Brexit and the reversal of financial influence: the UK’s shift from net volatility transmitter to receiver

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Brexit and the reversal of financial influence: the UK's shift from net volatility transmitter to receiver

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ABSTRACT

This paper examines the long-term impact of Brexit on financial market interdependence by analysing net volatility spillovers between the UK and eight key European economies. Using a VAR-DCC-GARCH model and the Diebold-Yilmaz connectedness framework applied to daily stock index returns, we compare the pre-Brexit (2011-2016) and the post-Brexit (2020-2025) periods. The results reveal a structural shift. The UK transitioned from a net transmitter of volatility shocks (+11.8) before Brexit to a net receiver (-5.5) afterward. This reversal was driven by a reduction in the UK's ability to propagate volatility to European markets rather than reduced sensitivity to European shocks. Concurrently, Germany and Italy emerged as the primary beneficiaries, strengthening their roles as dominant volatility transmitters. Although the UK's influence diminished, the total system connectedness remained stable at approximately 71%, suggesting that other European markets have compensated for this shift. Interpreted through theories of financial segmentation and cross-market information transmission, our findings show that Brexit has structurally reconfigured the UK's position within the European financial system, diminishing its informational leadership while maintaining its exposure to regional shocks.

JEL classification: C32; C58; F36; G12; G15

Keywords: Brexit; Diebold-Yilmaz connectedness; Financial integration; VAR-DCC-GARCH; Volatility spillover

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1. Introduction

The 2016 Brexit referendum marked a break in the United Kingdom's institutional and economic ties with the European Union, triggering a re-evaluation of its financial integration with the continent. Although proponents framed the departure as a recovery of sovereignty and a gateway to global trade, the pre-referendum reality was one of deep entanglement. In 2015, the EU accounted for 42.6% of UK exports and 53% of imports (Webb and Ward, 2025). Existing research has explored Brexit's short-run market reactions and trade implications (Cucinelli et al., 2021; Buigut and Kapar, 2023), yet our understanding of its long-term impact on financial market interdependence remains incomplete, particularly regarding volatility transmission patterns.

To examine this, our analysis draws on the literature concerning financial market segmentation and how institutional structures shape cross-border risk transmission. When equity markets are highly integrated, common shocks are rapidly transmitted through prices, creating persistent cross-market volatility spillovers (Forbes and Rigobon, 2002). Segmentation, driven by frictions such as capital controls, regulatory divergence, or political barriers, dampens cross-border risk sharing and can alter which markets serve as primary transmitters of shocks (Bekaert et al., 2011). Brexit, as a process of institutional and economic disintegration involving the loss of passporting rights, growing regulatory divergence, and reduced capital mobility, is therefore expected not only to affect the level of UK–EU integration but also to reconfigure the pattern of financial leadership within the regional network (Sampson, 2017).

A second strand of theory emphasises market leadership and volatility transmission. Large, liquid, and information-rich financial centres tend to act as originators of volatility that propagates to satellite markets, reflecting both informational dominance and institutional centrality (King and Wadhwani, 1990). In the European context, London historically served as a key hub for trading, price discovery, and intermediation, suggesting that the UK would be a natural net transmitter of volatility to its regional peers. The reallocation of trading activity, the relocation of financial firms, and the gradual regulatory decoupling associated with Brexit create conditions under which this leadership role may weaken. It could be partially assumed by core euro area markets, particularly Germany, whose deep domestic exchanges and central position within the EU financial system make it a prime candidate.

These frameworks imply that Brexit should not merely alter the intensity of UK–EU spillovers but may qualitatively shift the direction and concentration of volatility flows. If the UK loses institutional centrality while remaining exposed to common European and global shocks, its role as a net transmitter of volatility would likely diminish. However, its vulnerability to incoming shocks from other markets would not decline proportionately. Our empirical analysis tests this predicted reconfiguration, by comparing pre- and post-Brexit windows using a VAR-DCC-GARCH model integrated with the Diebold-Yilmaz connectedness framework.

Several studies have tracked volatility dynamics around the referendum period, though none tests whether the UK'S structural role has permanently changed. Nishimura and Sun (2018) and Li (2020) find the UK's transmitting role lessened, but their analyses are confined to narrow event windows that cannot distinguish transient disruption from lasting configuration. Similarly, Belke et al. (2018) and Ben Ameur and Louhichi (2022) demonstrate that Brexit-related uncertainty elevated cross-market spillovers, yet neither extends beyond the transition phase nor examines the directional structure of net flows. Koch et al. (2024) employ textual analysis of over 34,000 Financial Times articles within a Diebold–Yilmaz framework and find that sentiment-driven spillovers intensified during key Brexit events. They observe a stronger effect from UK-specific than EU-focused news, suggesting markets perceived Brexit as a UK-centric risk. However, their focus on transitory sentiment dynamics (2015–2019) does not address whether these asymmetric effects became embedded in the post-Brexit equilibrium. Izzeldin et al. (2026), using a Brexit Intensity Measure, find the UK shifted from transmitter to receiver during the negotiation period, yet their sample ends in 2021, capturing fluctuating rather than settled transmission patterns. Beyond Brexit, Helmi et al. (2025) demonstrate that volatility is the dominant channel for cross-border contagion, and that a market's net spillover role is strongly determined by its relative size, a structural regularity consistent with the market-leadership mechanism of King and Wadhwani (1990).

The literature thus leaves two key gaps. First, studies such as Aristeidis and Elias (2018) argue that contagion was largely transient, with dependence reverting to pre-referendum patterns, while Wu et al. (2020) find REIT markets were largely shielded from Brexit effects, yet these assessments predate the establishment of the post-Brexit trading regime and cannot speak to the structural equilibrium that has since emerged. Second, the within-process analyses of Koch et al. (2024) and Izzeldin et al. (2026) find fluctuations in the UK's role but do not establish whether those patterns crystallised into permanent features. As sufficient post-departure data now exist, a rigorous long-run analysis is both possible and overdue.

In this respect, our contribution is threefold. First, we provide the first long-term analysis of directional volatility spillovers between the UK and eight major European equity markets, that isolates the post-Brexit equilibrium from the negotiation phase, comparing two five-year windows (2011–2016 and 2020–2025). Second, we move beyond prior connectedness applications that emphasise overall spillover intensity by combining time-varying conditional correlations with net directional and pairwise indices, allowing us to quantify shifts in market leadership and identify which economies have absorbed the UK's former transmitting role. Third, by explicitly linking our empirical findings to theories of segmentation, disintegration, and market leadership, we show that the observed reversal, from the UK as a net volatility transmitter to a net receiver, alongside strengthened transmitting roles for Germany and Italy, constitutes evidence of a reconfigured European financial network rather than a transient manifestation of global shocks.

The paper proceeds as follows. Section 2 describes the data, and section 3 discusses the methodology. Section 4 presents the empirical results, and section 5 concludes.

2. Data and preliminary analysis

The data set is sourced from Bloomberg and consists of daily closing prices for the FTSE 100 (UK) and eight major European indices: AEX (Netherlands), ISEQ 20 (Ireland), OMXS 30 (Sweden), CROBEX 10 (Croatia), WIG 20 (Poland), FTSE MIB (Italy), CAC 40 (France), and DAX (Germany). Our analysis focuses on two separate five-year periods: from February 20, 2011, to February 20, 2016 (pre-Brexit), and from January 31, 2020, to January 31, 2025 (post-Brexit)[1]. Selected based on exposure rankings from Irwin (2015), these indices offer geographical diversity and represent economies with varying degrees of trade and financial linkage to the UK. We calculated daily log returns as $R_t = \ln(P_t/P_{t-1})$, where P_t denotes

[1] The negotiation period (2016–2020) is deliberately excluded. This window encompasses the referendum, the Article 50 notification, three parliamentary rejections of the withdrawal agreement, and the final Trade and Cooperation Agreement, generating acute but transitory political uncertainty. Izzeldin et al. (2026) demonstrate that volatility transmission patterns fluctuated substantially across these phases, with the UK alternating between transmitter and receiver roles. Koch et al. (2024) similarly show that sentiment-driven spillovers intensified episodically around key events. Including this period would conflate transitional dynamics with the long-run structural shift that is our focus.

the closing price on day t. Weekends and non-synchronous holidays across markets were excluded using listwise deletion to avoid artificial serial correlation (Lo and MacKinlay, 1990), yielding 1,193 and 1,200 observations for the pre- and post-Brexit periods, respectively.

Table 1 reports the descriptive statistics. Pre-Brexit, mean returns are close to zero, while post-Brexit, all markets exhibit positive mean returns. Volatility, captured through standard deviation, ranges from 0.0105 (FTSE100) to 0.0178 (FTSEMIB) pre-Brexit, with Western European indices displaying lower volatility than their Eastern and Southern European counterparts. Post-Brexit, most series experience a moderate rise in volatility, though their relative ordering remains unchanged. Both periods exhibit negative skewness and high kurtosis, intensifying after Brexit. Jarque-Bera statistics reject normality for all series. Furthermore, unit root tests (ADF and PP) confirm stationarity, while significant Ljung-Box Q^2 and ARCH-LM statistics validate the presence of conditional heteroskedasticity, supporting the use of a DCC-GARCH model with Student's t-distributed errors.

Table 1
Descriptive statistics of daily market returns.

	FTSE100	AEX	ISEQ	OMXS30	CRO10	WIG20	FTSEMIB	CAC	DAX
Panel A: pre-Brexit (February 20, 2011 - February 20, 2016, 1193 observations)									
Mean	0.0000	0.0001	0.0006	0.0002	-0.0002	-0.0004	-0.0002	0.0000	0.0002
Std. Dev.	0.0105	0.0121	0.0119	0.0129	0.0169	0.0122	0.0178	0.0142	0.0140
Skewness	-0.3803	-0.2626	-0.3402	-0.2357	-0.0901	-0.5349	-0.2196	-0.1404	-0.3003
Kurtosis	5.7605	4.9647	4.8403	5.3780	5.9133	6.5514	4.0395	4.8653	5.2230
JB	408*	206*	191*	292*	423*	684*	63*	177*	264*
LB-Q	10.74	5.35	9.82	10.45	6.61	12.37	11.68	6.83	6.86
LB- Q^2	284*	231*	156*	270*	26*	123*	180*	213*	216*
ARCH-LM	158*	135*	100*	159*	21*	80*	118*	133*	130*
ADF	-34.42*	-33.65*	-33.46*	-35.73*	-34.06*	-32.59*	-37.12*	-35.13*	-33.17*
PP	-34.54*	-33.64*	-33.71*	-36.18*	-34.05*	-32.54*	-37.12*	-35.26*	-33.14*
Panel B: post-Brexit (January 31, 2020 - January 31, 2025, 1200 observations)									
Mean	0.0001	0.0004	0.0003	0.0003	0.0005	0.0001	0.0004	0.0003	0.0004
St. Dev.	0.0112	0.0122	0.0142	0.0125	0.0088	0.0163	0.0147	0.0134	0.0135
Skewness	-1.1742	-0.8186	-0.6467	-0.7018	-3.2572	-0.8103	-2.2351	-0.9129	-0.6778
Kurtosis	18.801	13.497	9.0183	10.314	44.938	11.093	29.736	15.508	16.414
JB	12759*	5643*	1894*	2772*	90060*	3405*	36741*	7989*	9088*
LB-Q	7.73	4.82	6.17	5.12	94.98*	4.95	19.53*	8.93	10.59
LB- Q^2	285*	275*	473*	168*	484*	220*	182*	307*	187*
ARCH-LM	206*	227*	320*	117*	284*	169*	147*	231*	163*
ADF	-38.39*	-38.61*	-37.61*	-36.01*	-42.01*	-35.29*	-38.55*	-38.55*	-38.97*
PP	-36.07*	-34.81*	-33.64*	-36.02*	-37.78*	-36.29*	-36.06*	-35.42*	-35.46*

Note: * indicates significance at the 1% level. JB, LB-Q, LB-Q^2, ARCH-LM are the Jarque-Bera test, the Ljung-Box Q-test, the Ljung-Box Q^2-test and the ARCH Lagrange Multiplier test, respectively. ADF and PP are the Augmented Dicky-Fuller and Phillips-Perron unit root tests, respectively.

3. Methodology

We use a two-stage methodology that first models time-varying volatility and correlation using a VAR-DCC-GARCH framework and then quantify volatility spillovers using the connectedness approach of Diebold and Yilmaz (2012, 2014), as extended by Gabauer (2020, 2025). The full model specification is provided in Appendix A.

The conditional mean is specified as a VAR(1) for the 9×1 vector of returns ($\boldsymbol{z}_t$), where lag length selection criteria (AIC, HQ, FPE) favoured this specification. To model the conditional variance-covariance matrix $\boldsymbol{H}_t$, we use the DCC-GARCH specification of Engle (2002), which decomposes $\boldsymbol{H}_t$ into a diagonal matrix ($\boldsymbol{D}_t$) of conditional variances (h_t) from univariate GARCH-type structures, and a time-varying correlation matrix ($\boldsymbol{R}_t$). The DCC-GARCH is preferred over more complex multivariate GARCH models (e.g. BEKK) for its parsimony in multivariate settings (Bauwens et al., 2006). The dynamic correlations evolve according to a mean-reverting process governed by two non-negative scalar parameters (λ_1 and λ_2), satisfying $\lambda_1 + \lambda_2 < 1$. Estimation proceeds by quasi-maximum likelihood under Student's t-distributed errors to account for fat tails.

From the estimated DCC-GARCH model, we extract the conditional volatility series and use them as inputs into the generalised connectedness framework. The framework is based on forecast error variance decompositions from a generalised VAR of the volatility series (Koop et al., 1996; Pesaran and Shin, 1998). The generalised forecast error variance decomposition (GFEVD) quantifies the share of forecast error variance in market i attributable to shocks in market j, and is normalised so that rows sum to unity. The total connectedness index (TCI) captures system-wide spillovers as the scaled average of off-diagonal elements.

The key metric of interest is the net spillover (NS) for each market. The difference between volatility transmitted to all other markets (TO) and volatility received from all others (FROM). A positive (negative) NS indicates a net transmitter (receiver). The net pairwise directional spillover (NPDS) quantifies bilateral dominance in volatility flows. Our analysis uses the Connectedness Approach package (Gabauer, 2025) with a 10-step-ahead forecast horizon and 200-day rolling window.

4. Empirical results

Table 2 reports diagnostic statistics for the VAR(1)-DCC-GARCH(1, 1) model. The univariate Ljung-Box and ARCH-LM tests indicate no remaining autocorrelation or ARCH effects, respectively. The multivariate Portmanteau test is insignificant at lags 6 and 12, confirming adequate specification. Importantly, the dynamic conditional correlations are persistent and stationary, with the sum of the DCC parameters ($\lambda_1 + \lambda_2$) is slightly higher in post-Brexit (0.9765) versus pre-Brexit (0.9708). Furthermore, the evidence of multivariate non-normality using Doornik-Hansen test is comm8on in financial return data and validates our choice of Student's t-distributed errors.

Table 2
Diagnostic statistics for model adequacy of VAR(1)-DCC-GARCH(1,1).

	FTSE100 (GBR)	AEX (NLD)	ISEQ (IRL)	OMXS30 (SWE)	CRO10 (HRV)	WIG20 (POL)	FTSEMIB (ITA)	CAC (FRA)	DAX (DEU)
Panel A: pre-Brexit									
LB-Q (6)	2.34	8.84	4.79	4.33	3.02	8.21	4.96	8.33	3.74
LB-Q (12)	6.36	13.48	17.24	7.68	8.17	10.23	10.74	13.01	17.08
ARCH (6)	3.77	2.06	10.94	5.04	4.97	6.41	6.13	7.63	6.73
ARCH (12)	6.07	8.16	17.01	7.82	18.89	11.55	8.00	12.65	10.58
Multi-Q (6)	544.52								
Multi-Q (12)	1041.68								
Multi-ARCH (6)	55.80								
Multi-ARCH (12)	115.03								
Multi-DH	10631*								
$\lambda_1 + \lambda_2$	0.9708								
Panel B: post-Brexit									
LB-Q (6)	8.64	4.30	11.66	2.97	4.61	4.13	4.94	12.30	5.93
LB-Q (12)	10.74	6.82	15.48	12.04	8.05	12.94	11.21	15.39	11.86
ARCH (6)	9.12	3.96	5.72	4.17	1.50	2.82	4.19	7.06	7.64
ARCH (12)	14.56	13.54	9.26	6.57	19.62	9.95	8.21	10.42	13.20
Multi-Q (6)	572.58								
Multi-Q (12)	1017.70								
Multi-ARCH (6)	53.51								
Multi-ARCH (12)	136.46								
Multi-DH	28700*								
$\lambda_1 + \lambda_2$	0.9765								

Note: * indicates significance at the 1% level. LB-Q, ARCH, Multi-Q, Multi-ARCH, Multi-DH are the univariate Ljung-Box Q-test at lags 6 and 12, the ARCH Lagrange Multiplier test, the multivariate Ljung-Box (Portmanteau) test, the multivariate ARCH-LM test and the Doornik-Hansen test for multivariate normality, respectively.

The Diebold-Yilmaz connectedness results are presented in Table 3 and Figures 1 to 4. The most notable finding is the reversal in the United Kingdom's role within the European volatility system. In the pre-Brexit period, the UK was a net transmitter of volatility (Net: +11.78), ranking among the most influential markets. It transmits 88.22% of spillovers to others while receiving 76.44% from them. In the post-Brexit period, this position shifted: the UK became a net receiver of volatility (Net: -5.5). Its pairwise transmitter count also fell from five to two. This shift was driven not by a surge in received shocks - which remained stable at 76.93% - but by an approximately 17% decline in shocks transmitted from the UK to European peers. This asymmetry is precisely what the market-leadership framework predicts. As the UK's institutional ties weakened through the loss of passporting rights and regulatory alignment, the informational relevance of its market signals for continental investors diminished. This reduced the cross-border propagation of UK-originated volatility without altering the UK's exposure to common European shocks. Koch et al. (2024) provide corroborating evidence that investors perceived Brexit primarily as a UK-centric risk. Our results indicate that this asymmetric perception has now crystallised into a permanent structural feature of the post-Brexit financial landscape.

Concurrently, Germany strengthened its position as the dominant net transmitter, with its net spillover increasing from +16.31 to +24.36, a result of both increasing its outward transmissions (from 96.61% to 102.99%) and slightly reducing its inward vulnerability. Moreover, Italy underwent a remarkable transformation, moving from a net receiver (-11.49) to the second-largest net transmitter (+13.53) in the post-Brexit period. These shifts are consistent with the segmentation framework of Bekaert et al. (2011). As the UK's regulatory connections eroded, the European financial network reorganised around its remaining core economies. Germany and Italy absorbed the transmitting role formerly shared with the UK - a pattern reinforced by the established finding that market size and institutional centrality determine spillover roles (Helmi et al., 2025; Izzeldin et al., 2026).

As a robustness check, we estimated a VAR(0)-DCC-GARCH(1, 1) model as suggested by the SBIC. The qualitative conclusion - the UK's shift from a net transmitter to a net receiver remained unchanged, confirming that our core finding is not sensitive to the mean equation specification.

Table 3
Results of the DY spillovers for nine selected European stock markets.

	FTSE100 (GBR)	AEX (NLD)	ISEQ (IRL)	OMXS30 (SWE)	CRO10 (HRV)	WIG20 (POL)	FTSEMIB (ITA)	CAC (FRA)	DAX (DEU)	FROM others
Panel A: Pre-Brexit										
FTSE 100	23.56	15.84	7.88	12.89	0.67	6.42	7.09	13.41	12.23	*76.44*
AEX	14.10	19.68	7.7	13.29	0.73	5.31	9.19	15.93	14.07	*80.32*
ISEQ	11.17	13.35	25.19	12.39	1.23	4.27	7.36	12.76	12.29	*74.81*
OMXS30	12.38	14.52	7.53	23.3	0.53	6.04	7.55	13.78	14.36	*76.70*

CRO10	3.92	5.04	4.94	3.85	65.77	3.07	4.99	4.00	4.43	*34.23*
WIG20	11.30	10.42	5.55	9.93	1.32	34.75	7.32	8.81	10.6	*65.25*
FTSEMIB	10.26	13.71	6.37	10.48	1.01	4.41	24.75	15.73	13.3	*75.25*
CAC	12.75	15.92	6.61	12.86	0.82	4.86	11.20	19.64	15.34	*80.36*
DAX	12.35	14.89	7.36	13.87	1.07	5.63	9.06	16.08	19.7	*80.30*
TO others	88.22	103.69	53.93	89.55	7.39	40.01	63.76	100.5	96.61	643.67
Inc. own	111.78	123.37	79.12	112.86	73.16	74.76	88.51	120.14	116.31	**TCI**
Net (NS)	**11.78**	**23.37**	**-20.88**	**12.86**	**-26.84**	**-25.24**	**-11.49**	**20.14**	**16.31**	**71.52**
Pairwise	5	7	2	5	0	1	3	8	5	
Panel B: Post-Brexit										
FTSE 100	23.07	11.31	7.59	9.79	3.74	8.13	12.47	11.98	11.92	*76.93*
AEX	10.87	23.91	7.34	11.22	2.47	5.13	11.8	12.71	14.56	*76.09*
ISEQ	9.97	7.52	25.85	9.8	3.98	7.26	11.49	11.71	12.42	*74.15*
OMXS30	9.62	11.26	8.38	22.6	2.58	6.25	12.38	11.44	15.48	*77.4*
CRO10	4.22	2.8	3.75	3.7	62.52	8.67	4.31	5.19	4.83	*37.48*
WIG20	7.41	7.08	6.14	7.62	7.65	38.61	8.16	6.51	10.83	*61.39*
FTSEMIB	10.07	9.4	8.02	9.7	2.8	5.93	22.24	15.17	16.67	*77.76*
CAC	10.15	10.24	8.22	10.09	2.92	5.48	15.57	21.07	16.26	*78.93*
DAX	9.13	10.67	8.23	12.01	2.95	6.34	15.11	14.2	21.37	*78.63*
TO others	71.43	70.29	57.67	73.93	29.07	53.19	91.29	88.9	102.99	638.77
Inc. own	94.5	94.2	83.52	96.54	91.59	91.8	113.53	109.97	124.36	**TCI**
Net (NS)	**-5.5**	**-5.8**	**-16.48**	**-3.46**	**-8.41**	**-8.2**	**13.53**	**9.97**	**24.36**	**70.97**
Pairwise	2	5	0	4	1	3	7	6	8	

Note: The table reflects the spillover effects across nine stock market returns. The row 'TO others' represents the spillover from one stock return to all other, and the last column 'FROM others' represents the spillover received by one stock market from all others. The row 'Net' represents the net directional spillover for a specific market, indicating whether it is a net transmitter or a net recipient of shocks. The row 'Pairwise' counts the number of other markets to which a given index is a net transmitter, derived from NPDS. TCI is the Total Connectedness Index.

Figures 3 and 4 show the rolling-sample net pairwise directional spillovers (NPDS). Pre-Brexit, the UK exerted strong net transmitting influence over several markets, notably Poland (WIG20) and Italy (FTSE MIB). Post-Brexit, these relationships inverted: the UK became a net receiver of volatility from both Poland and Italy. The UK's net spillover deficit with Germany (DAX) also deepened. These pairwise results align with the cross-border transmission of policy uncertainty to vulnerable economies (Belke et al., 2018) but now show the UK on the receiving end of such flows.

The stability of the Total Connectedness Index (TCI: 71.5% to 71.0%) is particularly telling when compared with Izzeldin et al. (2026), who find a sharp decline to 60% immediately after the referendum. The acute fragmentation they capture was transitory; by the post-Brexit equilibrium, system-wide connectivity had largely recovered, yet the internal distribution of influence had permanently changed. In the terminology of Forbes and Rigobon (2002), what occurred was not contagion, a temporary intensification of linkages, but a reconfiguration of the underlying interdependence structure. A potential counterargument is that the post-Brexit period was affected by common global shocks such as the COVID-19 pandemic and the

Russia-Ukraine war. However, symmetric shocks elevate volatility across all markets but do not systematically rewire the network's transmitter–receiver structure. The directional reversal in the UK's role, occurring alongside the strengthening of EU core transmitters, is consistent with the institutional disintegration mechanism rather than common-shock effects.

5. Conclusion

This paper provides robust empirical evidence of a structural shift in financial market interdependence between the UK and key European economies following Brexit. The UK transitioned from a net transmitter to a net receiver of volatility, a change driven by a sharp decline in its ability to propagate shocks to continental markets, rather than by increased insulation from them. Interpreted through the frameworks of King and Wadhwani (1990) and Bekaert et al. (2011), this reversal reflects the erosion of the UK's informational leadership within European equity markets, a consequence of the institutional disintegration that Sampson (2017) anticipated.

Our findings extend the transitional evidence of Koch et al. (2024) and Izzeldin et al. (2026) by confirming that the fluctuating patterns they observed have crystallised into a permanent reconfiguration. Germany strengthened its role as the dominant transmitter, and Italy transformed into a prominent transmitter, while total system connectedness remained stable at approximately 71%, indicating a resilient but fundamentally reorganised European financial network.

These findings carry implications for financial stability monitoring: supervisory frameworks should account for the UK's diminished capacity to propagate, but continued vulnerability to absorb, continental shocks. For portfolio managers, the redistribution of spillover roles requires updated cross-border hedging strategies reflecting the new hierarchy of European volatility transmitters. Future research could investigate whether the UK has developed stronger volatility links with global financial centres outside Europe as a potential counterbalance to its reduced influence within the continent, and whether extending the analysis to bond and currency markets reveals similar patterns of reconfiguration.

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Appendix A

This appendix provides the formal specification of the VAR-DCC-GARCH model, and the Diebold-Yilmaz connectedness framework summarise in Section 3.

A.1 VAR-DCC-GARCH model

The conditional mean equation is specified as a vector autoregressive (VAR) model to capture short-term interdependencies across market returns. Lag length selection criteria (AIC, HQ, FPE) favoured a VAR(1) specification for the 9×1 vector of returns ($\boldsymbol{z}_t$):

$$\boldsymbol{z}_t = \phi_0 + \phi_1 \boldsymbol{z}_{t-1} + \boldsymbol{\varepsilon}_t$$

where ϕ_0 is a 9-dimensional constant vector, ϕ_1 is a 9×9 coefficient matrix, and $\boldsymbol{\varepsilon}_t$ is a vector of innovations with mean zero and conditional variance-covariance matrix $\boldsymbol{H}_t$ which is positive-definite.

To model the matrix $\boldsymbol{H}_t$, we use the Dynamic Conditional Correlation GARCH (DCC-GARCH) specification of Engle (2002), which decomposes $\boldsymbol{H}_t$ as:

$$\boldsymbol{H}_t = \boldsymbol{D}_t^{1/2} \boldsymbol{R}_t \boldsymbol{D}_t^{1/2}$$

where $\boldsymbol{D}_t = diag(h_{11,t}, \dots, h_{99,t})$ is a diagonal matrix containing the conditional variances (h_t) from the univariate GARCH-type structures, and $\boldsymbol{R}_t$ is a 9×9 conditional time-varying correlation matrix given by

$$\boldsymbol{R}_t = \boldsymbol{Q}_t^{*-\frac{1}{2}} \boldsymbol{Q}_t \, \boldsymbol{Q}_t^{*-\frac{1}{2}}$$

$$\boldsymbol{Q}_t^{*-\frac{1}{2}} = diag\left(q_{11,t}^{-1/2}, \dots, q_{99,t}^{-1/2}\right)$$

and $\boldsymbol{Q}_t = (q_{ij,t})$ is a 9×9 symmetric positive definite matrix and is defined in the DCC as

$$\boldsymbol{Q}_t = (1 - \lambda_1 - \lambda_2)\overline{\boldsymbol{Q}} + \lambda_1 \boldsymbol{\eta}_{t-1} \boldsymbol{\eta}'_{t-1} + \lambda_2 \boldsymbol{Q}_{t-1}$$

where λ_1 and λ_2 are non-negative scalar parameters satisfying $\lambda_1 + \lambda_2 < 1$, $\boldsymbol{\eta}_t$ is the standardised error vector, where $\eta_{it} = \varepsilon_{it} / \sqrt{h_{ii,t}}$, and $\overline{\boldsymbol{Q}}$ is unconditional covariances matrix. The model is estimated via the quasi-maximum likelihood under Student's t-distributed errors to account for fat tails.

A.2 Diebold-Yilmaz connectedness framework

From the estimated DCC-GARCH model, we extract the conditional volatility series for each market. These series are then used as inputs into the generalised connectedness framework of

Diebold and Yilmaz (2012, 2014) as implemented by Gabauer (2020, 2025). The framework is based on forecast error variance decompositions from a generalised VAR (GVAR) of the volatility series $\boldsymbol{x}_i$ that are due to shocks in $\boldsymbol{x}_j, i, j = 1, 2, \dots, k$ (Koop et al., 1996; Pesaran and Shin, 1998). Consequently, the generalised forecast error variance decomposition (GFEVD) at horizon f can be computed as,

$$\theta_{i\leftarrow j}^{gen}(F) = \frac{\sum_{f=0}^{F-1}(\mathbf{e}_i'\mathbf{A}_f\boldsymbol{\Sigma}\mathbf{e}_j)^2}{(\mathbf{e}_j'\boldsymbol{\Sigma}\mathbf{e}_j)\sum_{f=0}^{F-1}(\mathbf{e}_i'\mathbf{A}_f\boldsymbol{\Sigma}\mathbf{A}_f'\mathbf{e}_i)}$$

where $\boldsymbol{\Sigma}$ is the variance-covariance matrix of the error vector in the GVAR, $\mathbf{A}_f$ is the coefficient matrix from the MA representation from the GVAR, and $\mathbf{e}_i$ is a vector with one in the ith element and zeros elsewhere.

As the shocks in the GVAR model are not orthogonal, the GFEVD is normalised so that each row sums to unity:

$$gSOT_{i\leftarrow j}(F) = \frac{\theta_{i\leftarrow j}^{gen}(F)}{\sum_{j=1}^{k}\theta_{i\leftarrow j}^{gen}(F)}$$

with $\sum_{j=1}^{k} gSOT_{i\leftarrow j}(F) = 1$ and $\sum_{i,j=1}^{k} gSOT_{i\leftarrow j}(F) = k$.

Accordingly, the total connectedness index (TCI), measuring system-wide spillovers, can be defined as:

$$TCI(F) = \frac{\sum_{i,j=1,i\neq j}^{k} gSOT_{i\leftarrow j}(F)}{k} \times 100$$

The directional spillovers transmitted from market i to all other markets, TO_i, and received by market i from all others, $FROM_i$, are defined in the following two equations, respectively:

$$TO_i = \frac{\sum_{j=1,i\neq j}^{k} gSOT_{j\leftarrow i}(F)}{k} \times 100$$

$$FROM_i = \frac{\sum_{j=1,i\neq j}^{k} gSOT_{i\leftarrow j}(F)}{k} \times 100$$

The key metric of interest is the net spillover (NS) for market i, defined as:

$$NS_i = TO_i - FROM_i$$

A positive (negative) NS_i indicates the market is a net transmitter (receiver) of volatility. Similarly, the net pairwise directional spillover (NPDS) between markets i and j is:

$$NPDS_{ij} = \left[\frac{gSOT_{i\leftarrow j}(F) - gSOT_{j\leftarrow i}(F)}{k}\right] \times 100$$

A positive NPDS suggests that stock price in index i is influenced by those in index j, while a negative NPDS suggests the stock price in index i influences those in index j.

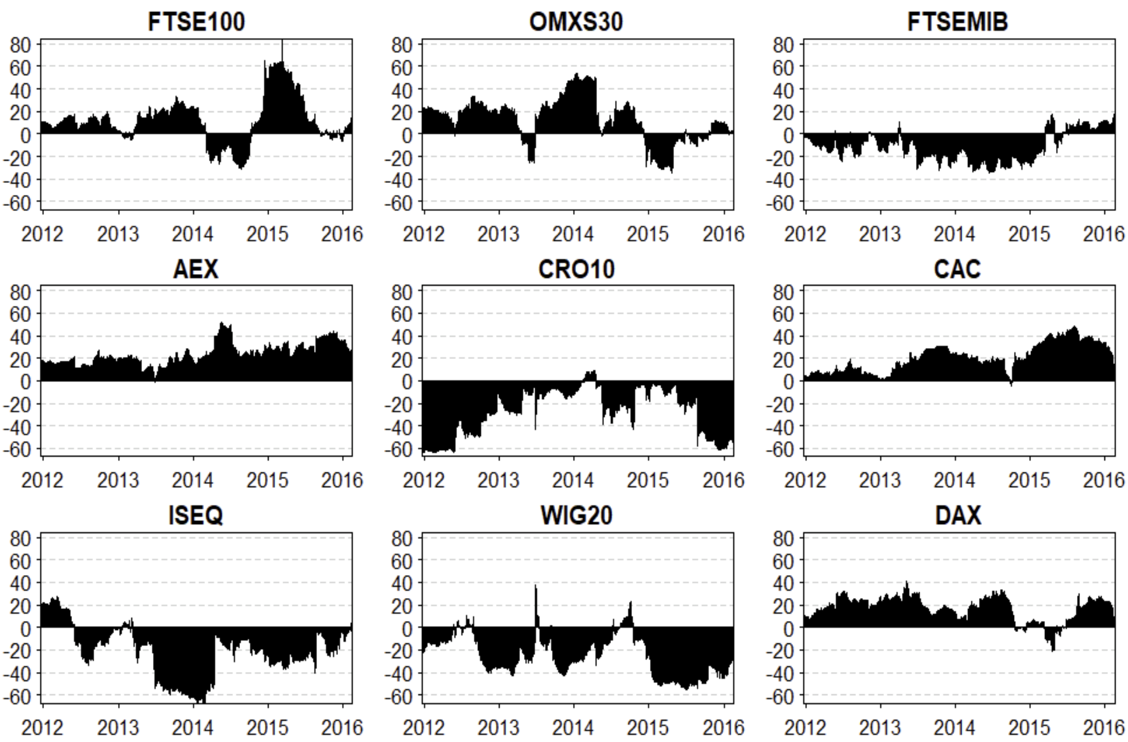

Fig. 1: The net spillover indices of major European markets (pre-Brexit, 2011-2016).

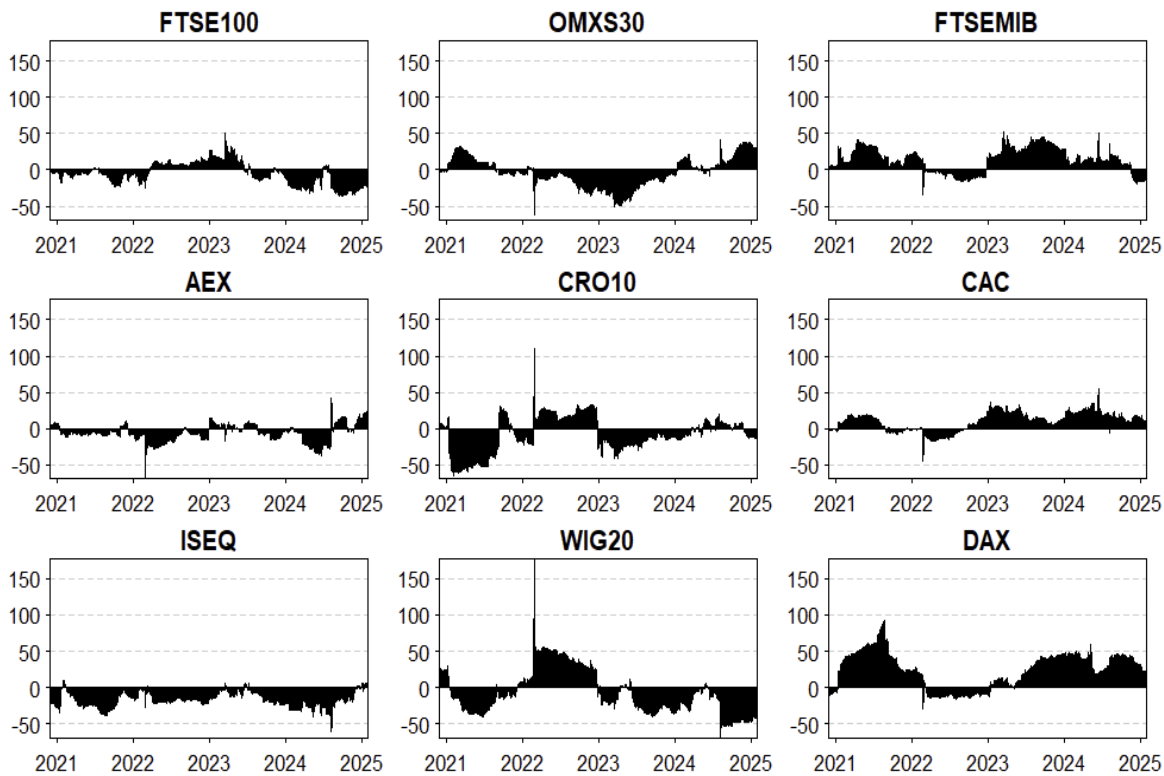

Fig. 2: The net spillover indices of major European markets (post-Brexit, 2020-2025).

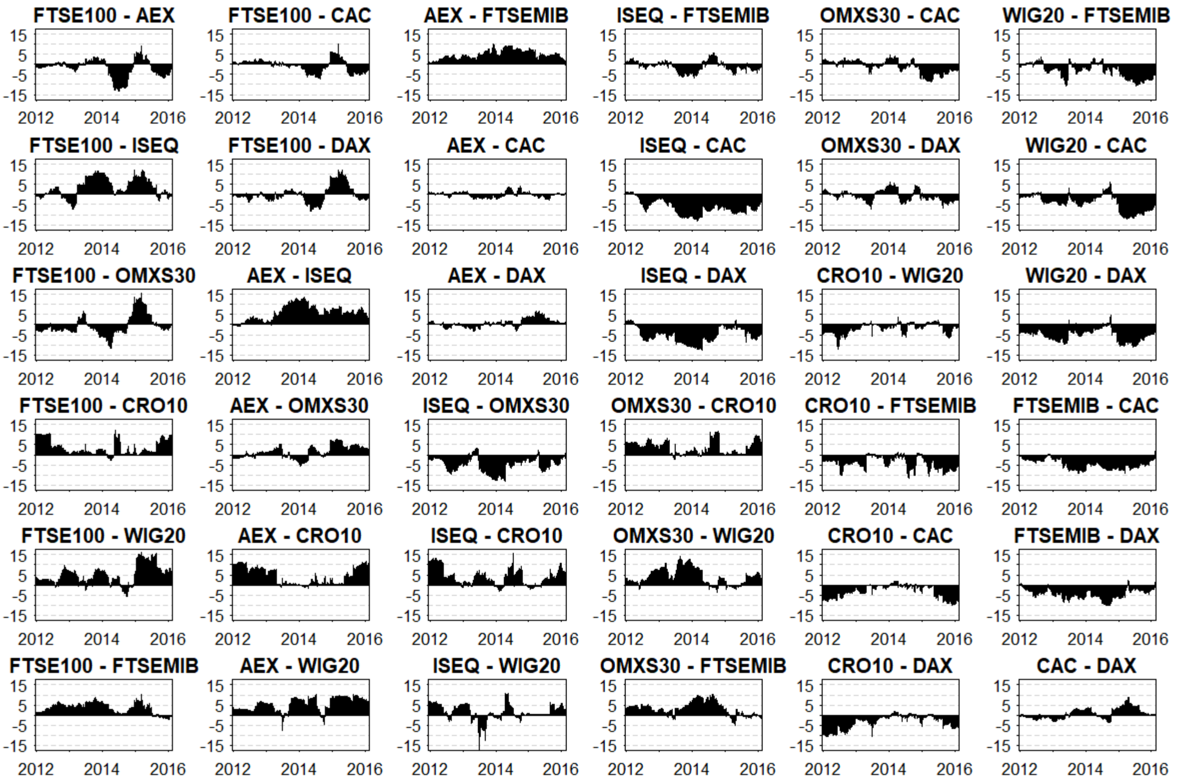

Fig. 3: The net pairwise directional spillover indices (NPDS) among major European markets (pre-Brexit, 2011-2016).

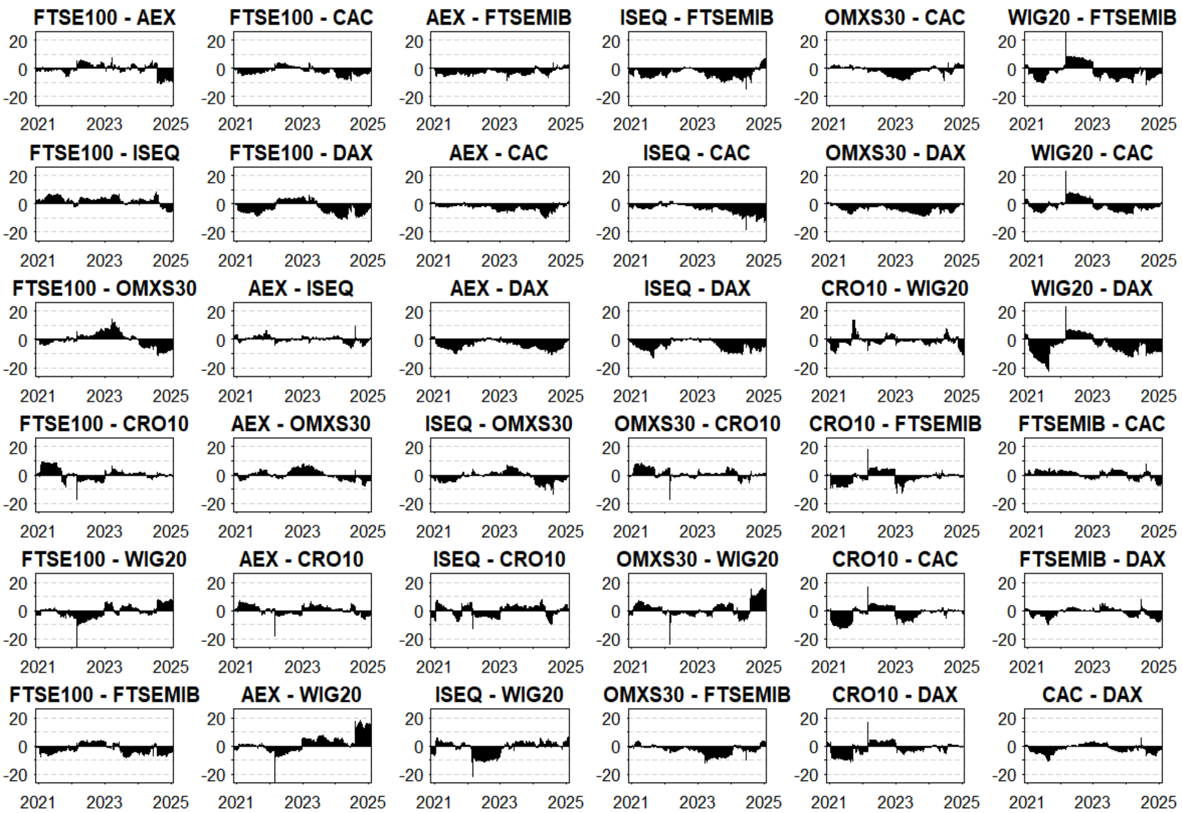

Fig. 4: The net pairwise directional spillover indices (NPDS) among major European markets (post-Brexit, 2020-2025).