk indicator to another, offering critical insights into systemic risk and banking vulnerability.

An important step in the analysis is understanding how much a specific institution or risk indicator contributes to the volatility of the entire system and how much a bank` instability is generated by external factors. Tables 8, 9 and 10 present the spillovers for the three banking sectors analysed. For the analysis, only values above the average were considered.

Table 5. Spillover table for European banks

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	19
1	29.89	8.73	6.73	9.03	8.38	5.73	7.54	6.74	6.82	5.46	0.51	0.07	0.33	1.06	2.76	0.20	70.11
2	5.27	16.76	11.71	9.98	8.06	5.89	12.00	7.56	7.23	10.12	0.37	0.14	0.23	1.77	2.90	0.01	83.24
3	4.10	12.18	17.54	9.15	7.03	7.93	11.74	6.69	7.32	9.57	0.23	0.41	0.43	2.24	3.26	0.17	82.46
4	6.09	10.92	9.89	18.04	6.25	6.66	10.69	7.44	7.42	10.66	0.10	0.25	0.21	2.58	2.57	0.23	81.96
5	6.04	9.52	8.20	6.82	19.28	6.73	10.20	10.18	9.97	7.17	0.47	0.09	0.40	2.63	2.08	0.23	80.72
6	4.50	7.96	9.99	7.86	7.08	21.67	10.60	7.54	7.76	8.29	0.24	0.37	0.91	1.56	3.43	0.25	78.33
7	4.49	11.57	11.11	9.42	8.16	7.76	16.00	8.29	7.22	10.94	0.18	0.21	0.31	1.71	2.65	0.02	84.00
8	4.23	9.35	8.06	8.39	10.90	7.33	10.56	19.66	6.18	9.04	0.22	0.28	0.29	2.47	2.94	0.12	80.34
9	6.87	8.79	9.16	8.34	10.70	7.72	9.46	6.05	20.57	6.62	0.59	0.13	0.43	2.47	2.07	0.03	79.43
10	3.36	11.03	10.47	10.79	6.71	7.03	12.52	8.35	5.94	18.04	0.15	0.27	0.44	2.66	2.17	0.09	81.96
11	0.82	1.73	0.62	2.26	0.56	0.77	1.00	1.23	1.73	1.21	87.12	0.19	0.07	0.05	0.06	0.55	12.88
12	0.12	0.61	2.26	0.54	0.42	0.60	0.36	1.38	0.44	0.34	1.05	69.73	21.41	0.40	0.07	0.27	30.27
13	0.31	1.28	3.80	0.90	0.92	2.41	1.26	1.07	1.10	2.01	0.34	25.54	56.82	0.74	0.57	0.92	43.18
14	1.60	3.93	4.94	6.17	6.44	3.18	4.57	5.60	5.72	5.25	0.58	0.34	0.62	48.60	1.25	1.21	51.40
15	3.24	6.86	7.31	5.99	4.86	5.18	6.46	5.78	4.23	4.77	0.05	0.08	0.17	5.50	39.37	0.14	60.63
16	1.07	0.07	1.10	2.33	1.25	0.84	0.04	1.51	0.20	0.35	0.10	1.06	0.83	1.39	0.08	87.79	12.21
17	52.10	104.52	105.34	97.96	87.71	75.78	109.02	85.39	79.30	91.79	5.17	29.44	27.09	29.23	28.86	4.44	63.32
18	81.99	121.28	122.88	116.00	106.99	97.45	125.02	105.05	99.87	109.82	92.29	99.17	83.91	77.83	68.23	92.23	1600.00

1-HSBC, 2-BNP, 3-ACA, 4-SAN, 5-BARC, 6-UBS, 7-SOG, 8-DBK, 9-LLOY, 10-ISP, 11-GPR, 12-PRI, 13-TRI, 14-EPU, 15-VIX, 16-WUI, 17-C. to others (spillover), 18-C. to others including own, 19-C. from others

Source: Authors' processing.

The spillover table for European banks highlights that the most influential bank contributors to systemic risk are SOG (Société Générale SA), ACA (Crédit Agricole Group) and BNP (BNP Paribas SA), revealing an increased influence for French banks within the European banking sector. For example, SOG`s contribution to other`s spillover of 109.02% suggests a wide-reaching influence on the banking system. These banks have a systemic role in risk transmission, promoting shocks throughout the entire system.

The results also emphasise significant influences between specific banks. For example, SOG has the most significant influences (over 10%) compared to all other banks, followed by its French peers. Also, the analysis reveals a more pronounced influence between banks from the same country, which was an expected result. These bilateral spillovers emphasise significant interdependencies that could serve as risk transmission channels, making them focal points of interest for both a top-down and a bottom-up approach in risk management during periods of financial stress.

Separately from the interbank spillovers, the results indicate that also the global financial risk indicators such as GPR, PRI, TRI, EPU, VIX, and WUI contribute to the instability of banking sector, although they have a less significant influence. Among these indicators, EPU emerges as the most influential on all banks, followed by the other indicators, which register similar spillover values. The results reflect a complex European banking sector, with various sensitivities which can exacerbate financial instability and risk during turbulent periods and also the most vulnerable banking sector to the non-financial dimension of risk, registering the highest spillover values.

Table 6. Spillover table for US banks

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	19
1	15.32	12.33	9.43	9.03	3.56	6.95	8.27	14.45	8.14	9.60	0.01	0.47	0.37	0.44	1.23	0.40	84.68
2	8.92	20.25	17.62	9.31	2.25	8.52	4.48	11.61	6.74	7.31	0.18	0.30	0.37	0.54	1.08	0.50	79.75
3	7.53	15.10	25.24	8.80	2.17	9.05	4.49	11.03	6.06	5.97	0.04	1.36	0.17	0.81	1.22	0.97	74.76
4	7.55	9.88	8.39	22.46	1.65	3.56	12.79	11.30	8.43	9.12	0.08	2.19	0.64	0.50	1.28	0.18	77.54
5	8.39	14.47	11.20	9.46	10.32	12.61	3.70	11.64	3.31	9.38	0.35	0.20	0.42	1.40	2.67	0.47	89.68
6	8.25	15.75	13.24	6.88	7.92	18.93	2.20	11.48	2.65	6.72	0.37	0.13	0.37	1.67	2.60	0.84	81.07
7	7.94	7.37	8.18	12.78	1.24	3.71	16.90	15.41	12.38	9.91	0.04	2.04	0.23	0.56	1.30	0.02	83.10
8	8.48	9.24	8.36	10.87	1.66	5.66	11.14	20.79	10.40	9.93	0.10	0.91	0.35	0.61	1.25	0.26	79.21
9	8.65	9.15	7.91	10.78	1.54	4.18	13.73	15.41	17.17	8.90	0.05	0.52	0.19	0.54	1.19	0.08	82.83
10	7.33	7.45	8.31	10.85	2.18	4.62	12.43	15.09	7.71	19.87	0.07	1.45	0.24	0.91	1.46	0.05	80.13
11	0.23	0.19	0.26	0.10	0.18	0.42	0.19	0.10	0.14	0.14	96.68	0.18	0.16	0.10	0.18	0.76	3.32
12	4.20	1.45	2.71	5.19	1.16	2.00	4.92	1.74	1.41	1.27	1.10	53.19	18.79	0.18	0.42	0.26	46.81
13	2.20	0.52	1.14	1.08	1.90	1.79	1.59	3.04	2.27	1.65	0.40	22.35	57.82	0.23	0.70	1.33	42.18
14	1.45	1.34	1.96	1.44	4.21	5.83	2.69	1.89	1.90	2.45	0.93	0.30	0.56	69.20	2.05	1.78	30.80
15	5.86	4.13	4.34	3.59	9.59	9.05	5.24	5.66	3.79	4.21	0.09	0.06	0.30	5.28	38.65	0.16	61.35
16	2.26	0.45	1.86	0.32	2.31	1.47	0.31	2.05	1.06	0.60	0.07	1.65	0.89	1.30	0.08	83.33	16.67
17	89.25	108.82	104.92	100.49	43.52	79.44	88.17	131.91	76.38	87.14	3.87	34.09	24.04	15.08	18.71	8.05	63.37
18	104.56	129.07	130.17	122.95	53.85	98.37	105.07	152.70	93.55	107.00	100.55	87.28	81.86	84.28	57.35	91.38	1600.00

1-JPM, 2-BAC, 3-CGI, 4-WFC, 5-GSG, 6-MSB, 7-USB, 8-PNC, 9-TFC, 10-COF, 11-GPR, 12-PRI, 13-TRI, 14-EPU, 15-VIX, 16-WU, 17-C. to others (spillover), 18-C. to others including own, 19-C. from others

Source: Authors' processing.

The US spillover table highlights a complex interconnection network and risk transmission channels between major banking organisations.

The most susceptible to vulnerabilities generated by other institutions is Goldman Sachs Group Inc. (GSG), with a total spillover of 89.68, followed by JPMorgan Chase & Co. (JPM) at 84.68 and U.S. Bancorp (USB) at 83.10 of spillover coming from other banks. They form the trio of most influenced US banks by shocks originating from other banks. On the other hand, Citigroup Inc. (CGI) appears to be the least influenced by external shocks generated by other banking organisations, making it safer in terms of risk spillover.

Analysing the spillover transmitted to other institutions, the results indicate that PNC (PNC Financial Services Group Inc.), BAC (Bank of America Corp.) and CGI are potentially the most significant contributors to the vulnerabilities of other banks in the US financial sector.

The spillover of each bank to itself (diagonal values) reflect that CGI has a considerable internal spillover, suggesting a significant risk that is generated by its internal operations. This self-generating risk could be determined by the bank's business model, risk concentration, or internal governance.

The increased sensitivity to internal risk factors is contrasting with externally driven risks, generated by the broader economic framework or volatility generated by other banks, suggesting the fundamental role of internal risk management function and risk behaviour at all levels of responsibility.

Regarding the spillover generated by the non-financial risk indicators, the influential matrix consists of TRI and WUI as factors with the most significant contributions. Differently from the European banks, GPR seems to have less influence on the selected banks, suggesting a stronger banking sector in face of geopolitical risk factors. The results indicate that the climate-related indicator TRI generates more contributions that its related peer PRI and that the US banks are better prepared to withstand the market fear generated by spikes of the VIX indicator.

Table 7. Spillover table for Chinese banks

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	19
1	16.20	7.21	11.73	10.83	8.84	8.63	8.33	9.24	7.49	8.82	0.10	0.05	0.03	1.11	1.14	0.25	83.80
2	10.98	24.66	7.74	8.85	6.62	6.35	6.63	7.05	8.14	6.46	0.29	0.10	0.27	2.56	2.83	0.47	75.34
3	12.27	5.29	17.68	11.99	8.40	9.34	7.91	9.78	7.04	8.92	0.25	0.15	0.06	0.55	0.32	0.04	82.32
4	10.01	5.19	10.58	15.25	9.79	9.38	9.68	10.12	8.94	9.57	0.18	0.12	0.01	0.56	0.56	0.04	84.75
5	8.86	4.26	8.08	10.60	16.30	8.41	11.21	10.84	10.03	9.54	0.04	0.03	0.07	1.10	0.21	0.41	83.70
6	9.17	4.44	9.68	10.73	9.03	17.47	8.24	10.13	8.35	10.28	0.19	0.15	0.28	0.76	1.03	0.05	82.53
7	8.25	4.25	7.68	10.50	11.21	7.74	16.25	10.91	10.20	10.77	0.01	0.35	0.04	1.08	0.59	0.17	83.75
8	8.92	4.54	9.15	10.57	10.66	9.13	10.58	16.05	8.93	10.35	0.06	0.15	0.06	0.45	0.24	0.17	83.95
9	7.92	5.50	7.23	10.19	10.80	8.34	10.65	9.69	17.53	9.68	0.02	0.22	0.10	1.42	0.49	0.22	82.47
10	8.84	4.31	8.66	10.41	9.59	9.61	10.86	10.71	9.23	16.15	0.02	0.16	0.18	0.81	0.38	0.08	83.85
11	0.33	0.37	1.49	0.97	0.24	0.50	0.02	0.44	0.19	0.07	94.47	0.12	0.05	0.02	0.20	0.54	5.53
12	0.58	0.02	0.37	0.32	0.47	0.41	1.63	0.64	1.51	0.46	0.65	70.41	22.02	0.15	0.12	0.23	29.59
13	0.87	0.13	0.32	0.41	0.73	0.46	1.43	0.35	1.22	1.64	0.28	28.70	61.05	0.43	0.75	1.22	38.95
14	2.93	4.96	2.00	1.98	2.75	2.40	3.53	1.69	4.74	2.46	0.93	0.31	0.50	65.3	1.78	1.73	34.70
15	3.98	6.32	2.24	2.91	2.73	4.18	2.89	1.59	3.98	2.11	0.13	0.06	0.24	8.48	57.98	0.18	42.02
16	2.32	3.18	1.25	2.01	3.51	2.41	0.87	3.34	2.09	0.86	0.17	1.08	1.34	1.45	0.14	73.97	26.03
17	96.23	59.97	88.21	3.26	95.37	87.30	94.44	96.53	92.09	91.99	3.32	31.75	25.26	7.20	10.79	5.81	62.70
18	112.43	84.63	105.89	18.51	11.68	104.76	110.69	112.58	109.62	108.15	97.79	102.17	8.86	97.86	68.77	79.78	1600.00

1-ICBC, 2-CCB, 3-BOC, 4-BOCOM, 5-IB, 6-CITIC, 7-SPD, 8-CMBC, 9-PAB, 10-HXB, 11-GPR, 12-PRI, 13-TRI, 14-EPU, 15-VIX, 16-WUI, 17-C. to others (spillover), 18-C. to others including own, 19-C. from others

Source: Authors' processing.

The spillover table for the Chinese banking sector highlights that the least affected institution by shocks originating from other banks is CCB (China Construction Bank Corp.), with a spillover from the other of 75.34. Comparing with the rest of the local banking system, which has similar values, CCB emerges as not being as interconnected with the system as the other banks, making it less vulnerable during periods of systemic stress.

On the other hand, the impact transmitted to other banks emphasise CMBC (China Minsheng Banking Corp. Ltd.), IB (Industrial Bank Co. Ltd.) and ICBC (Industrial and Commercial Bank of China Ltd.) as the most influential contributors to local systemic risk, contributing significantly to the spillover experienced by other banks.

The interbank connections suggest that most institutions form a strong network of influence, except one bank – CCB. This tight relationship highlights a potential systemic risk, as vulnerabilities can affect a broad range of institutions, and additional risk management strategies should be established.

Chinese banks are also affected by non-financial risk indicators, with PRI and EPU generating the most significant spillover contributions to the local banks, followed by WUI-GPR pair. As regards the influence of TRI, the Chinese banking sector seems to be the most prepared in face of vulnerabilities linked to the climate-related transition risk, registering the least significant spillovers when comparing with the US and European banking sectors. The results highlight a particular vulnerability to economic and global policy risks, besides the physical risks generated by climate change, which indicate a globally interconnected banking sector with prevalence to vulnerabilities generated by international issues.

5.2 Net spillover graphs

The net spillover graphs highlight both positive and negative net spillovers for all the three regions analysed, with significant influences especially during global or regional crises – the Covid-19 pandemic, the sovereign debt crisis in Europe, or the global financial crisis.

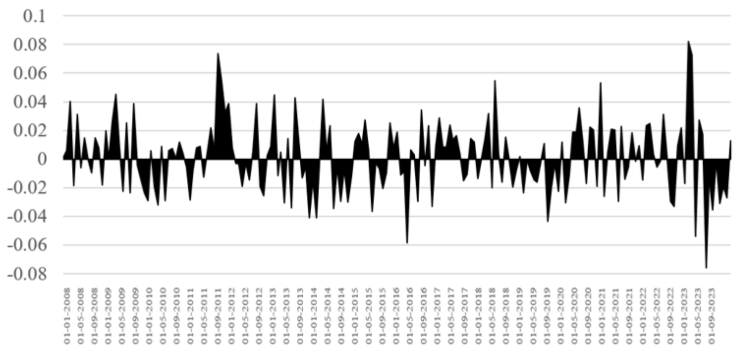


Figure 4. Net spillover for European banks
Source: Authors' own creation.

The European banks experienced a higher overall volatility during the entire period, with frequent fluctuations, especially in periods of stress like the sovereign debt crisis, Brexit, and Covid-19 years. The European banks register a more prolonged instability periods and seems to be more sensitive to non-financial risk drivers, with spillovers oscillating around zero, highlighting a permanent effort to find the balance between recovery and disturbances.

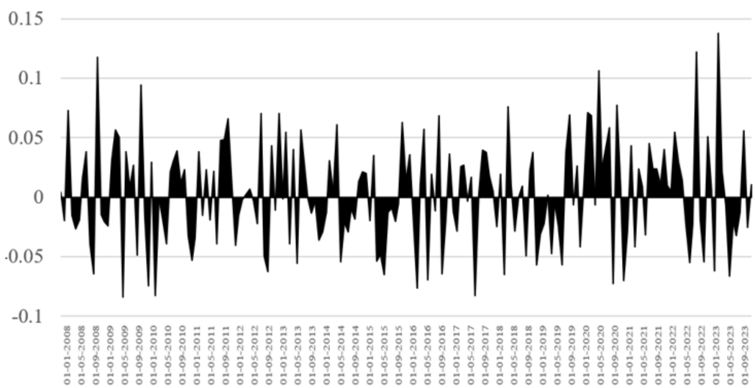


Figure 5. Net spillover for US banks
Source: Authors' own creation.

The US banking sector is also characterised by high volatility, but with a different pattern compared to European and Chinese banks. The US banks` net spillover reveal fewer and smaller fluctuations, suggesting a stronger and more developed recovery post-crisis function. However, the net spillover for US banks highlights that they are still vulnerable to emerging risks, particularly those with global impact.

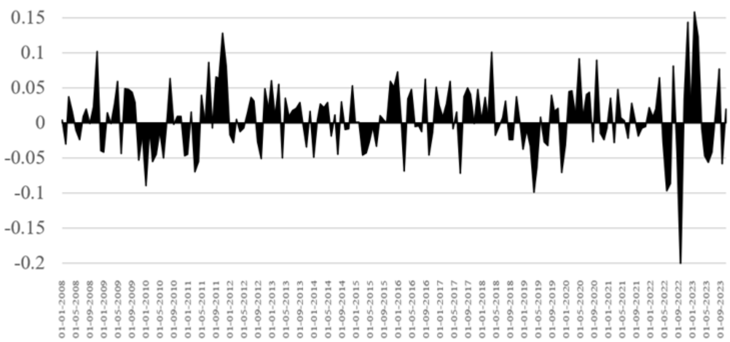


Figure 6. Net spillover for Chinese banks
Source: Authors' own creation.

The Chinese banking sector emerges as the first in terms of positive net spillovers, suggesting that non-financial risk factors influence the banks` share price more than in the US and Europe. The spikes indicate a highly responsive banking sector to both the domestic and international framework. The negative spillovers are fewer and emphasise a short-lived impact from the global disruptions, suggesting that local banks have a strong capacity to recover quickly.

6. Conclusions

The globalisation trend determined significant transformations in multiple business areas, including banking. Although the academic community has written many articles on the benefits and drawbacks related to globalisation¸ one single event can still trigger diverse market reactions globally. At the same time, market risk spillover is significantly asymmetric, evidenced by the fact that extreme negative shocks have a significantly larger market effect than extreme positive shocks, and the total risk spillover for negative shocks increases with the size of the shock.

Non-financial risks affect differently the banking sectors in US, Europe, and China, revealing significant disparities between these regions. The resilience of US banks reveals a stable banking sector with a risk management framework less susceptible to external-induced uncertainty. This stability could be due to a holistic approach to non-financial risks, which enriches US banks` capacity to absorb and mitigate stress, particularly related to global uncertainty and market volatility.

In contrast, the European banks are highly sensitive to economic policy uncertainty and geopolitical risks, revealing both an interconnected and vulnerable banking framework. This interconnectedness brings potential benefits in stable times, but in volatile periods it creates channels through which systemic risk can rapidly escalate.

Chinese banks also display a strong interbank connection and potential systemic risks that could have far-reaching consequences. Despite their exposure to global economic and policy risks, Chinese banks tend to be more resilient in face of climate-related transition risks, with lower spillover effects than US and European banks, suggesting more potential to address environmental risks.

The net spillover graphs highlight both positive and negative net spillovers for all the three regions analysed, with significant influences especially during global or regional crises – the Covid-19 pandemic, the sovereign debt crisis in Europe, or the global financial crisis.

These regional differences emphasise the importance of precise approaches to management of non-financial risks. Despite their well-developed ability to quickly recover from volatile situations, US banks remain vulnerable to emerging global risks. On the other hand, European banks tend to be more sensitive to non-financial risk factors and their prolonged periods of volatility require a continuous effort to develop and balance their risk management function. Meanwhile, Chinese banks appear to be more adaptable and responsive to both local and international risks, but they still remain exposed to global vulnerabilities.

The results indicate that emerging risks factors require the reassessment of the policy design and risk management strategies in the banking sector. A better understanding of the diverse impact that non-financial risk factors have in banking and quantification of these risks are of the utmost importance in maintaining customers` trust. If there is a track record and experience in managing financial risks, the area of non-financial risks and the impact on customer relations represent uncharted territory. Following this new map requires a risk culture and trust in banking organisations.

The different regional context and interest of banking organisations require a more integrated and coordinated risk management function, a top-down/bottom-up approach, and risk behaviour at all levels of responsibility. Additionally, it is necessary to strengthen market information sharing and coordination. The importance of non-financial risks is emphasised also by the differences in financing methods for the banks in the three regions analysed and by the variances in the connection between banks and the economy. This requires an approach specific to each context and a consistent effort by all stakeholders to understand the impact and quantification of non-financial risks for designing better policies and risk management strategies.

The results in this paper are the proof that there is always a trade-off between global development and emerging challenges, with different implications for regulators, supervisors, financial institutions, and customers. Future research should strive to better understand how these emerging risks affect banking organisations and provide solutions for a better risk management in cross-regional banking operations, as non-financial risks are an outstanding concern and there should be a call to raise the awareness in order for the banking sector to effectively address and manage it.

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